
RUBRICS

Key Drivers in Flood and Drought Risk Assessment: Unveiling Risk Factors through a Multi-Metric Network Approach

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Abstract—Flood and drought risks in river basins are driven by a complex interplay of natural and anthropogenic factors, making their assessment and management particularly challenging. This paper presents a novel approach to systematically identify and evaluate the most influential parameters contributing to these risks. We employed Interpretive Structural Modelling (ISM) and Causal Loop Diagrams (CLD) to construct a comprehensive framework of 116 interconnected parameters. By applying 11 network metrics, including betweenness centrality, PageRank, and closeness centrality, we identified the key parameters that act as critical influencers within the system [4]. The Cross-Entropy method was then utilized to refine this set, pinpointing the most significant 30 percent of parameters across all metrics. This analysis led to the development of causal networks for flood and drought risks, highlighting the dynamic relationships and critical drivers in each context. The findings provide a robust foundation for decision-makers to prioritize resources, optimize risk management strategies, and predict future risks. This work offers valuable insights for policymakers and river basin managers to converge socio-environmental planning and transboundary water management, while also supporting the proactive mitigation of flood and drought impacts.

Keywords: flood and drought risk assessment, network metrics, key risk factors, river basin management, resilience and risk mitigation

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INTRODUCTION

Flood and drought risks are significant environmental challenges, particularly within river basins that are crucial for agriculture, water supply, and energy production. These risks are influenced by a combination of natural processes, such as rainfall variability and topography, as well as human activities, including land use changes, water management policies, and socio-economic dynamics [30]. Effective risk management in river basins requires a deep understanding of how these diverse factors interact across temporal and spatial scales.

Many traditional flood and drought risk assessment models have focused on specific, isolated drivers and emphasized the probability of occurrence or the magnitude of these events. For example, conventional flood risk models frequently prioritize hydrological factors, such as river discharge and precipitation extremes [13, 22, 31], while drought models often focus on meteorological parameters like rainfall defi-

cits or temperature anomalies [9]. These models, though valuable for estimating the probability or severity of specific events, tend to rely on a limited number of parameters – sometimes just one – and neglect the broader system dynamics that influence these risks. This narrow focus can overlook critical interconnections that shape the overall vulnerability of a region.

Recent studies have expanded the definition of risk to include not only the likelihood or magnitude of a flood or drought but also the potential for mitigation, resilience, and socio-economic interdependencies [14]. For example, the risk of flooding or drought can be reduced through the enhancement of community resilience or through mitigation strategies such as improved land use planning, water management, and policy interventions [28, 32]. Furthermore, flood and drought risks often have a two-way relationship with local economies, where economic development can either exacerbate vulnerabilities or provide the means to buffer against extreme events [2]. Therefore, the

broader definition of risk explored in this research considers not only hydrological or meteorological events but also a complex network of interconnections between natural processes, human interventions, and socio-economic factors.

Addressing flood and drought risks through a broader, interconnected perspective remains a critical challenge in water resource management. Traditional models often focus on isolated drivers, such as high river discharge or heavy rainfall, and fail to account for the complex feedback loops and interdependencies between these events and other influencing factors, including land use, socio-economic resilience, and governance [8, 23]. As a result, opportunities for reducing risk through enhancing community resilience or leveraging socio-economic development are often missed. Upcoming subsections highlight some of such challenges, current approaches and possible developments.

Traditional Approaches to Risk Assessment

Traditional risk assessments for floods and droughts have predominantly focused on quantifying the probability of occurrence and the magnitude of these events, often relying on a small number of parameters [13, 22]. For instance, many floods risk models centre around hydrological data, such as river discharge rates and rainfall extremes, to estimate the probability and potential severity of flooding [30]. Similarly, drought models typically focus on meteorological indicators like precipitation deficits, temperature anomalies, or soil moisture content [9]. However, these approaches often fail to consider the broader system dynamics, including socio-economic resilience, land-use practices, and governance factors, which can either exacerbate or mitigate the impacts of extreme events [28].

Recent research highlights the importance of incorporating a wider range of parameters into risk assessments to better understand the role of mitigation capacities and socio-economic factors in shaping risk outcomes. These studies argue that addressing flood and drought risks in isolation from broader socio-economic systems overlooks critical opportunities for reducing vulnerabilities through resilience-building and adaptation strategies [8, 14]. The shift towards a more comprehensive approach to risk assessment is supported by evidence that interconnected risks can be moderated through enhancing community resilience and economic development [2].

Integrated Systems Thinking in Water Risk Management

The application of systems thinking to water risk management has gained prominence in recent years, particularly for understanding the complex interconnections between flood and drought risks. Systems-based approaches recognize that flood and drought

risks are shaped by feedback loops between natural, social, and economic systems [25]. For example, [23] demonstrated that human interventions in river basins, such as irrigation or infrastructure development, can either mitigate or exacerbate flood and drought risks, depending on how these interventions interact with other system components. This underscores the importance of assessing flood and drought risks in an integrated manner, accounting for the interplay between natural hazards and human interventions [5].

Additionally, systems thinking [27] emphasizes the role of resilience and adaptability in risk management. By focusing on the capacity of communities to absorb shocks and recover from extreme events, integrated models provide more actionable insights for policy-makers and river basin managers [7]. This approach shifts the focus from merely predicting events to understanding how socio-economic factors, governance structures, and infrastructure investments can influence long-term risk reduction.

Network Theory in Environmental Risk Assessment

Network theory has emerged as a valuable tool for uncovering key drivers within complex environmental systems, particularly in the context of risk assessments. By modelling parameters as nodes and their interactions as edges, network theory enables the identification of influential factors within a system that disproportionately affect flood and drought risks [21]. This method has been applied successfully to water management studies, where network metrics such as betweenness centrality and eigenvector centrality have been used to identify critical nodes that exert significant influence on overall system behaviour [6, 7, 17].

Applying network theory to flood and drought risk assessments can reveal hidden vulnerabilities and potential leverage points for mitigating risk. For instance, [8] used network analysis to explore transboundary water governance, identifying key institutional actors and pathways for more effective policy interventions. This approach aligns with the goals of many recent studies, which seek to identify the most influential parameters affecting flood and drought risks across various interconnected systems.

Cross-Entropy and Risk Optimization

The Cross-Entropy (CE) method has been increasingly adopted in environmental modelling for its ability to optimize complex datasets and identify the most impactful variables [26]. CE methods are particularly valuable in risk assessments for reducing the complexity of models by isolating critical parameters from a larger set of variables [11]. This is especially relevant for flood and drought risk assessments, where numerous factors ranging from climate patterns to economic activities can influence outcomes. By

focusing on the most influential parameters, CE methods enable more targeted and efficient risk management strategies [8].

The CE method has been used in this research to refine a broader set of parameters identified through network analysis, ensuring that the most critical factors influencing flood and drought risks are prioritized. This approach not only improves the efficiency of the model but also ensures that key socio-economic and governance factors are incorporated into the risk assessment process, further broadening the scope of traditional risk models.

Policy Implications and Future Directions

The integration of systems thinking, network theory, and CE methods offers a promising pathway for developing more comprehensive flood and drought risk management strategies. Bottom-up, localized risk assessments that integrate socio-economic factors with climatic data have been shown to be crucial for informing effective policy decisions [5, 12]. In addition, adaptive risk assessments that consider socio-economic resilience and governance structures across different spatial and temporal scales are essential for transboundary river basins, where cooperation between regions is vital for sustainable water management [19, 30].

By emphasizing the interconnected nature of flood and drought risks and incorporating mitigation capacities and resilience-building strategies into the risk assessment process, this framework provides policymakers with more accurate tools for long-term risk reduction. Such approaches align with the growing recognition that both the natural and socio-economic dimensions of risk must be addressed to effectively mitigate vulnerabilities and build resilience in river basins [2].

Recent advancements in the field advocate for the integration of multiple risk drivers and emphasize the interplay between natural hazards and human systems [5, 30]. However, systems-based approaches that holistically assess these interconnections and account for socio-economic mitigation capacities remain underdeveloped. This study addresses this gap by presenting a framework that incorporates both flood and drought risks using a network-based methodology. The framework leverages a large set of parameters encompassing not only natural drivers but also socio-economic factors, resilience-building strategies, and mitigation capacities. The primary objective of this research is to develop a systematic, network-based method for identifying and evaluating the critical parameters that contribute to flood and drought risks at the river basin scale. Interpretive Structural Modelling (ISM) [10] and Causal Loop Diagrams (CLD) are employed to map out the complex interdependencies among 116 parameters, including hydrological, cli-

matic, socio-economic, and land-use factors [3]. Eleven different network metrics such as betweenness centrality, eigenvector centrality, and PageRank are applied to rank these parameters based on their influence within the system [21, 30]. The Cross-Entropy method is utilized to refine the focus by isolating the top 30 percent of influential parameters across all metrics [26].

Unlike traditional risk models that concentrate primarily on the probability or magnitude of events, this study adopts a broader definition of risk, encompassing mitigation capacities and socio-economic resilience. The framework aims to assess flood and drought risks by considering the ways these risks are shaped by a diverse range of interconnected factors, from local governance and infrastructure to community adaptability and economic development. This research contributes to environmental risk management by offering a rigorous, systems-based approach to assessing both flood and drought risks in an integrated manner. By capturing the full spectrum of interactions between various parameters, this framework provides valuable insights for optimizing resource allocation, developing effective transboundary water management policies, and enhancing long-term resilience against climate variability. Moreover, by incorporating projections for key parameters—such as water demand, precipitation trends, and land-use changes—the framework enables predictive assessments of flood and drought risks in the near to mid-term future. This predictive capability allows policymakers and river basin managers to anticipate and mitigate risks before they materialize, improving the overall sustainability of water resources management in vulnerable regions [11].

METHODS

Building on a foundation of established research and methodological rigor, the current study adopts a multi-methodological approach to assess the intertwined risks of flooding and drought across river basins.

This section details the stepwise methodology, beginning with data collection through a systematic literature review, followed by structural analysis through Interpretive Structural Modelling (ISM) and Causal Loop Diagramming (CLD). The subsequent application of network metrics and optimization using the Cross-Entropy (CE) Monte Carlo algorithm are described to refine the identification of key parameters influencing flood and drought risk.

The choice of methods reflects the complexity of the system being studied. River basins represent interconnected physical and socio-economic systems; therefore, traditional univariate or linear approaches to risk analysis are inadequate. Methods such as ISM and CLD allow for the hierarchical classification of

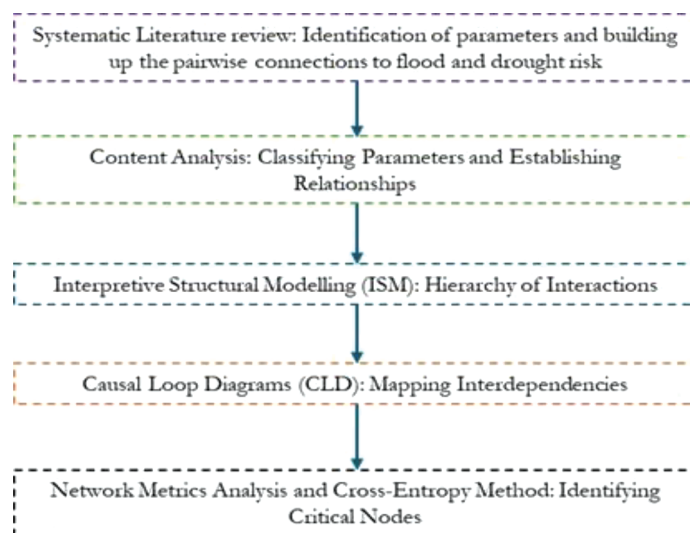


Fig. 1. Flowchart outlining the methodological approach to identify key risk factors for flood and drought management.

parameters and the mapping of their interdependencies, while network metrics offer a robust toolset to quantify their roles within the system. The CE Monte Carlo optimization further refines the analysis by aggregating these metrics into a consolidated ranking of influential parameters.

The entire methodological framework is depicted in the flowchart below (Fig. 1), which visualizes the transition from systematic data collection to advanced analytical techniques:

Data Collection: Systematic Literature Review and Content Analysis

The methodological process began with a systematic literature review, following the protocols outlined by [20] for ensuring rigor in environmental research. The primary objective was to identify and classify parameters relevant to flood and drought risk. Keywords related to “flood risk,” “drought risk,” and “river basins” were used to search peer-reviewed publications across major academic databases (e.g., Web of Science, Scopus). Studies were screened based on inclusion criteria that required a direct focus on flood or drought risk in the context of river basin management.

As a result of this review, 116 parameters were identified. These parameters covered a broad spectrum of hydrological, climatic, and socio-economic factors, including both natural drivers (e.g., precipitation, soil moisture) and human-induced pressures (e.g., urbanization, agricultural demand).

A content analysis was performed on the identified parameters to further categorize and structure them. Following the methodology proposed by [15] the parameters were coded into distinct categories, which

would later form the basis for structuring the interactions between them [18].

Structural Modelling: ISM and Causal Loop Diagramming

To analyse the relationships among the parameters, Interpretive Structural Modelling (ISM) was employed. ISM is widely used in complex system analysis, allowing for the hierarchical structuring of variables based on their mutual influences [29]. The pairwise relationships between parameters were determined through expert judgement, and a reachability matrix was constructed to map out direct and indirect interactions. This process generated a hierarchical framework, which was further analysed using MICMAC (Matrix of Cross-Impact Multiplications Applied to Classification) analysis [24]. Parameters were categorized based on their driving power (DP) and dependency power (DeP). The outcome was a three-tiered hierarchy that captured the systemic importance of each parameter. The Causal Loop Diagram (CLD) then visualized these interdependencies, highlighting critical feedback loops within the system. The first diagram below (Fig. 2) illustrates this ISM-CLD development process. The transition from the literature review to pairwise parameter classification, and ultimately to the hierarchical structure and causal mapping, is depicted to provide a clearer understanding of the methodological flow:

The CLD framework (Fig. 2) captured the complexity of interactions among parameters, emphasizing how certain drivers, such as water use and urbanization, both exacerbate and mitigate flood and drought risks depending on the feedback loops they activate.

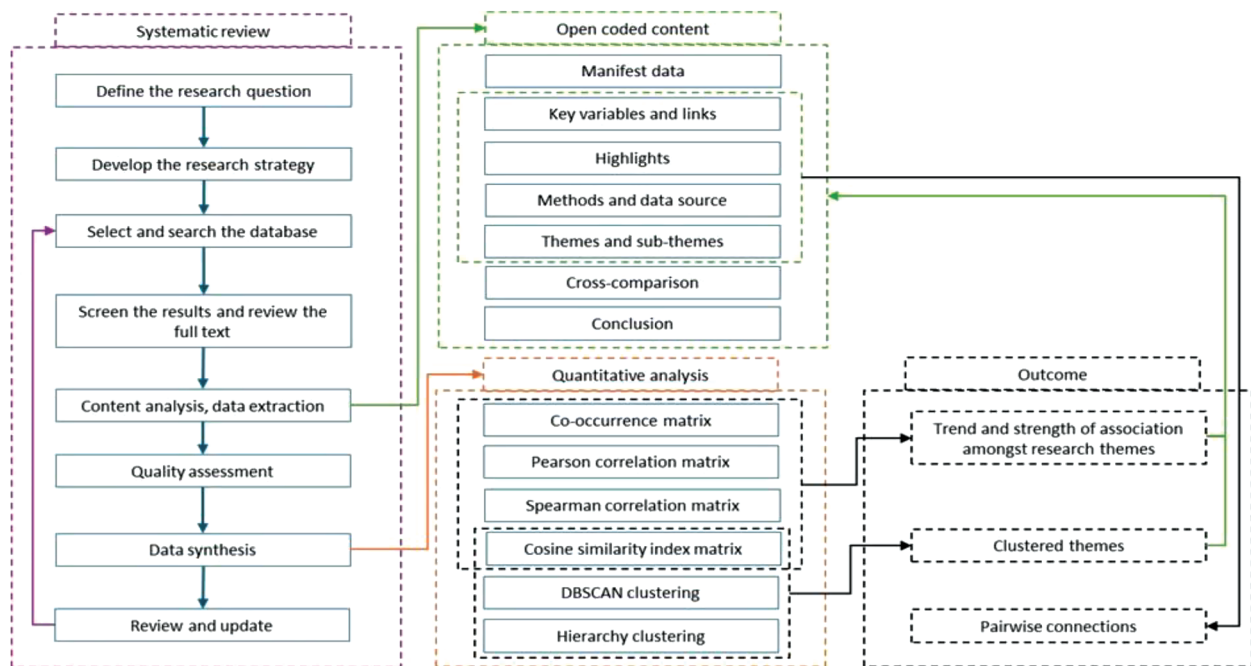


Fig. 2. Methodological flowchart of data synthesis from systematic review and quantitative analysis.

Network Metrics Analysis

Following the development of the hierarchical and causal structures, network metrics were employed to quantitatively assess the roles of the identified parameters within the system. Each parameter was treated as a node, and the connections established in the ISM-CLD framework were treated as edges in a directed graph [21].

A variety of network metrics were calculated to quantify the significance of each node (parameter) within the network. These metrics included:

- closeness centrality: Assesses how easily a node can interact with all other nodes, indicating its accessibility within the network;
- betweenness centrality: Measures the degree to which a node serves as a bridge in the shortest paths between other nodes, highlighting key connectors;
- eigenvector centrality: Evaluates the influence of a node, considering the centrality of its neighbouring nodes;
- authority and Hub metrics: Derived from [16], these metrics assess nodes' roles as sources of valuable information (Authorities) or aggregators of information (Hubs) [1].

The second diagram (Fig. 3) below illustrates the application of network metrics to the ISM-CLD framework. The analysis quantified the centrality of each parameter, thereby helping to identify the most critical nodes in managing flood and drought risks.

Cross-Entropy Monte Carlo Optimization

To refine the findings from the network analysis, a Cross-Entropy (CE) Monte Carlo algorithm was employed. The CE method, widely recognized for its efficacy in solving complex optimization problems within dynamic systems [26], operates by iteratively sampling from a probability distribution and progressively optimizing toward an optimal solution. In this study, the CE algorithm was applied to aggregate rankings derived from the network metrics, with the goal of identifying the top 30% of parameters that hold the greatest influence over flood and drought risks.

The process begins by generating a series of potential solutions, followed by repeated iterations that adjust probability distributions based on the performance of previous iterations. This allows the model to converge toward a refined set of influential parameters. The final outcome is a ranked list of key parameters, reflecting the optimization of their influence within the system, and highlighting the nodes that are most critical in assessing and managing flood and drought risks.

Through the application of systematic literature review, ISM-CLD development, network metrics, and optimization techniques, this study presents a rigorous, multi-disciplinary approach to understanding flood and drought risks. The findings of this comprehensive analysis will be discussed in the following section, where the implications of the identified key parameters for future risk mitigation strategies will be examined.

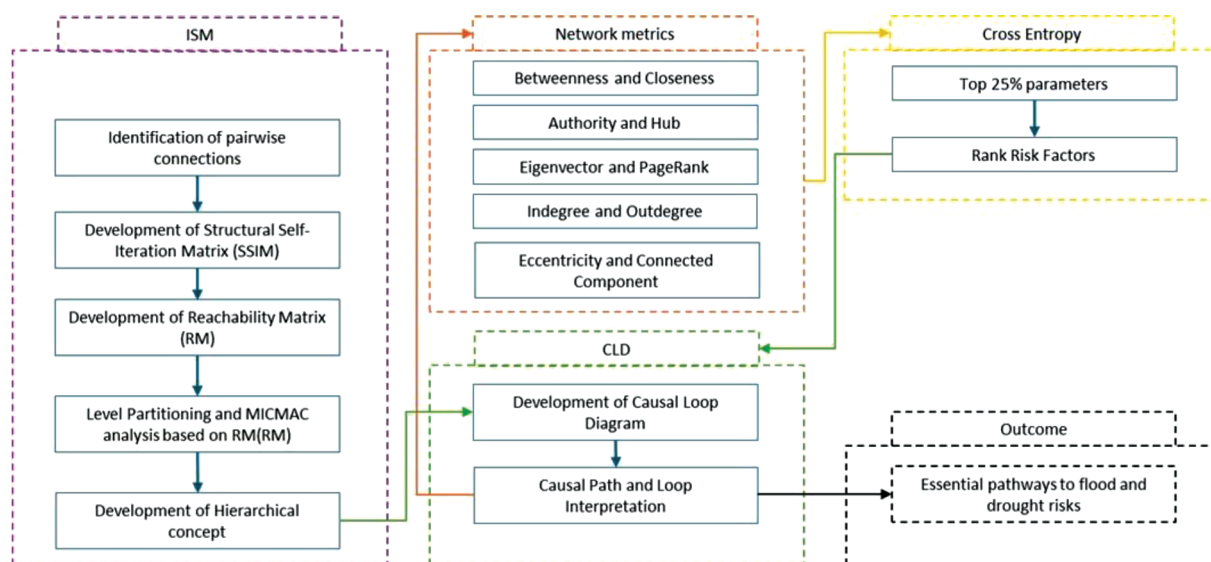


Fig. 3. Flowchart of methodologies and processes used to identify the essential causal pathways to assess flood and drought risk.

RESULTS AND DISCUSSION

Parameter Hierarchy and Strategic Implications

The hierarchical structure derived from the MICMAC analysis categorizes 116 parameters into three distinct levels, highlighting the varying degrees of influence and dependency within the system (Table 1). Level 1 includes 17 parameters, mainly natural and foundational elements such as Precipitation (P22), Elevation (P6), and Soil Type (P17). These parameters are critical because they represent the underlying environmental conditions that directly shape flood and drought risks. Addressing these factors early in the risk management process is essential for creating a resilient foundation for water resource management.

Level 2 encompasses 98 parameters, which are more complex and socio-economically driven, such as Flood Risk (P2), Water Supply (P28), Drought Risk (P75) and Population Growth Rate (P64). These parameters serve as critical intermediaries between natural systems and socio-economic outcomes. Their sheer number and the complexity of their interactions illustrate the intricacies of flood and drought risk assessment. The diversity of parameters at this level indicates that risk mitigation efforts must be multidimensional, involving both infrastructural improvements and socio-economic interventions.

Level 3 contains a single parameter, Water Conflict (P73), which stands at the top of the hierarchy. The prominence of this element underscores its critical role as an outcome driven by the compounded pressures of environmental, infrastructural, and socio-economic factors. Preventing the escalation to water conflict requires a holistic and integrative approach that addresses pressures from lower levels, particularly

those related to water distribution, resource management, and governance.

The hierarchical framework implies that to manage flood and drought risks effectively, interventions must cascade from natural factors in Level 1 through socio-economic and infrastructural changes in Level 2, ultimately preventing adverse outcomes such as Water Conflict. This insight is vital for policymakers, as it highlights the importance of targeting systemic issues before they culminate in severe conflicts over water resources.

MICMAC Analysis: Driving and Dependency Powers

The MICMAC analysis provides further clarity on the dynamics within this system by classifying the parameters based on their driving and dependency power (Fig. 4). Parameters in the Linkage Quadrant, including Water Use (P30), Flood Risk (P2), and Irrigation Efficiency (P76), demonstrate high driving power (115) and moderate dependency power (99). These parameters are central to maintaining the balance and stability of the network, as they are both influenced by many factors and exert significant influence themselves. This classification suggests that targeted interventions in these areas, such as optimizing water use and improving flood risk management can stabilize the entire system and help mitigate both flood and drought risks.

The importance of linkage parameters cannot be overstated. These parameters act as bridges within the system, transmitting and moderating the effects of changes across the network. For instance, improving Irrigation Efficiency (P76) could have a dual effect of reducing water consumption and increasing agricultural resilience to both droughts and floods. Likewise,

Table 1. Parameters involved in understanding the risk of flood and drought along with their clustering and hierarchy levels explained in sections 3.2 and 3.3.2 respectively

Parameter name	Id	Hierarchy level	Clustering Group	Parameter name	Id	Clustering Group	Hierarchy level
Change Factor	p1	L1	G2	Industrial added value	p59	G2	L2
Flood Risk	p2	L2	G7	Domestic added value	p60	G2	L2
Flood shelter	p3	L2	G1	Agricultural added value	p61	G2	L2
Urbanization	p4	L2	G1	Per capita water consumption	p62	G4	L2
Migration	p5	L2	G1	Population growth rate	p63	G4	L2
Elevation	p6	L1	G3	Population	p64	G4	L2
Slope	p7	L1	G6	Per capita domestic water demand	p65	G4	L2
Transportation network	p8	L2	G1	Per capita domestic water demand growth rate	p66	G4	L2
Early warning systems	p9	L2	G1	Per capita industrial water demand	p67	G4	L2
Health facility	p10	L1	G1	Per capita industrial water demand growth rate	p68	G4	L2
Distance to river	p11	L1	G6	The ratio of basin's GRP to neighbouring basins	p69	G4	L1
NDVI	p12	L2	G3	Per capita agricultural water demand	p70	G4	L2
Snowmelt pattern	p13	L2	G3	Per capita agricultural water demand growth rate	p71	G4	L2
Biodiversity	p14	L1	G5	Water resources sustainability index	p72	G2	L2
LC/LU	p15	L3	G3	Water conflict	p73	G2	L3
Soil moisture	p16	L2	G3	Watershed economic development rate	p74	G4	L1
Soil type	p17	L1	G3	Drought Risk	p75	G7	L2
Wind speed	p18	L1	G3	Irrigation efficiency	p76	G8	L1
River density	p19	L1	G1	Net agricultural water use	p77	G8	L2
Flood level	p20	L1	G1	Delivery rate	p78	G5	L2
Soil erosion	p21	L2	G5	Actual land area for crop	p79	G5	L2
Precipitation	p22	L2	G2	Expected agricultural water requirement	p80	G5	L2
Temperature	p23	L2	G3	Cultivation cost	p81	G5	L2
1 Evapotranspiration	p24	L2	G3	Net benefit	p82	G5	L2
Available surface water	p25	L2	G6	Production of crops	p83	G5	L2
Available groundwater	p26	L2	G6	Expected land area	p84	G5	L2
Returned flow	p27	L2	G2	Irrigation water requirement	p85	G5	L2
Water supply	p28	L2	G2	Benefit from crops	p86	G5	L2
Water use	p29	L2	G2	Crop pattern	p87	G8	L1
Water demand	p30	L2	G2	Expected water requirement	p88	G5	L2

Table 1. (Contd.)

Parameter name	Id	Hierarchy level	Clustering Group	Parameter name	Id	Clustering Group	Hierarchy level
Surface water inflow	p31	L2	G3	Public demand for mitigation	p89	G1	L2
Domestic demand	p32	L2	G4	Flood alleviation investment	p90	G1	L2
Industrial demand	p33	L2	G4	Flood premium	p91	G1	L2
Agricultural demand	p34	L2	G8	Required insurance	p92	G1	L2
Domestic water use	p35	L2	G2	Access to insurance	p93	G1	L2
Agricultural water use	p36	L2	G2	Flood relief	p94	G7	L2
Industrial water use	p37	L2	G2	Dependence on flood relief	p95	G7	L2
Agricultural returned flow	p38	L2	G2	Community resilience	p96	G7	L2
Industrial returned flow	p39	L2	G2	Drought relief	p97	G7	L2
Domestic returned flow	p40	L2	G2	Drought premium	p98	G1	L2
Groundwater withdrawal	p41	L2	G2	Dependence on drought relief	p99	G7	L2
Groundwater outflow	p42	L2	G6	Drought alleviation investment	p100	G1	L2
Groundwater returned flow	p43	L2	G2	Risk perception	p101	G7	L2
Groundwater inflow	p44	L2	G6	Dike/Levee	p102	G1	L2
Natural groundwater inflow	p45	L2	G6	Storm control	p103	G1	L2
Surface water returned flow	p46	L2	G2	Subsurface storage	p104	G1	L2
Transferred inflow	p47	L1	G3	Dam/Reservoir	p105	G1	L2
Natural surface water inflow	p48	L2	G3	Flood impact	p106	G7	L2
Surface water outflow	p49	L2	G6	Drought impact	p107	G7	L2
Percolation	p50	L2	G6	Flood Vulnerability	p108	G4	L2
Surface water withdrawal	p51	L2	G2	Drought Vulnerability	p109	G6	L2
Seepage from groundwater to surface water	p52	L2	G6	Flood Exposure	p110	G3	L2
Evaporation	p53	L2	G3	Drought Exposure	p111	G3	L2
Runoff	p54	L2	G3	Flood hazard	p112	G1	L2
Environmental flow	p55	L1	G2	Drought hazard	p113	G1	L2
Residents' utility	p56	L2	G4	Flood awareness	p114	G1	L2
National economic growth rate	p57	L1	G4	Drought awareness	p115	G1	L2
Added value	p58	L2	G2	Air humidity	p116	G3	L2

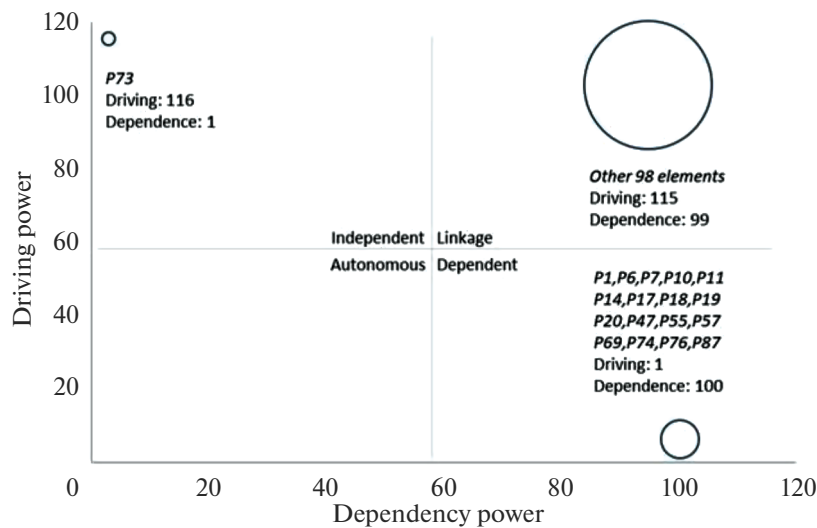


Fig. 4. Classification of Parameters Based on Driving and Dependency Power in MICMAC Analysis.

enhancing Water Use (P30) through better governance and infrastructure can create ripple effects across the network, contributing to a more resilient water management system.

On the other hand, parameters in the Dependent Quadrant, such as Population Growth Rate (P64) and Industrial Water Use (P37), exhibit low driving power (1) and high dependency power (100). Although these parameters are less responsive to other system dynamics, they exert substantial influence over the network. For example, rapid population growth can lead to increased water demand and resource strain, further escalating the risks of flood and drought. Managing these dependent parameters requires strategic interventions that anticipate and mitigate their potential to amplify system-wide vulnerabilities. Water Conflict (P73), located in the Independent Quadrant, exhibits extremely high driving power (116) and low dependency power (1), making it a critical outcome of systemic failures. The fact that water conflict is driven by multiple pressures across the system underscores the need for proactive measures in governance, infrastructure, and resource-sharing mechanisms. Addressing the foundational and socio-economic issues within the system can prevent the escalation of conflicts, particularly in regions with high transboundary water stress.

Exploring Centrality and Cluster Dynamics in Flood and Drought Risk Networks

The visualization highlights the varying roles of parameters within the network by emphasizing their Betweenness Centrality and Closeness Centrality (Fig. 5). Parameters that have both high betweenness and closeness centrality are crucial for maintaining network cohesion and for ensuring that resources and

information are efficiently distributed across the system.

Betweenness Centrality (Size of Circles in Fig. 5) measures the extent to which a node lies on the shortest path between other nodes. High-betweenness nodes are considered bridges within the network, controlling the flow of resources or information. The largest circles in the visualization indicate parameters that are key intermediaries. These parameters act as critical conduits through which effects propagate throughout the system, making them essential for maintaining the connectivity and resilience of the network. High Betweenness Centrality Nodes: Parameters such as Population (P64), Flood Hazards (P112), Precipitation (P22), and Drought Vulnerability (P109) are likely to be crucial connectors or bridges within the network. Their central position suggests that they play a significant role in shaping flood and drought risks. For instance, Population (P64) directly influences water demand and land use, which in turn affects both flooding and drought conditions. Flood Hazards (P112) and Drought Vulnerability (P109) represent key risks that depend on a wide range of upstream factors. Parameters with high betweenness centrality should be the focus of strategic interventions, as they have the greatest potential to control the flow of impacts across the system. For example, targeting Flood Hazards (P112) with mitigation efforts can prevent cascading effects that might otherwise increase flood risks across the network. Similarly, managing Drought Vulnerability (P109) through improved water governance and infrastructure could stabilize the system by reducing the risk of prolonged drought conditions.

Closeness Centrality (colour intensity of circles in Fig. 5) measures how quickly a node can reach all other nodes in the network. Nodes with high closeness

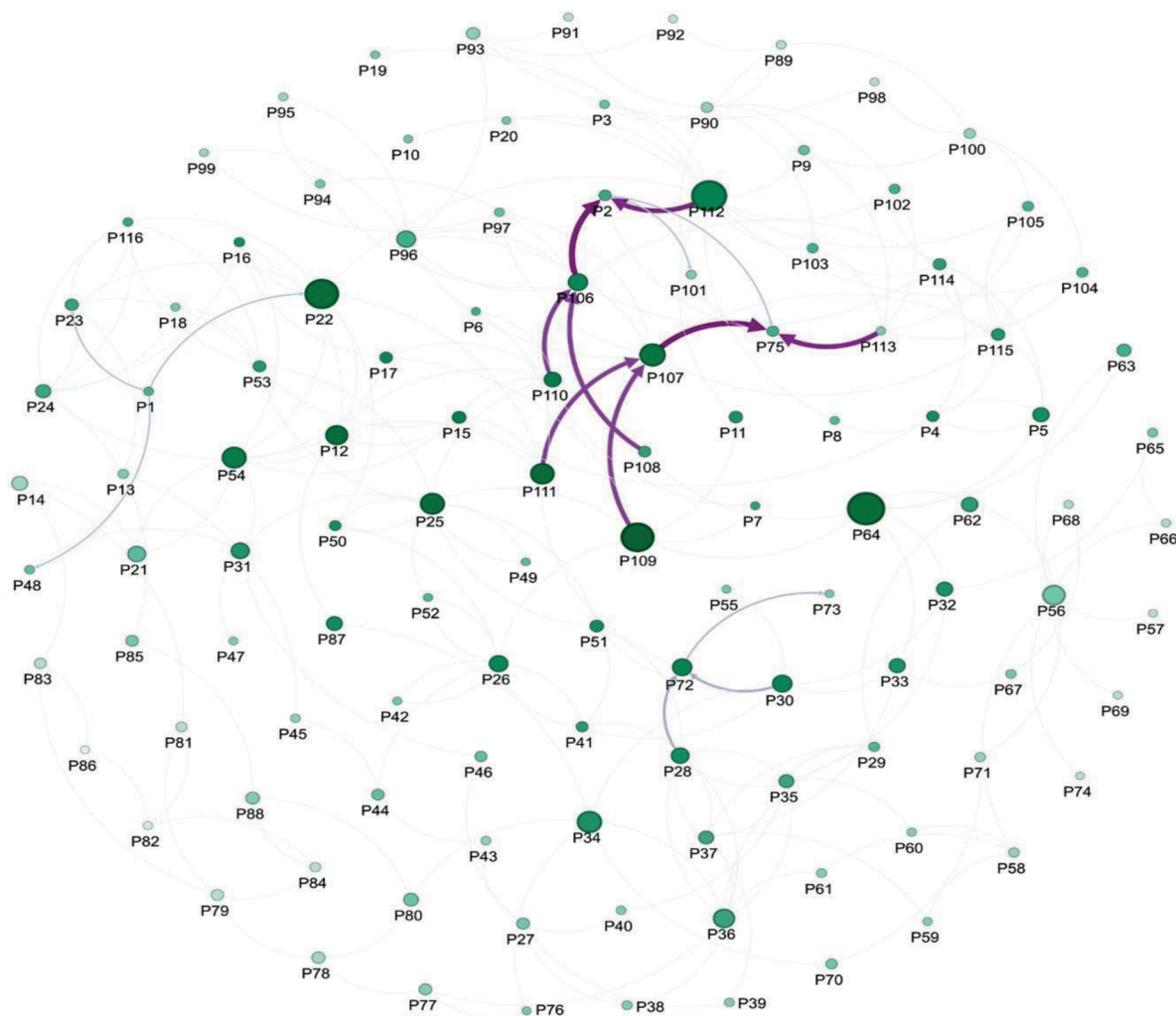


Fig. 5. Visualization of Betweenness centrality (size of circles) and Closeness centrality (colour intensity of circles) network metrics for the overall framework.

centrality are well-positioned to spread information or resources efficiently. The darker, more intense circles in the visualization represent parameters that are central in terms of their ability to communicate across the network. Parameters such as Drought Vulnerability (P109), Flood Exposure (P110), and Available Surface Water (P25) are well-placed to quickly interact with other nodes. Their proximity to many other parameters means they can influence the system rapidly, making them important for immediate responses during extreme events like floods and droughts. High closeness centrality parameters should be targeted for improving early warning systems and rapid response mechanisms. For instance, Flood Exposure (P110) and Drought Vulnerability (P109), with their central positions, are ideal candidates for being focal points in risk communication strategies. Enhancing monitoring and reporting mechanisms around these parameters could ensure that critical information about risks is

disseminated quickly and effectively throughout the network.

The combination of Betweenness and Closeness Centrality metrics provides a deeper understanding of the network's structure and resilience. Parameters with both high betweenness and high closeness centrality, such as Drought Vulnerability (P109) and Flood Exposure (P110), are particularly influential. These nodes not only act as bridges, facilitating the flow of information and resources, but they can also spread their influence quickly throughout the network. Conversely, parameters with low betweenness but relatively high closeness, such as Available Surface Water (P25), may act as localized influencers. These parameters are well-connected within their immediate vicinity, making them important for local-scale interventions that do not necessarily influence the entire system. Improving water availability at the local level,

for instance, can strengthen community resilience without requiring system-wide interventions.

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. 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 analysis of Betweenness and Closeness Centrality highlights key parameters that play significant roles in the propagation of flood and drought risks across the system. Parameters with high betweenness centrality act as bridges within the network, controlling the flow of resources and information, while those with high closeness centrality are well-placed to disseminate influence rapidly. By focusing interventions on these strategically important parameters, stakeholders can enhance the system's resilience to both floods and droughts.

Analysing Eigenvector Centrality and PageRank

The analysis of Eigenvector Centrality (circle size) and PageRank (colour intensity) in Fig. 6 provides valuable insights into the roles that various parameters play within the overall flood and drought risk management network. Both metrics allow us to understand the influence of parameters not only based on their immediate connections but also in the context of their position in the broader network. Drought Impact (P107) emerges as a standout parameter with high scores in both Eigenvector Centrality and PageRank, making it a critical node within the network. Its high eigenvector centrality indicates that it is connected to other influential nodes, suggesting that Drought Impact plays a significant role in the network's integrity. The high PageRank score further confirms its importance by showing that it is a trusted node, receiving many incoming links from other critical nodes.

Drought Impact (P107) is likely a key hydrological or climatic factor that directly affects the overall flood and drought risk in the system. Given its importance

in both metrics, this parameter should be a primary focus for intervention strategies aimed at mitigating the effects of drought. Targeted actions here are likely to have far-reaching impacts across the network, influencing other connected parameters.

Surface Water Availability (P25) and Flood Risk (P2), Surface Water Availability (P25) and Flood Risk (P2) also score highly in eigenvector centrality, suggesting that they are connected to other influential parameters and play central roles in flood and drought risk management. However, Surface Water Availability (P25) has a more moderate PageRank score, indicating that while it is influential, it may not be a primary source of information flow in the network. It acts more as a supporting player, reinforcing the processes governed by other central nodes. Surface Water Availability (P25) is crucial for sustaining water resources across the basin and mitigating drought risk. Although it may not drive the network's processes, interventions here could stabilize key areas by ensuring water security. Meanwhile, Flood Risk (P2), with its higher PageRank, represents a more direct influence over the system's behaviour, making it a crucial factor in managing flood hazards.

Parameters like Risk Perception (P101) and Community Resilience (P96) exhibit strong PageRank but moderate Eigenvector Centrality. These parameters play critical roles in influencing the flow of information within the network, suggesting that they are important for shaping public and institutional responses to risks. Risk Perception (P101) is central to how communities react to flood and drought warnings, influencing how information spreads and shaping public preparedness. Community Resilience (P96), meanwhile, indicates the system's capacity to withstand shocks and recover from extreme events. Targeting these parameters could improve public awareness and adaptive capacity, which are vital for long-term resilience. Drought Vulnerability (P109), though not as central as Drought Impact (P107), still holds an important place in the network, particularly in the directed flows related to drought risk. It may serve as an intermediary node, helping to transmit the effects of drought-related risks across different parts of the system. Drought Vulnerability (P109) should be viewed as a secondary but still critical factor in shaping the system's response to droughts. Enhancing resilience in this area could prevent smaller risks from cascading into larger systemic issues.

Flood Hazard (P112) and Evaporation (P53) exhibit moderate scores in both Eigenvector Centrality and PageRank, indicating that while they are not central to the overall network structure, they still play significant roles within certain pathways or processes. Their influence is more localized, suggesting that interventions targeting these nodes may have less systemic impact but could be critical in specific contexts. Flood Hazard (P112), for example, might be involved

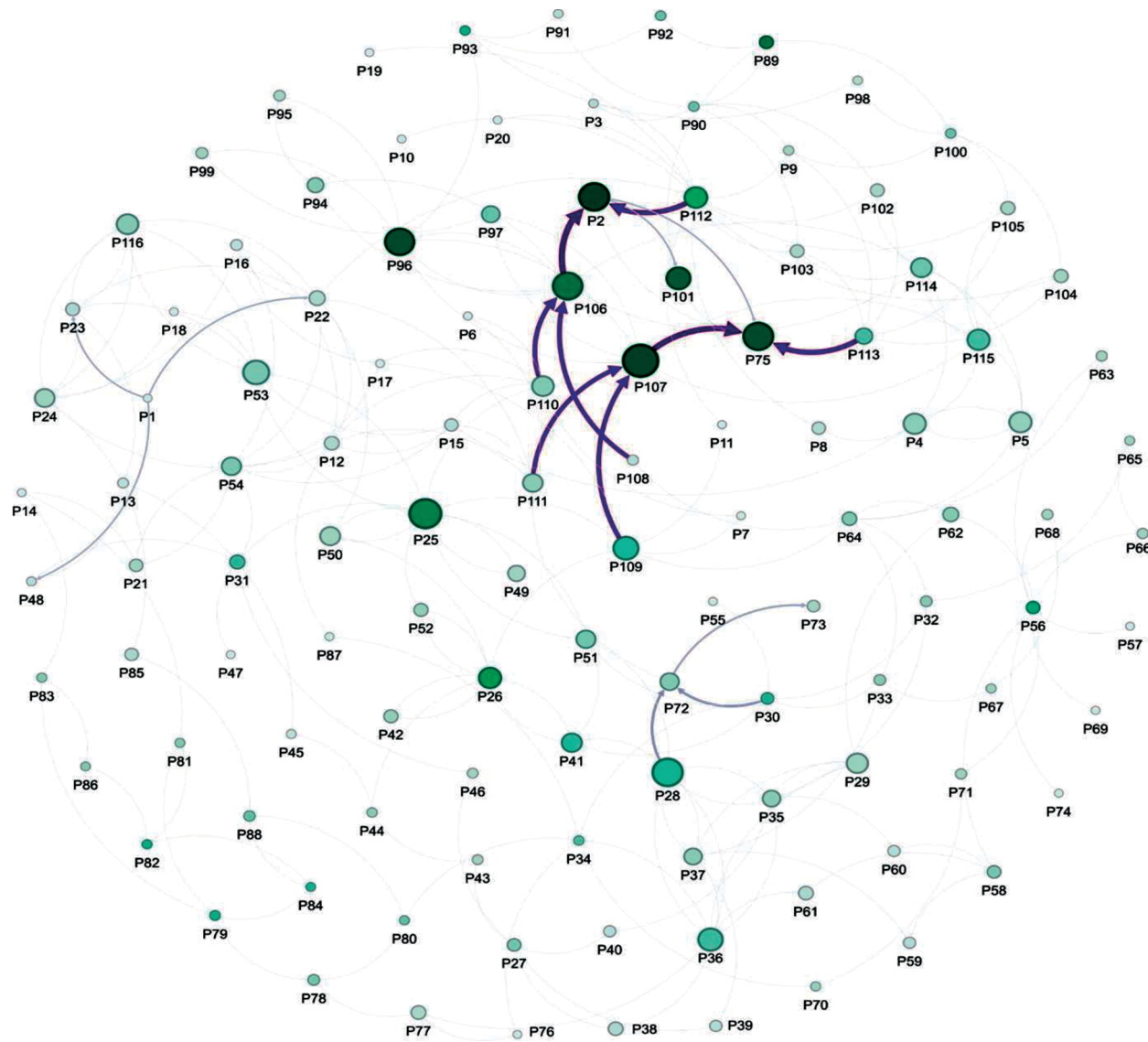


Fig. 6. Visualization of Eigenvector (size of circles) and PageRank (colour intensity of circles) network metrics for the overall framework.

in several risk pathways but does not dominate the network. Targeting it could mitigate localized flood risks without affecting the broader network. Similarly, Evaporation (P53) could be important in specific drought scenarios, where it acts as an intermediate step in the water cycle.

Parameters such as Drought Awareness (P115), Urbanization (P4), and Migration (P5) have low Eigenvector Centrality but moderate PageRank scores. These nodes are not central to the network's structure but still influence the directed flow of information or resources, particularly in specialized contexts related to flood and drought risks. These parameters may come into play under certain conditions or in specific pathways, such as when drought awareness campaigns or migration patterns are triggered by

extreme weather events. While they may not be central to the network's overall connectivity, their influence in particular scenarios warrants attention.

Available Groundwater (P26) and Water Resources Sustainability Index (P72) exhibit moderate Eigenvector Centrality and low PageRank. These parameters are somewhat central to the network's structure, but they do not drive the flow of information or resources as much as others. These parameters may represent underlying conditions that are essential for long-term stability but do not actively drive immediate responses or decision-making processes. Strengthening these areas could provide a stable foundation for the network without needing to focus on them as primary intervention points. Parameters such as Change Factor (P1), Elevation (P6), and Slope (P7) have low

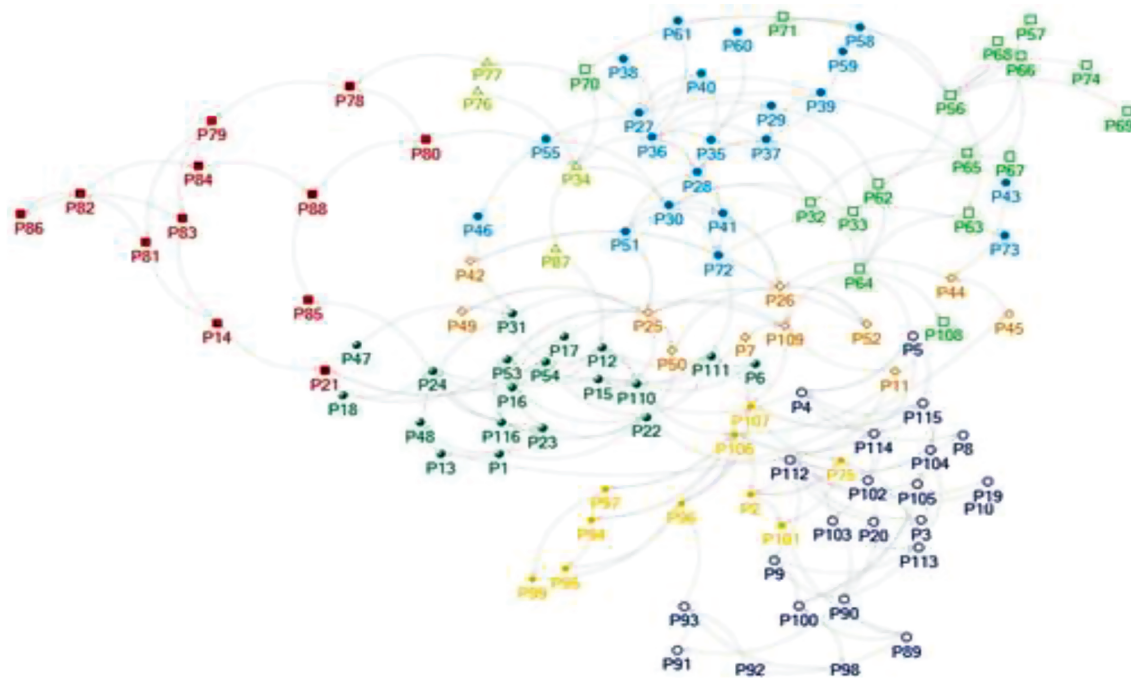


Fig. 7. Schematic representation of produced clusters of the framework parameters G1 (dark blue), G2 (light blue), G3 (dark green), G4 (light green with squares), G5 (Red), G6 (orange), G7 (yellow), G8 (light green with triangles).

scores in both Eigenvector Centrality and PageRank, positioning them as peripheral within the network. These nodes likely represent localized issues or factors that do not broadly impact the river basin's flood and drought dynamics but may become relevant under specific circumstances. While these parameters are not central to the overall network, they may still play a role in localized risk management efforts, particularly in regions where specific topographical or environmental conditions drive flood or drought risks.

The combined analysis of Eigenvector Centrality and PageRank reveals a hierarchy of parameters within the network, each playing a distinct role in managing flood and drought risks. High-scoring parameters like Drought Impact (P107), Flood Risk (P2), and Surface Water Availability (P25) are critical to the network and should be primary targets for intervention strategies. Parameters with moderate scores, such as Flood Hazard (P112) and Risk Perception (P101), may require more contextual investigation to understand their function within specific processes. By focusing on both central influencers and secondary but strategically important parameters, policymakers and resource managers can develop more nuanced and effective strategies for flood and drought risk mitigation. Understanding not only the presence of connections in the network but also the nature and influence of those connections is essential for prioritizing research, monitoring efforts, and policy interventions. This combined analysis provides a deeper understanding of each parameter's role, allowing for more

informed decision-making in the context of integrated water resource management.

The clustering outcomes, as represented by the provided figures and tables, categorize the parameters into distinct groups (G1–G8) (Fig. 7).

Each group is defined by unique network metrics that describe the structure, connectivity, and influence of the parameters within the network. These clusters reveal the underlying organization of the network and help to identify which groups of parameters are most influential in the propagation of flood and drought risks across the river basin system.

Cluster G1. Cluster G1 is the largest and most moderately connected group in the network. With 23 vertices and 43 unique edges, it forms a broad and moderately dense network. The low reciprocated vertex pair ratio (0.049) and reciprocated edge ratio (0.093) indicate that many of the connections in this cluster are one-way, suggesting a hierarchical structure where information or influence flows in a directed manner from one parameter to another without much feedback. The maximum geodesic distance (diameter) of 5 and average geodesic distance of 2.431 imply that the elements in G1 are relatively close to each other, facilitating efficient communication or influence across the group. This group includes essential parameters such as Flood Shelter (P3), Urbanization (P4), Transportation Network (P8), Early Warning Systems (P9), and Flood Hazard (P112). These parameters are crucial in establishing preventive mea-

tures and preparing for floods and droughts, within the river basin. The parameters in G1 form a critical infrastructure-focused cluster. They represent physical and organizational elements that contribute to mitigating the impacts of flooding and drought. The hierarchical nature of this cluster suggests that certain parameters, such as Early Warning Systems (P9) and Flood Hazard (P112), may serve as central points of influence, directing actions and responses throughout the network. Improving the connectivity and resilience of these parameters could enhance the basin's preparedness and response capabilities.

Cluster G2. Cluster G2 has 21 vertices and 34 unique edges. It exhibits slightly higher reciprocity compared to G1, with a reciprocated vertex pair ratio of 0.097 and a reciprocated edge ratio of 0.176. This suggests a more balanced flow of information or influence, with some feedback mechanisms present within the cluster. The maximum geodesic distance of 7 and average geodesic distance of 2.753 indicate a more dispersed network structure, meaning that some nodes are further apart, which may slow the transmission of information or influence. Parameters in this group include Precipitation (P22), Water Supply (P28), Water Use (P29), Agricultural Water Use (P36), and Water Conflict (P73). forms a water-focused cluster, dealing with supply, demand, and usage of water resources. The moderate reciprocity within the cluster indicates that while there is some exchange of influence, certain key nodes, such as Water Conflict (P73) and Water Supply (P28), may play more dominant roles. These parameters are crucial for addressing both the supply-side and demand-side challenges that contribute to flood and drought risks. Interventions targeting these nodes could stabilize water distribution and usage, potentially reducing the frequency and severity of water conflicts.

Cluster G3. Cluster G3 consists of 19 vertices and 41 unique edges. It has moderate reciprocation, with a vertex pair ratio of 0.079 and an edge ratio of 0.146, suggesting a similar structure to G2. However, the maximum geodesic distance of 5 and the average geodesic distance of 2.161 suggest that G3 is more tightly connected, facilitating faster communication or influence across the network. This cluster includes parameters related to environmental factors, such as Elevation (P6), NDVI (P12), Soil Moisture (P16), Temperature (P23), and Evapotranspiration (P24). The parameters in G3 form an environmental cluster that deals with the physical and ecological conditions of the river basin. These parameters are central to understanding the natural processes that contribute to flood and drought risks. Enhancing data collection and monitoring within this cluster could provide valuable insights into how environmental changes affect water availability and risk factors across the basin.

Cluster G4. Cluster G4 features 16 vertices and 18 unique edges, making it one of the smaller clusters.

It has relatively low reciprocation, with a vertex pair ratio of 0.036 and an edge ratio of 0.056. The maximum geodesic distance of 6 and average geodesic distance of 2.383 indicate that the cluster is relatively spread out. This group includes socio-economic parameters, such as Domestic Demand (P32), Population Growth Rate (P63), Population (P64), Watershed Economic Development Rate (P74), and Flood Vulnerability (P108). G4 represents socio-economic factors that influence flood and drought risk. This cluster highlights the importance of population dynamics and economic growth in shaping the demand for water resources. Targeting interventions within this cluster could address underlying socio-economic drivers of vulnerability, helping to mitigate the risks associated with both floods and droughts.

Cluster G5. Cluster G5 is a small but well-defined cluster with 12 vertices and 15 unique edges. It has no reciprocation, with both the vertex pair ratio and edge ratio at 0.0, suggesting a strictly hierarchical structure. The maximum geodesic distance of 6 and average geodesic distance of 2.250 indicate moderate connectivity within the cluster. This cluster includes parameters related to agricultural productivity, such as Biodiversity (P14), Soil Erosion (P21), Expected Agricultural Water Requirement (P80), and Irrigation Water Requirement (P85). G5 represents the agricultural sector's influence on flood and drought risks. The strictly hierarchical structure suggests that certain parameters, such as Irrigation Water Requirement (P85) and Soil Erosion (P21), play dominant roles in shaping the dynamics of this cluster. Interventions that improve water management practices in agriculture could mitigate risks by reducing the demand for water and protecting soil resources.

Cluster G6. Cluster G6 is relatively small, with 11 vertices and 16 unique edges. It has a relatively high level of reciprocation, with a vertex pair ratio of 0.385 and an edge ratio of 0.556. The maximum geodesic distance of 4 and average geodesic distance of 1.920 indicate a tightly connected network. This group includes hydrological parameters, such as Available Surface Water (P25), Groundwater Inflow (P44), Natural Groundwater Inflow (P45), and Drought Vulnerability (P109). G6 focuses on the interactions between surface water and groundwater, which are critical for managing water availability during periods of drought. The high level of reciprocation suggests that there is significant feedback between parameters, such as Groundwater Inflow (P44) and Surface Water Outflow (P49). Strengthening the management of both surface and groundwater resources could enhance the resilience of the system to drought conditions.

Cluster G7. Cluster G7 contains 10 vertices and 18 unique edges. It is characterized by moderate reciprocation, with a vertex pair ratio of 0.176 and an edge ratio of 0.444. The maximum geodesic distance of 5

and average geodesic distance of 2.153 suggest a relatively well-connected network. This cluster includes high-impact risk parameters, such as Flood Risk (P2), Drought Risk (P75), Community Resilience (P96), Flood Relief (P94), and Drought Impact (P107). G7 represents critical risk factors and the corresponding responses. The parameters in this cluster are central to understanding how communities respond to floods and droughts. The moderate reciprocation suggests that while these parameters influence each other, certain parameters, such as Drought Impact (P107) and Community Resilience (P96), may have dominant roles. Interventions targeting this cluster should focus on enhancing resilience to both floods and droughts, as well as improving response mechanisms.

Cluster G8. Cluster G8 is the smallest cluster, with only 4 vertices and 3 unique edges. It has no reciprocation, with a vertex pair ratio and edge ratio of 0.000, indicating a simple, non-reciprocal structure. The maximum geodesic distance of 3 and average geodesic distance of 1.250 indicate a tightly connected and compact group. This group includes parameters related to economic risk, such as Dependence on Drought Relief (P99) and Drought Premium (P98). G8 represents a small, focused cluster dealing with economic factors related to drought relief. The lack of reciprocation suggests that these parameters are influenced by external factors rather than driving the dynamics of the network themselves. While small, this cluster plays a critical role in determining how economic relief measures are allocated during drought conditions.

The clustering analysis provides a deeper understanding of the river basin's flood and drought risk management network. Each cluster represents distinct aspects of the system, from infrastructure and socioeconomic factors to agricultural and environmental influences. By targeting interventions based on the dynamics within each cluster, policymakers and managers can enhance the overall resilience of the basin to both floods and droughts. This approach enables more effective and efficient resource allocation and planning, ensuring that the right strategies are applied to the most critical areas of the network.

Derived Risk Factors using Cross-Entropy Monte Carlo (CE) Optimization

The comprehensive network analysis encompassed 116 distinct parameters, each evaluated against 11 network metrics, including weighted indegree, weighted outdegree, closeness centrality, betweenness centrality, eigenvector centrality, authority, and hub scores. The goal was to identify the most influential parameters that contribute to flood and drought risk management within the river basin system. A synthesis of these network metrics through a Cross-Entropy Monte Carlo algorithm (CE) allowed for the aggregation of the top-ranking parameters across all metrics,

providing a holistic view of the key drivers in the system.

Approximately 80% of the parameters appeared in at least one top-ranking list across the 11 metrics, indicating that influence is dispersed widely throughout the network. No parameter consistently ranked in the top 25% across all metrics, underscoring the diversity of parameter roles within the network. This suggests that different parameters have varying levels of influence depending on the specific metric being considered. A standout parameter in the analysis was Available Surface Water (P25), which ranked highly in 10 out of 11 network metrics. This demonstrates its critical role in the network, especially in the context of flood and drought risk assessment. Available Surface Water (P25) appears to be a pivotal element in the network. Given its consistent high ranking across multiple metrics, it likely plays a central role in regulating water availability, influencing both supply and demand dynamics within the basin. Managing this parameter effectively could have significant ramifications for overall water resource management.

The Cross-Entropy Monte Carlo method was used to consolidate and optimize the rankings derived from the 11 network metrics. This method aggregates rankings across metrics and identifies the most influential parameters that hold the greatest importance in the network. The visualization of the CE method's optimization process in Fig. 8 includes three key components:

Minimum Path Plot, the top left plot depicts the trajectory of the objective function's minimum values over time, highlighting the global minimum achieved after approximately 200 iterations. This provides insight into the optimization process and the convergence of the CE algorithm toward a solution. Final Sample Distribution, the adjacent histogram shows the distribution of objective function scores at the final iteration, indicating the convergence rate and offering insights into how tightly clustered the final rankings were around the optimal solution. Eventually, Rank Aggregation Plot, the bottom plot visualizes the rank aggregation results, displaying the individual ranked lists along with the final solution. The red line represents the CE solution, while the black line represents the mean of the ranked lists.

The CE method allowed for an effective synthesis of the diverse rankings across the network metrics, culminating in a final optimal list that highlights the most critical parameters within the network (Table 2). This approach offers a data-driven method for pinpointing parameters that hold the greatest overall importance, ensuring that future risk assessments focus on these key factors.

The top parameters identified through the rank aggregation process, as shown in Table 3, include influential risk factors such as Drought Impact (P107), Flood Risk (P2), Precipitation (P22),

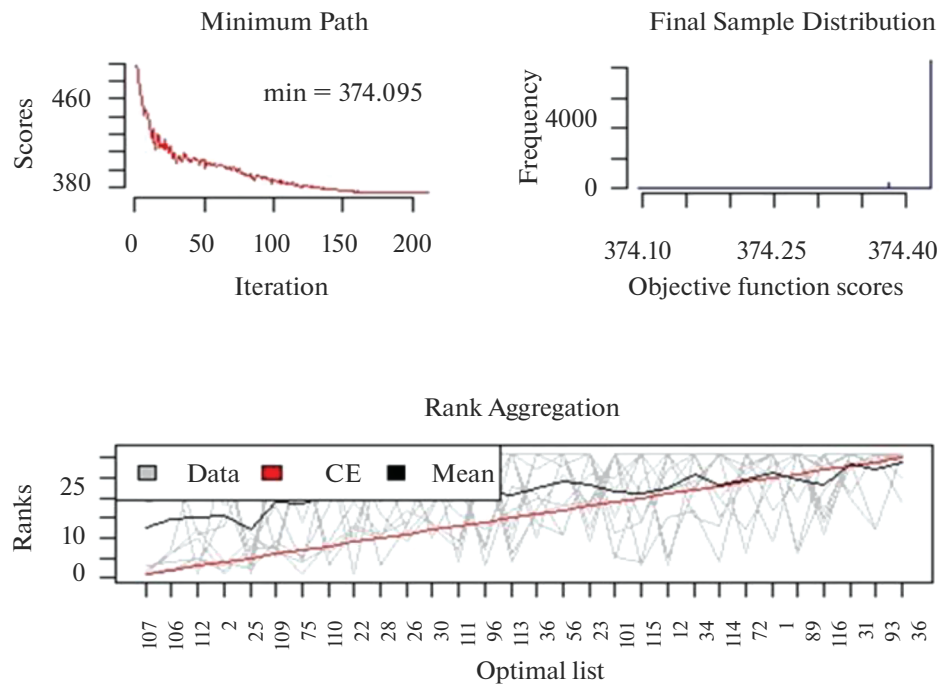


Fig. 8. Visual representation of the rank aggregation results indicating the optimal list of parameters.

Drought Risk (P75) and Available Groundwater (P26). These parameters are recognized as key drivers in the context of flood and drought risks. Their influence spans multiple dimensions of the network, from environmental factors like Precipitation (P22) to resource management concerns like Available Groundwater (P26). Interventions aimed at mitigating flood and drought risks should prioritize these top parameters, as they represent the most significant points of leverage within the system.

The combination of individual network metric analysis and the Cross-Entropy Monte Carlo algorithm provides a robust framework for understanding the key parameters driving flood and drought risks [6, 33]. Parameters such as Available Surface Water (P25) and Drought Impact (P107) emerge as critical nodes within the network, requiring focused management

efforts to mitigate risks effectively. By leveraging the insights gained from both the network metrics and the CE optimization, decision-makers can develop more targeted and effective strategies for managing water resources in the face of climate variability and extreme weather events.

To address the inherent uncertainty in flood and drought risk assessment, covering both parametric and scenario-based uncertainties, this framework can adopt probabilistic weights or confidence intervals for each link, using historical data, expert judgment, or fuzzy overlay techniques. Recomputing centrality measures under multiple realizations clarifies which parameters remain influential across varying conditions, while scenario-based inputs (such as extreme vs. moderate precipitation) highlight the relative resilience of key nodes. Additionally, the cross-entropy

Table 2. Key risk factors for flood and drought in river basins (ranked descending, top left higher and bottom right lower)

Risk Factors			
Drought impact	Flood exposure	Agricultural water use	Change factor
Flood impact	Precipitation	Residents' utility	Public demand for mitigation
Flood risk	Water supply	Temperature	Air humidity
Flood hazard	Available groundwater	Risk perception	Surface water inflow
Available surface water	Water demand	Drought awareness	Access to insurance
Drought vulnerability	Drought exposure	NDVI	Domestic water use
Flood awareness	Community resilience	Agricultural demand	
Drought risk	Drought hazard	Water resources sustainability index	

Table 3. Network metrics for each of the produced cluster of parameters

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	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	0.12
G4		Square	16	18	18	0	0	16	18	5	2.383	0.075
G5		Solid Square	12	15	15	0	0	12	15	6	2.25	0.114
G6		Diamond	11	16	16	0.333	0.333	11	16	5	2.116	0.145
G7		Solid Diamond	10	18	18	0.385	0.556	10	18	4	1.92	0.2
G8		Triangle	4	3	3	0	0	4	3	3	1.25	0.25

optimization may incorporate stochastic draws from uncertain variables (e.g., precipitation, water demand), yielding more robust rankings that extend beyond purely deterministic assumptions. Although certain links are currently highlighted as of major relevance, this probabilistic approach recognizes that their impact on basin-level risk can shift when measured across diverse datasets and aggregated via fuzzy overlay functions, thereby providing a deeper, non-deterministic perspective on the interconnectedness of flood and drought drivers.

Although our network-centric framework (integrating Interpretive Structural Modelling, Causal Loop Diagrams, multiple centrality metrics, and Cross-Entropy refinement) is novel, it aligns closely with existing multi-parameter approaches that have guided river basin management around the globe. One prominent illustration is in the Ganges-Brahmaputra-Meghna (GBM) region, where researchers have combined hydrological and socio-economic variables within network-like models to identify high-impact parameters and trace cascading effects of interventions [7, 8]. While these studies did not use precisely the same multi-metric or rank-aggregation processes, they employed a similar perspective one that recognizes how climatic, environmental, and policy factors connect in a large-scale system, enabling decision-makers to pinpoint critical nodes (such as reservoir operations or upstream land-use practices) for effective risk mitigation.

Related efforts in the Mekong River Basin have used simulation-based methods, some with graph-inspired analytics to highlight flood hotspots and prioritize reservoir operations under drought scenarios. While these efforts differ in their analytic details, they share the concept of examining various parameters (e.g., precipitation, governance capacity, population growth) as part of an interconnected network. In prac-

tice, this approach reveals how small adjustments (e.g., optimized water releases from a single reservoir) can generate larger system-wide benefits, mirroring the principles of betweenness and centrality in your proposed framework.

A more recent example is unfolding in the Danube River Basin, where, since 2022, cross-border collaborations have focused on integrating flood-hazard data, climate projections, and socio-economic indicators into a holistic decision-support environment. Although they do not replicate the entire suite of multi-metric centrality rankings or cross-entropy optimization found in this paper, Danube authorities are adopting a single model that captures interdependencies among diverse factors, ranging from upstream forest management to the design of urban flood defences. By experimenting with scenario variations, such as new wetlands restoration or changes in reservoir operation, they can observe how localized interventions reshape flood probabilities and resilience across multiple countries. This resonates strongly with the network-based emphasis of our method: each parameter (e.g., precipitation trends or water demand) becomes part of a broader system whose individual nodes and edges can be quantitatively ranked or tested under different future states.

Collectively, these real-world experiences across the GBM, Mekong, and Danube Basins demonstrate that a multi-parameter, network-oriented perspective is both feasible and effective for tackling complex flood and drought challenges. By systematically mapping hydrological, climatic, and socio-economic factors and then assessing their relative importance under varied scenarios, such methods equip policymakers to invest resources where they can yield the greatest system-wide improvements. Our framework, with its expanded suite of network metrics and cross-entropy optimization, builds on this foundation by providing a

more fine-grained prioritization of risk factors, ultimately assisting basin authorities in making robust, evidence-based decisions under conditions of uncertainty.

CONCLUSIONS

This study presents a comprehensive and innovative approach to flood and drought risk assessment within river basins by integrating Interpretive Structural Modelling (ISM), Causal Loop Diagrams (CLD), network metrics, and Cross-Entropy Monte Carlo optimization. Through the systematic identification and evaluation of 116 interconnected parameters, we have illuminated the key drivers of flood and drought risks, moving beyond traditional univariate models to embrace the complexity of socio-environmental interactions. The application of network theory allowed us to identify critical parameters such as Drought Impact (P107), Flood Risk (P2), and Available Surface Water (P25) that serve as pivotal nodes within the system, offering valuable insights for targeted risk mitigation strategies.

The use of the Cross-Entropy method to optimize parameter rankings across multiple network metrics further refined the focus, revealing the most influential parameters that should be prioritized in risk management efforts. This holistic, data-driven approach enables policymakers and river basin managers to better allocate resources, develop effective transboundary water management policies, and enhance resilience against the impacts of climate variability and extreme weather events. The findings underscore the importance of addressing both natural and socio-economic factors in an integrated manner, highlighting the need for a paradigm shift in how flood and drought risks are assessed and managed.

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CONFLICT OF INTEREST

The authors of this work declare that they have no conflicts of interest.

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