Enhancing Flood Management in Road Transport System via News Media Data Analytics

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Abstract

Road networks are crucial parts of urban infrastructure, enabling the movement of goods, logistics, and people in normal and emergency situations. Inadequate performance of road transport can lead to significant disruptions in urban systems. Road transport systems are particularly vulnerable to surface water flooding, especially in areas with insufficient land surface permeability and drainage systems. Moreover, the frequency and severity of flood events have increased due to climate change and rapid urbanisation, posing significant challenges to flood management in the road transport system.

Scholars and experts recommended prioritising the creation of flexible and adaptable strategies to tackle changing and unpredictable circumstances. The utilisation of digital media data for flood detection and mapping has gained traction and is seen as a valuable asset for improving disaster management. While recent initiatives have emphasised the use of social media for flood management, news media, often viewed as more objective and dependable, remains relatively unexplored in the context of flood management for the road transport system. More in-depth research is needed to advance the utilisation of news media for flood management in the road transport system.

This study proposes a central research question: How can flood management in the road transport system be enhanced via news media data analytics? An integrated framework was developed to address this question, with the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) as a case study. The research focused on three phases of flood management: 1) examining news media activities related to floods and transport networks, with an emphasis on preparedness and early warning (Chapter 4); 2) exploring government agency collaboration for flood management in the transport system, particularly in the phase of response and recovery (Chapter 5); and 3) integrating news media analysis and vulnerability assessment to assess potential flood impacts on the road transport system, with a focus on mitigation, risk, and vulnerability modelling (Chapter 6).

This thesis contributes significantly to both academic research and practical applications. It offers new insights into using news media analysis for flood preparedness and early warning (Chapter 4). The study not only extracts information from news media articles but also examines the role of news media itself. Chapter 5 introduces a perspective and method for analysing government agency networks using news media data. Additionally, Chapter 6 enhances flood damage assessment by integrating news media analytics and vulnerability assessment.

In practical terms, the thesis recommends that city authorities manage floods in the road transport system. These recommendations cover various aspects, including road design and planning, government operations, and news media applications. Overall, the research findings will improve the understanding of flood managers and transport managers regarding the role of news media during floods and the development of effective flood management strategies.

Keywords: Road transport system, News media data, Network analysis, Flood management

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Lu, X., Chan, F. K. S., Chen, W. Q., Chan, H. K., & Gu, X. (2022). An overview of flood-induced transport disruptions on urban streets and roads in Chinese megacities: Lessons and future agendas. *Journal of Environmental Management*, 321, 115991.

Lu, X., Chan, F. K. S., Li, N., Chen, C., Chen, W. Q., & Chan, H. K. (2022). Improving urban flood resilience via GDELT GKG analyses in China's Sponge Cities. *Scientific Reports*, 12(1), 20317.

Lu, X., Chan, F. K. S., Chan, H. K., & Chen, W. Q. (2023, February). Investigation of Transport Logistics Disruptions from Urban Floods: A Case Study of the Chinese Coastal Megacity—Guangzhou, China. In Intelligent and Transformative Production in Pandemic Times: *Proceedings of the 26th International Conference on Production Research (pp. 637-647)*. Cham: Springer International Publishing.

Lu, X., Chan, F. K. S., Chan, H. K., & Chen, W. Q. (2024). Mitigating flood impacts on road infrastructure and transportation by using multiple information sources. Resources, Conservation and Recycling, 206, 107607.

Chan, F. K. S., Paszkowski, A., Wang, Z., **Lu, X**., Mitchell, G., Tran, D. D., ... & Zhu, Y. G. (2024). Building resilience in Asian mega-deltas. *Nature Reviews Earth & Environment*, 1-16.

Chan, F. K. S., **Lu, X**., Li, J., Lai, Y., Luo, M., Chen, Y. D., ... & Chan, H. K. (2024). Compound flood effects, challenges and solutions: Lessons toward climate-resilient Chinese coastal cities. *Ocean & Coastal Management*, 249, 107015.

Chan, F. K. S., Wang, Z., Chen, J., **Lu, X**., Nafea, T., Montz, B., ... & Wang, J. (2023). Selected global flood preparation and response lessons: implications for more resilient Chinese Cities. *Natural Hazards*, 118(3), 1767-1796.

Chan, F. K. S., Yang, L. E., Mitchell, G., Wright, N., Guan, M., **Lu, X**., ... & Adekola, O. (2022). Comparison of sustainable flood risk management by four countries–

the United Kingdom, the Netherlands, the United States, and Japan–and the implications for Asian coastal megacities. *Natural Hazards and Earth System Sciences (NHESS)*, 22(8), 2567-2588.

Chan, F. K. S., Gu, X., Qi, Y., Thadani, D., Chen, Y. D., **Lu, X**., ... & Chen, W. Y. (2022). Lessons learnt from Typhoons Fitow and In-Fa: implications for improving urban flood resilience in Asian Coastal Cities. *Natural Hazards*, 110(3), 2397-2404.

Chan, F. K. S., Chen, W. Y., Sang, Y., Chen, Y. D., Huang, W. W., Chen, W. Q., … **Lu, X**., … & Zhu, Y. G. (2021). Build in prevention and preparedness to improve climate resilience in coastal cities: Lessons from China's GBA. *One Earth*, 4(10), 1356-1360.

Chan, F. K. S., Yang, L. E., Scheffran, J., Mitchell, G., Adekola, O., Griffiths, J., ... **Lu, X**., … & McDonald, A. (2021). Urban flood risks and emerging challenges in a Chinese delta: The case of the Pearl River Delta. *Environmental Science & Policy*, 122, 101-115.

Chapter 1: Introduction

1.1 General background and problem identification

1.1.1 Increasing flood damage on road transport

Infrastructure systems such as water, railway and road networks are essential for cities, particularly in an era of growing global connectivity (Rodrigue and Notteboom 2013). Among these, road networks are pivotal, supporting the movement of goods, logistics, and individuals in regular and emergency scenarios (Rozenberg and Marianne 2019). As cities are the centres of population and economic activity, road networks expand rapidly to accommodate various human and productivity needs. This rapid expansion is particularly noticeable in developing and emerging countries or regions, driven by factors such as a) an increase in daily trips due to urban population growth, b) longer journey distances due to urban expansion, c) higher travel rates due to rising incomes, and d) increased commercial and industrial activities due to global economic growth (Phan Nhut Duy 2019).

Poor performance of road transport can cause significant disruptions to urban systems (Hernandez-Fajardo and Dueñas-Osorio 2013). For instance, disruptions in road transport can lead to the inability to make daily trips (e.g., commuting to work and school), interruptions in economic and business activities, and increased costs of public services (Rozenberg and Marianne 2019). These disruptions can be exacerbated by adverse natural hazards, particularly floods (Koetse and Rietveld 2009). Surface water floods are the most common natural hazard in urban areas (CRED and UNISDR 2015), occurring when water overflows from water bodies, such as rivers, lakes, and oceans, or accumulates due to saturated ground (Plate 2002). Surface water floods significantly threaten urban transport systems, especially in areas with inadequate land surface permeability and drainage systems. Previous studies have shown that approximately 84% of global transport infrastructure is susceptible to flooding (Koks et al., 2019). Road transport disruption and reduced transport system performance due to floods can lead to costs exceeding 900,000 RMB/hour for each impacted main road (Pregnolato et al., 2016).

Furthermore, flood events have become more frequent and severe due to climate change and rapid urbanisation (Kendon et al., 2012). According to the Human Cost of Disasters report, the number of flood disaster events worldwide increased from 1389 (32% of all disaster events) during 1980-1999 to 3254 (44% of all disaster events) during 2000-2019 (CRED and UNISDR 2020). Over the past two decades, floods have affected 1.6 million people worldwide, the highest figure among all types of disasters. China has been particularly affected by flooding, experiencing an average of 20 floods annually (EM-DAT 2023). During this period, a total of 900 million individuals in China were affected by floods, accounting for about 55% of the global population affected by flooding (CRED and UNISDR 2020). Rainstorms are projected to increase at an average annual rate of approximately 5% to 7% in urban areas across China (Lu et al., 2022).

Consequently, flood management in the road transport system encounters challenging circumstances marked by heightened complexity and reduced predictability of operational scenarios. For example, during the ‘7·20’ Zhengzhou Flood in 2021, inadequate risk perception, emergency facilities, and management capacity were evident, reflecting the extreme and difficult-to-predict nature of the event (Jiahong et al., 2023; Zhao et al., 2022). As a result, Zhengzhou experienced 380 fatalities and 40.9 billion RMB in direct economic losses (Xinhua News Agency, 2022). Scholars and experts suggest developing more flexible and adaptable strategies to cope with such dynamic and uncertain conditions. One potential approach to facilitate such strategies is to leverage digital media.

1.1.2 The application of digital media for flood management

The use of digital media data for flood detection and mapping has gained popularity and is recognised as a valuable tool for enhancing disaster management (Horita et al., 2015; Ouyang et al., 2022). Digital media offers a dynamic platform where users may both actively generate and consume material, in contrast to traditional media forms like TV, radio, and print, which primarily supply content for passive consumption (Truong and Clayton 2020). Instantaneous access to a wealth of information and the ability for users to share information quickly and creatively are two qualities that define digital media (Plantin et al., 2018). The advent of big data and artificial intelligence, which use the vast volumes of data produced by digital media for a variety of purposes, are further developments that characterise the digital media period (Dou et al., 2019).

Digital media can be applied to four phases of flood disaster management (see Figure 1.1): mitigation, preparedness, response and recovery (Sarvari et al., 2019; Fauzi 2023). In the preparedness phase, digital media can disseminate timely information about weather forecasts, flood alerts, and evacuation notices to at-risk public areas (Xiao et al., 2015). During the response phase, digital media, such as social media, enable authorities to deliver real-time updates on flood conditions, evacuation orders, road closures, and emergency shelter information. Digital media also provides communication channels for authorities to coordinate response efforts, share updates with the public, and gather feedback from affected communities (Ahmed et al., 2019).

In the recovery phase, digital media, especially social media, can be used to help government agencies assess the recovery situation and provide victims with timely assistance to improve their living conditions (Tan, Schultz 2021). Digital media also provides a potential venue for dynamic change in the residents' behaviour during long-term recovery (Yeo et al., 2022). Meanwhile, media data can be analysed to gain insights into public sentiment, perception of risk and pattern of communication. The information can inform future flood management strategies (Wang et al., 2020).

In the mitigation phases, digital media coverage raises public awareness about flood risks, preparedness measures, and response actions (Fauzi, 2023). Residents learn about the importance of flood insurance, evacuation plans, and emergency supplies through news reports and features. Moreover, media data is widely employed to investigate the spatial distribution of flooded areas and flood risk mapping, aiding decision-making (Fohringer et al., 2015; Darabi et al., 2019; Scotti et al., 2020).

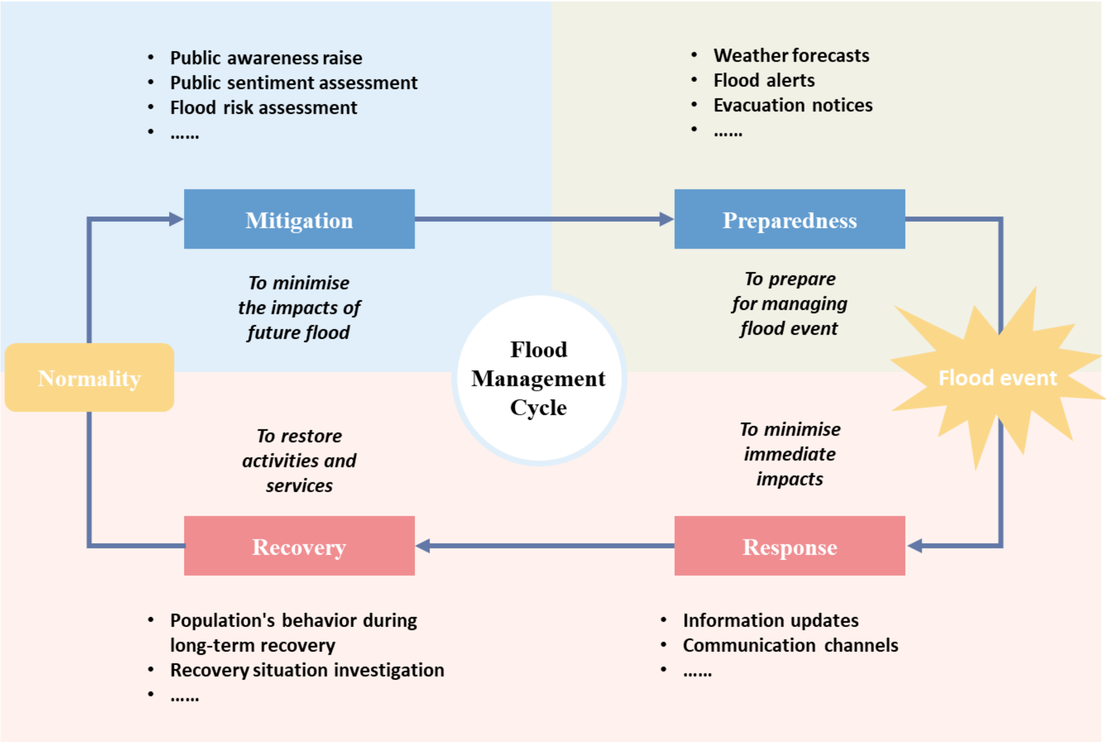

Figure 1.1 The application of digital media, such as social media and news media, for flood management

1.1.3 Identification of the problem

Recent research and practices have increasingly focused on using social media for flood management. Social media data are often more timely than news media and provide more localised details during flood events than agency-based news articles. However, several challenges exist in using social media for flood management (Singla and Agrawal 2022). The lack of rules or regulations on using social media for flood management is a significant issue, as social media is not an official platform. Additionally, social media is a free source, which may lead to spreading misinformation and fake news (Sergio 2019). There are also cultural biases among people of different ages or areas, with some individuals choosing not to share information on social media. Implementing social media may introduce new risks and, in some cases, exaggerate the impacts of a disaster.

In comparison, news media is often viewed as more objective and reliable (Miles, Morse 2007). Agency-based news websites verify information sources before reporting it (Liu et al., 2018). With the development of news media technology, many news agencies publish news on their websites and social media platforms (Griessner 2012). Therefore, exploring the potential benefits of news media for flood management is noteworthy. However, implementation and research on news media adoption for flood management in the transport system remain limited. More detailed work is needed to promote the use of news media for flood management in the road transport system.

1.2 Research motivations

This research is motivated by the practical issue and existing knowledge gaps outlined above. There is an urgent need to adapt road transport to reduce damage from adverse flood events using more flexible strategies. However, there is a limited understanding of how news media can improve flood management in the road transport system. Furthermore, the proportion of impermeable surfaces is rising in many modern cities. In recent decades, road networks in Chinese cities have been hastily designed and built without consideration for long-term climate trends (Lu et al., 2022). For several decades, the urban land drainage system has struggled to manage runoff and hydrological shifts.

Recent studies have explored the adoption of digital media to improve flood management strategies, with a focus on social media data analysis rather than news media data analysis (Wang et al., 2020; Tan, Schultz 2021; Ouyang et al., 2022; Shoyama et al., 2021). This focus can be attributed to news media data analysis requiring significant time and data resources. Understanding how news media enhances flood preparedness in transport systems is not straightforward. Research on news media's performance during flood events is crucial for improving preparedness and notifying the early warning, but unfortunately, it is still unclear.

As for the response and recovery phases of flood management, existing approaches to analysing media data related to flood and transport networks only capture public participation and response. There are few studies conducting network analysis to explore government agency engagement and collaboration for flood response and recovery. Government agency engagement and collaboration play a crucial role in flood management in transport systems. For example, the 2002 flood in Kristianstad, Sweden, promoted learning and fostered increased cooperation and integration within the municipality, demonstrating how extreme events can stimulate collaboration (Johannessen and Hahn 2013). Inadequate coordination among agencies can result in avoidable casualties and harm to economies.

Advances in flood damage assessment confirmed that vulnerability assessment is one of the valuable tools for investigating flood impacts on road infrastructure (He et al., 2021; Li et al., 2015). These studies ignored the impacts of surface water floods on transport performance (e.g., disruption of public transportation, traffic accidents, etc.). With the development of digital media, media data, especially social media data, is becoming a more popular and promising way to fill in the gaps in conventional data. However, social media data is often mined to analyse the characteristics of flood impacts at the event level, making it hard to compare different areas. Few studies have captured the complexity of transport networks and surface water flooding at a regional scale by combining news media and vulnerability assessment.

Therefore, this thesis tries to tackle these challenges and contribute to flood management in the road transport system, using the Guangdong-Hong Kong-Macao Greater Bay Area (GBA) as a case study. An integrated framework linking three major phases of flood management is used to explore the adoption of news media for flood management. This study hopes that implementing this framework provides an important alternative for solving the shortage of conventional and social media data and providing valuable insights for decision-making.

1.3 Research aims, objectives and questions

Given the increasing challenge of surface water flood impacts, the road transport system needs more appropriate plans for long-term and sustainable development, especially in the face of climate change. This establishes the rationale and motivation for this research, which aims to investigate how to enhance flood management in road transport systems via news media analytics. To accomplish this aim, the research posits the following central question:

How can flood management in the road transport system be enhanced via news media data analytics?

According to the review of current research progress on surface water flood and transport systems, this research addresses the following sub-questions:

RQ (1): How to adopt the news media analysis for better flood preparedness and early warning?

To answer this sub-question, the first study of this thesis investigated news media activities related to flood and transport networks for enhancing flood preparedness and early warning via news media. Media attention and news sentiment were selected as two indexes to explore news media activities. According to the characteristics of news media activities, recommendations would be provided for the adoption of news media for better flood preparedness and early warning.

RQ (2): How useful is news media as a source for exploring government agency collaboration for flood response and recovery?

To answer this sub-question, the second study of this thesis explored the role of different government agencies in flood management via news media data. According to China's administrative relationships and functions, the government agency is selected and categorised from news media data. Government agency engagement was used to investigate the level of agency presence or involvement during flood events.

Government agency collaboration was conducted to characterise the collective action and governance that brings together agencies to work towards a common goal.

RQ (3): How can potential flood impacts on the road transport system be assessed by combining news media analytics and vulnerability assessment?

To answer this sub-question, the third study of this thesis assessed potential flood impacts on transport networks by combining vulnerability assessment and news media analytics, which contribute to flood mitigation, risk and vulnerability modelling. Vulnerability assessment was used to explore the flood impacts on road infrastructure (i.e., direct tangible impacts). News media analysis was conducted to investigate the flood impacts on road transport (i.e., indirect tangible impacts).

Addressing the three sub-questions would enhance flood management in road transport systems from different perspectives. The three sub-questions contribute to the major three phases of flood management, including (a) preparedness and early warning, (b) response and recovery, (c) mitigation, risk and vulnerability modelling.

1.4 Thesis outline

The thesis has seven chapters that align with the research aims (see Figure 1.2). Following this introduction, Chapter 2 reviews scientific research and current practices on flood management in road transport systems and describes the gaps in existing studies. Chapter 3 illustrates an original integrated framework adopted in this research and describes the study area (i.e., the Guangdong-Hong Kao-Macao Greater Bay Area). Chapter 4 investigates news media activities related to flood and transport networks, focusing on the preparedness and early warning phase. Chapter 5 explores the government agency collaboration for flood management in the road transport system., focusing on the response and recovery phase. Chapter 6 integrates news media analysis and vulnerability assessment to investigate the potential flood impacts on road transport systems, focusing on the phase of mitigation, risk and vulnerability modelling. Finally, Chapter 7 summarises this study and discusses the implications of transitioning to a flood-resilient transport system.

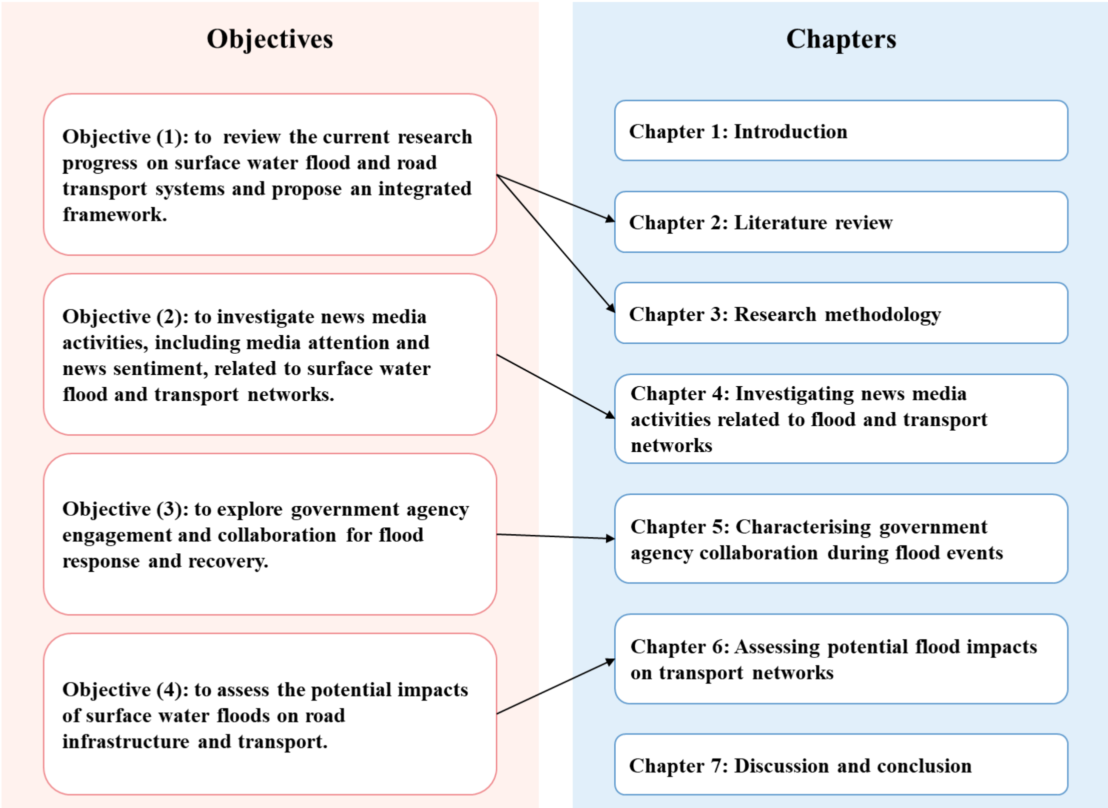

Figure 1.2 The overview of this thesis

Chapter 2: Literature review

2.1 Introduction

The complexity of interventions required to enhance flood management in the road transport system was introduced in Chapter 1, highlighting the need to improve adaptive capacity for efficient operation during surface water flood events. This chapter examines the development of road transport in relation to surface water flooding, reviewing scientific research on the use of digital media and vulnerability assessment for flood management. Furthermore, this chapter also reviews current practices in flood management in China and best practices worldwide. Finally, this chapter was concluded by identifying gaps in existing topics and methods.

2.2 Road transport development in relation to flooding

2.2.1 Urbanisation and road transport development

Urbanisation involves the migration of individuals from rural to urban regions, resulting in the expansion of cities. It is frequently linked with economic prosperity and impact. Cities act as centres for economic activities, services, and communication, crucial in contributing to a nation's Gross Domestic Product (GDP). More than 4.3 billion people reside in urban areas worldwide (see Figure 2.1) (Ritchie and Roser 2023; United Nations 2019). The global urban population is rapidly increasing, with projections indicating that nearly 7 billion people will live in urban areas by 2050 (Ritchie and Roser, 2023). This growth is particularly pronounced in the Global South and is expected to drive future urbanisation (Onodugo et al., 2019).

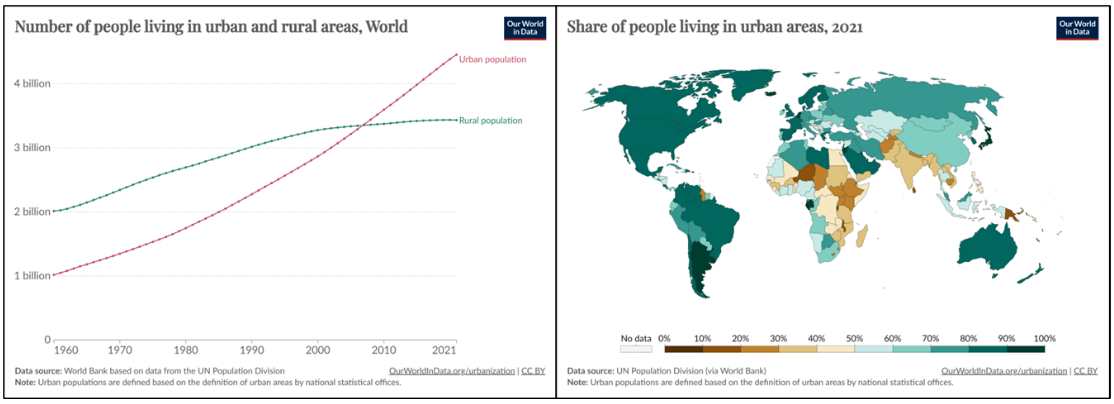

Figure 2.1 Growth and distribution of the world's urban population in 2021. Source: (Ritchie, Roser 2023)

Rapid urbanisation significantly drives the development of road transport infrastructure. As cities expand due to urbanisation, the demand for transport increases. Efficient transport is essential for people to commute to work, access services, and engage in urban activities. This growing demand necessitates expanding and enhancing road networks to accommodate the increasing number of vehicles (Tjallingii, 2000). Additionally, urban areas are economic activity centres, and effective road transport is vital for moving goods and services. As urbanisation fosters economic growth, there is a corresponding need to develop road infrastructure to support this expansion (Roeseler and Dosky 1991).

Consequently, the global road network and transport systems are undergoing rapid expansion. Since 2000, approximately 12 million kilometres of paved roads have been constructed worldwide, with an estimated $33 trillion allocated for an additional 25 million kilometres by 2050 (Andrasi et al., 2021; International Energy Agency 2009). The United States boasts the most extended road network, exceeding 6.6 million kilometres (Gedik 2020).

The development of road transport plays a crucial role in enhancing economic growth, employment, socio-economic development, and urban planning. Transport infrastructure is widely acknowledged as a fundamental social and economic development requirement, influencing population mobility, urban employment patterns, and overall socio-economic advancement (Okechukwu et al., 2021; Magazzino and

Mele 2021). Improving and maintaining road conditions can boost socio-economic growth by enhancing access between regional and rural communities, alleviating poverty, and fostering development (Asomani-Boateng et al., 2015). Transport is essential for providing access to employment, education, and healthcare and connecting goods and services to markets, all of which are critical drivers of growth and vital for addressing climate change. Furthermore, the development of urban roads is closely tied to regional development and urban planning, influencing the realisation of economic potential and transport infrastructure density (Fistung et al., 2014; Cojanu et al., 2012).

For example, since the late 20th century, China's urbanisation rate has experienced a dramatic increase, rising from 17.92% in 1980 to over 60% in recent years. The Chinese government has set a target to achieve an urbanisation rate of 70% by 2030, which would result in a billion urban inhabitants in China. China's urban land area has expanded nearly fivefold between 1992 and 2015 (Dang et al., 2020). With rapid urbanisation, China's total highway length has surpassed the million-kilometre mark, ranking third globally (Chen et al., 2021). In 2021, China's highway network density reached about 55.01 kilometres/100 square kilometres, showing a sustained growth trend (Statista 2021). Road transport has become the most popular means of land travel in China, offering high flexibility and point-to-point convenience, especially in areas with challenging geography (Chen et al., 2021).

2.2.2 The concept and causes of surface water flood

The definition and characteristics of surface water flooding are crucial for developing warning systems and ensuring that affected communities understand and respond appropriately to such events (Priest et al., 2011). Surface water flood refers to when intense rainfall exceeds an area's drainage capacity, causing water to flow or pool on the ground surface. It can occur when rainfall creates overland flow before entering a watercourse or drainage system or when the system cannot manage the water volume (Priest et al., 2011). Surface water flooding can affect urban areas where stormwater drainage and road transport systems cannot handle intense rainfall, leading to inundation and potential road closures (Yang et al., 2019). It can also include combined flooding in urban areas, encompassing pluvial, sewer, and groundwater (Li et al., 2020).

The causes of increasing surface water floods are closely linked to human activities, such as urban development and climate change, which result in increased runoff and overwhelmed drainage systems (Jiang 2018). These factors are compounded by natural phenomena like sea-level rise and more intense rainfall events. Thus, the causes of rising surface water floods are multifaceted, with several contributing factors identified as follows:

Climate change contributes to more frequent and intense rainfall events and sea-level rise, exacerbating surface water flooding (Yin et al., 2015; Zhou et al., 2012; Xu et al., 2018). Heavy rainfall events, which are becoming more common due to climate change, lead to more water than the ground and existing drainage systems cannot quickly absorb or remove (Lyu et al., 2019; Vardoulakis et al., 2015). For instance, there has been a 10% increase in the number of rainstorm days in China (Su 2020). Climatologists predict that extreme rainfall caused by global warming will worsen in the next 20 years. Rising sea levels can contribute to higher groundwater levels, reducing the unsaturated space available for infiltration and increasing the risk of flooding (Habel et al., 2017).

The expansion of urban areas increases the presence of impervious surfaces like buildings, roads, and car parks, leading to higher volumes of surface water runoff since less water is absorbed into the ground (Kaźmierczak and Cavan 2011). The process of rapid urbanisation has significantly altered land use globally (Chen et al., 2014), leading to the continuous replacement of many aquatic ecosystems (such as lakes and wetlands) and artificial water systems with urban infrastructure (such as roads, shopping malls, residential, and office buildings) (Jiang et al., 2012; Zhang et al., 2015). Additionally, construction activities and groundwater withdrawal can cause land subsidence, altering flow pathways and increasing flood risk (Liu et al., 2022).

In many cities, especially those experiencing rapid growth or with outdated infrastructure, the stormwater drainage systems may be insufficient to handle increased runoff, leading to overflow and flooding (Yang et al., 2019). For instance, the urban drainage protection standard in numerous Chinese cities is still relatively low, with a return period of only 1-in-1 to 1-in-5 years. In contrast, surrounding cities like Tokyo have a return period of 1-in-30 years, and Singapore has a return period of 1-in-30 to 1-in-50 years. (Chan et al., 2018). As a result, surface water floods occur due to the exceeded peak discharge from urban runoff and enhanced overflow on the road surface.

2.2.3 Flood impacts on transport networks

The interaction between surface water floods and road transport is complex and multifaceted. Surface water flooding significantly affects the road infrastructure and transport operation, including road design, planning, maintenance, network operation, and vehicle functionality (Wang 2020). Previous research has categorised the impacts of surface water floods on transport networks into four main categories: direct tangible impacts, indirect tangible impacts, direct intangible impacts, and indirect intangible impacts (Markolf et al., 2019; Rebally et al., 2021).

Direct tangible impacts encompass damage to the road infrastructure itself, such as pavement deterioration. This impact is observable through potholes, surface washouts, and undermined roadbeds, often resulting in road closures and necessitating substantial repair efforts. Surface water accumulation, known as road waterlogging, significantly threatens the road transport system (Hooper 2013). For instance, a 100-year surface water flood event led to 170 instances of road waterlogging in Shanghai on 25 August 2008 (Deng, Shen, and Xu, 2016). The frequency and intensity of heavy rainfall exacerbate surface water flooding (Hou and Du, 2020). In one example, a brief but intense rainfall event in Shenzhen on 11 April 2019 resulted in 137 road inundations and 29 flooded cars (Meteorological Bureau of Shenzhen Municipality, 2020). Studies have shown that under a 1-in-100-year surface water flood scenario, 47% and 15% of road sections experienced inundation with depths exceeding 20 cm and 30 cm, respectively (Li et al., 2018). Zhou et al., (2015) found that the impact levels of roofs, roads, pavements, and green spaces on waterlogging risks were 0.95, 0.85, 0.55, and 0.2, respectively.

Indirect tangible impacts are associated with immediate travel effects, such as changes in travel time due to detours or slower speeds enforced on waterlogged streets. This category also includes the increased risk of accidents due to slippery or submerged road surfaces. Traffic delays worsen as road water levels rise, reducing traffic speed and flow. For instance, during a heavy rainstorm in Beijing on 23 June 2011, many travellers were stranded due to severe road waterlogging, unable to return home until late at night (China Daily, 2011; Su and Li, 2016). Traffic speed and flow are crucial for assessing congestion during surface water flood events. Analysing traffic delays helps identify road closures and suitable stopping positions for vehicles. Li et al., (2018) showed that traffic delays could range from 0.5 to 8 times the average travel time, with approximately 1% to 7% of traffic volumes diverting to dry roads in the city centre of Shanghai during flooding. In Beijing, simulation of the second and fourth ring expressways indicated capacity reductions of 7.26% and 3.07% under light rainfall, 10.87% and 5.29% under moderate rainfall, and 17.09% and 6.64% under heavy rainfall, respectively (Zhang et al., 2019).

Direct intangible impacts are associated with disrupting critical infrastructure interconnected with the transport system, such as power outages or water pipe breaks. Disruptions to these elements can lead to heightened congestion, road closures, decreased road safety, limited fuel availability for evacuation and emergency power, and constrained access for emergency services and response teams. For example, vehicles exposed to floodwaters are susceptible to mechanical and electrical faults, leading to breakdowns and worsening traffic congestion (He et al., 2023). Surface water floods can also impair the energy supply, which leads to disruptions in systems reliant on electricity, such as road transport (Arrighi et al., 2021).

Indirect intangible impacts include broader socio-economic consequences, such as loss of accessibility to essential services like hospitals, which can have profound implications for community resilience and emergency response during flood events. The underperformance of the road transport system can result in diminished spatial accessibility, causing missed economic prospects and service interruptions (World Bank, 2016). During surface water flood events, traffic congestion and disruptions can reduce or eliminate spatial access to various locations. These disruptions impact residents' daily routines, such as commuting to school or work, and limit economic opportunities (Wiśniewski et al., 2020). For instance, in Guangzhou on 21 May 2020, heavy rainfall (80 mm/hour) led to 443 waterlogged roads, 164 bus routes being altered, and the suspension of Metro Line 13 (Monica, 2020). This scenario makes commuting to school and work challenging for individuals, while the movement of goods and delivery of public services are also affected. A study in Shanghai revealed that the proportion of communities with access to the metro decreased from 87% under normal conditions to 80% during surface water flood events (Li et al., 2018).

2.3 Use of digital media for flood management

2.3.1 The concept of digital media

The concept of digital media encompasses a wide array of electronic formats used for creating, distributing, viewing, and storing information. Unlike traditional media forms such as TV, radio, and print, which typically offer content for passive consumption, digital media provides a dynamic platform where users can both consume and actively create content (Truong and Clayton 2020). Digital media includes text, audio, video, and graphics transmitted online for viewing or listening (Feldman 1996; Howard, Hussain 2011). These media are characterised by their ability to provide instant access to vast amounts of information and the capacity for users to exchange information rapidly and innovatively (Plantin et al., 2018). The digital media era is also marked by the development of big data and artificial intelligence, which harness the immense amounts of data generated by digital media for various applications (Dou et al., 2019).

Digital media can be categorised into various subsets, including social and news media (see Table 2.1). In recent years, digital media data has been utilised to uncover and analyse actual events (Smith et al. 2017; Soomro et al. 2024), such as earthquakes, floods, high temperatures, tropical storms, and forest fires (Y. Wang et al. 2020; Ouyang et al. 2022; Xie et al. 2021; Cao et al. 2020; Zander et al. 2022).

Table 2.1 The differences between social media and news media

Distinctions	Social media	News media	References
Content creation and dissemination	Social media allows users to create and share content with minimal filtering.	This content goes through a rigorous review process before publication.	(Zhang et al., 2022; Liu et al., 2021)
Influence on public opinion	With its rapid information exchange, social media also significantly shapes public opinion and can influence corporate environmental governance.	News media has historically set the agenda for other media forms and influenced the opinion formation of decision-makers.	(Leitch, Bohensky 2014; Zhang et al., 2022)
Public engagement	Social media allows the public to engage as both audience and content creators.	News media typically present content to the public.	(Gao et al., 2023)
Information quality	Social media leads to faster dissemination but raises concerns about accuracy and quality.	News media has been recognized for providing quality data.	(Gundersen et al., 2022)

Social media refers to online platforms and tools (e.g., Twitter, Facebook) that enable users to create, share, and engage with content in a social context (Carr and Hayes 2015). These platforms are tailored for user-generated content and interpersonal communication rather than traditional news dissemination (Kaplan, Haenlein 2010). Social media is commonly utilised for personal communication, social networking, and self-expression, and it also serves as a platform for accessing news and information (Carr, Hayes 2015).

News media refers to traditional media organisations that produce and disseminate news and information to the public through various channels, including print, television, and online platforms (Harcup, O’Neill 2017; Dictionary 2014). These organisations employ professional journalists and editors who report and analyse current events, often aiming to provide factual and objective coverage. The primary objective of news media is to inform the public about significant events and issues and to facilitate public discourse and debate. Digital-native news media differ from traditional media in their presentation and reporting styles and have gained prominence, particularly in regions with less established traditional media outlets (Painter et al., 2018).

2.3.2 Digital media for flood damage assessment

In the era of big data, social media platforms like Twitter, Facebook, and Sina-Weibo are considered valuable and potent databases for managing disasters (Panteras et al., 2015; Xiao et al., 2015). Monitoring social media can quickly identify flood damages and facilitate recovery monitoring. For example, social media data from Weibo was utilised for rapid damage classification during a surface water flood in Chongqing from 18 to 20 August 2020 (Tan, Schultz 2021). This study also examined the feasibility of recovery based on word frequency analysis. Kankanamge et al., (2020) utilised real-time Twitter data to assess disaster severity and identify highly impacted areas during the 2010–2011 Southeast Queensland Floods. Social media can also be leveraged to analyse the sentiments of the affected individuals, aiding in better disaster response. For instance, a method based on big data was suggested for responding to disasters by analysing sentiments. (Ragini et al., 2018). Shoyama et al., (2021) integrated natural hazard monitoring and social media data to investigate emergency flood detection in some regions of Japan from 11-15 October 2020.

As mentioned in Table 2.1, social media is commonly used for personal communication and self-expression. It is often characterised by user-generated content that may not undergo the same editorial scrutiny as traditional media. Individuals may exaggerate or misreport flood events on social media, leading to confusion and false alarms for emergency responders (Tan, Schultz 2021). Furthermore, social media usage may exhibit bias towards certain demographic groups or geographical areas. For example, younger individuals are more likely to use social media, and urban areas may have more active social media users. This disparity makes it challenging to compare different areas.

Consequently, the representativeness of social media data may not always align with the extent or intensity of damage.

News media data can be precious for flood damage assessment as it can provide real-time updates on the situation, including the extent of flooding, affected areas, and the response of authorities (Avellaneda et al., 2020; Young 1990). Liu et al., (2018) examined the spatial and temporal patterns of various natural hazards, such as rainstorms, floods, wind, and hail, utilising news media data from a Chinese news outlet. News articles can provide insights into the causes of the flooding, such as heavy rain or river overflow, which can help inform future flood management strategies. They can also be used to evaluate the effectiveness of flood management strategies and authorities' response to flood events. For example, Bohensky and Leitch (2014) conducted a newspaper analysis to understand the roles of government in managing floods. Henrique and Tschakert (2019) underscore the importance of elite media coverage in shaping public knowledge and influencing government action on flood adaptation, particularly in the context of São Paulo's 2009-10 floods. This highlights the media's role in holding governments accountable and advocating long-term solutions to flood risks.

2.3.3 Digital media for engagement and collaboration analysis

Enhancing stakeholder engagement in flood management is expected to influence the effectiveness of flood management and reduce the information gap (Aluko et al., 2020). Digital media has been an instant source of information for the investigation of public participation and government agency engagement. Soomro et al., (2024) proposed an evaluation framework for assessing public participation and response via Twitter data analytics, taking urban flooding in Karachi during 2022 as a case study. Wehn et al., (2015) presented a framework for analysing the potential for participation via ICT-enabled citizen observatories (including social media). Aluko et al., (2020) collected primary data on residents' social media participation and investigated the influence of resident agencies' participation via social media on flood management in Nigeria.

According to the results, they recommended that government agencies should encourage the adoption of digital media in flood management, such as information gathering and dissemination, promote planning (Aluko et al. 2020).

Participation can be through collaboration with the government agencies and among stakeholders themselves, leading to the identification of commonly agreed flood management measures (Almoradie et al. 2015). This collaboration often involves consensus-building and joint problem-solving to address complex issues that no single agency can solve alone (Abdeen et al. 2021). Previous studies emphasised the importance of government agency collaboration in enhancing the efficiency and effectiveness of flood response and management. For example, following the 1993 flooding, the establishment of the Scientific Assessment and Strategy Team in the US involved specialists from various agencies, illustrating the value of interdisciplinary collaboration for floodplain management (Hipple et al., 2005). The 2002 flood in Kristianstad, Sweden, promoted learning and fostered increased cooperation and integration within the municipality, demonstrating how extreme events can stimulate collaboration (Johannessen and Hahn 2013). A study involving Aaranyak, CICERO, and ICIMOD adopted an iterative co-learning approach focused on flood management, highlighting the importance of collaboration between communities and governmental officials (Tschakert et al., 2016). The 2016 flood in China highlighted that government agency cooperation often occurred through on-site meetings, lacking formal agreements for data sharing and collaboration (Wu et al., 2019).

Collaborative network analysis provides an alternative method to understand and improve interactions and coordination among different agencies involved in flood management (Guo and Kapucu 2015; Abbasi and Kapucu 2012; Fliervoet et al., 2016). Numerous studies have utilised network analysis to examine agency collaboration. For example, Moore et al., (2003) examined the structure of inter-organisational relationships among non-governmental organisations involved in the 2000 Mozambique floods using network analysis. They evaluated the centrality of each participant in the disaster network structure and investigated its perceived effectiveness in evaluating the efficiency of disaster management. Zaw and Lim (2017). investigated the military's involvement in disaster management and response during the 2015 Myanmar floods using Social Network Analysis (SNA). Fan et al., (2022) assessed the effectiveness of emergency management networks using the Super Ministry Reform of Emergency Management in China as a case study.

Integrating digital media data into collaborative network analysis offers a robust framework for estimating collaboration during flood events. Previous studies have investigated social media data to understand networks and extract vital information to improve flood management plans. For example, Cheong and Cheong (2011) gained insights into online communities during the 2010-2011 Australian floods, identifying active participants and assessing their effectiveness in sharing crucial information using Twitter tweet data. Kim and Hastak (2018) applied SNA to explore the interactions of online users on Facebook during the 2016 Louisiana flood. News media data has also been used for collaborative network analysis. Aung and Lim (2021) investigated the evolution of collaborative governance in Myanmar's flood response based on news media articles related to the 2015, 2016, and 2018 flood disasters.

2.4 Surface water flood vulnerability

2.4.1 The concept of vulnerability

Vulnerability is a multifaceted concept that includes the likelihood of social or ecological systems being adversely affected by external pressures and disruptions (Fur et al., 2007). Vulnerability is crucial for understanding how individuals, groups, or organisms react to and recover from stressors, especially in nanotoxicology. This includes psychosocial stress, community dynamics, and population assessment and response (Adger 2006; Delor and Hubert 2000).

The concept of flood vulnerability pertains to the likelihood of a system, community, or environment experiencing harm due to exposure to flood hazards (Rehman et al., 2019). It involves evaluating the potential negative impacts of flooding and the ability of the system or community to cope with, respond to, and recover from flood events. The concept of flood vulnerability has evolved, with definitions refined based on practical experiences and research findings. It has transitioned from a purely physical perspective to a more integrated and dynamic approach that incorporates social factors and long-term impacts. This evolution has led to a deeper understanding of the complex and multifaceted nature of flood vulnerability. Moreover, it has provided a foundation for developing effective strategies to reduce vulnerability and enhance resilience.

The concept of flood vulnerability has evolved over the years, reflecting changing perspectives and approaches to understanding and managing flood risks. In the 1980s, initial efforts focused on identifying flood hazards and mapping vulnerable areas, with vulnerability primarily viewed in terms of physical exposure and potential damage (Andrade and Szlafsztein 2018). By the 1990s, technological advancements allowed for more sophisticated flood risk assessments, including using high-resolution spatial models and introducing early warning systems (Andrade and Szlafsztein 2018). The early 2000s saw a global decline in vulnerability to river floods, attributed to improved modelling techniques, increased resilience measures at the property-level, and enhanced flood management practices (Jongman et al., 2015).

During the late 2000s and early 2010s, there was a shift towards a more holistic understanding of vulnerability, incorporating socio-economic and cultural factors and the localised impacts of climate change on flood risk (Gandini et al., 2020). From the 2010s onwards, the concept of flood vulnerability has expanded to include a multi-stakeholder perspective, emphasising the importance of engaging various actors in urban development policies to promote sustainable adaptation strategies (Gandini et al., 2020). Additionally, empirical studies have shown a general decreasing trend in vulnerability at the global scale, although regional variations exist. This evolution highlights the dynamic nature of flood vulnerability assessment and the ongoing efforts to enhance resilience to flood hazards (Formetta and Feyen 2019).

According to previous studies, flood vulnerability is a multifaceted concept that includes physical, social, economic, and environmental dimensions (see Table 2.2).

Table 2.2 An overview of the concept of flood vulnerability

Category	Description	References
Physical vulnerability	It refers to the exposure of buildings, infrastructure, and other tangible assets to flood hazards. This vulnerability aspect concerns the location, design, and materials of structures that may be affected by flooding.	(Pricope et al., 2022; Choubin et al., 2019)
Social vulnerability	It considers the characteristics of populations that influence their capacity to anticipate, cope with, respond to, and recover from the impact of a natural disaster. Factors such as age, socio-economic status, health, and mobility play a role in determining social vulnerability.	(Mruksirisuk et al., 2023; Mahmoud and Gan 2018; Wang et al., 2023)
Economic vulnerability	It is related to the potential economic losses resulting from floods, including damage to property, loss of income, and the disruption of economic activities. It also considers the resources available for recovery and reconstruction.	(Hosseini et al., 2021; Jibhakate et al., 2023)
Environmental vulnerability	It involves the resilience of natural systems and their ability to absorb and recover from flood impacts. It also includes the role of environmental degradation in exacerbating flood risks.	(Rezende et al., 2020; Mahmoud and Gan 2018)

2.4.2 Conceptual model for vulnerability assessment

The conceptual model for vulnerability assessment encompasses several frameworks, including the Pressure-State-Response (PSR) model, the Driving Force-State-Response (DSR) model, the Driving Force-Pressure-State-Impact-Response (DPSIR) model, the Driving Force-Pressure-State-Exposure-Effect-Action (DPSEEA) model and Source-Pathway-Receptor-Consequence (SPRC) model.

(1) PSR Model

The PSR model, developed by the Organisation for Economic Cooperation and Development (OECD), comprises three interconnected components: Pressure (what has occurred), State (what is the current status), and Response (what action should be taken) (OECD, 1993) (Sun et al., 2020). The application of the PSR model in flood management provides a structured approach to understanding and addressing the complex dynamics of flood risks in urban environments.

Pressure refers to the factors that increase the risk of flooding. In urban areas, these pressures often include 1) increased impervious surfaces due to urbanisation, leading to higher runoff volumes and reduced infiltration (Huang et al., 2018); 2) climate change, contributing to more frequent and intense rainfall events (Chung and Lee 2009; Chaves and Alipaz 2007).

The state represents the current condition of the flood risk in the urban area. It can be characterised by 1) the extent and frequency of flooding events and 2) the condition of existing infrastructure and its capacity to manage floodwaters (Li et al., 2010; Seo et al., 2015).

Responses are the actions taken to manage the pressures and improve the state. These include 1) implementation of flood defence and sustainable urban drainage systems; 2) policy measures and land-use planning to control urban development in flood-prone areas (OECD, 1993; Senent-Aparicio et al., 2015).

(2) DSR Model

The DSR model is an analytical framework that builds upon the PSR model by incorporating a broader range of factors affecting sustainable development (Yan et al., 2016). In the DSR model, Driving Forces replace the concept of ‘pressure’ from the PSR model, encompassing natural phenomena and human activities that can increase flood risk (Liu et al., 2020). State component reflects the current condition of the system under the influence of the driving forces, including land use, water quality, and other environmental factors that can be affected by floods (Chen et al., 2005). Responses represent the human measures in response to changes in the state system, such as flood disasters. It includes policy decisions, infrastructure improvements, and other management strategies to mitigate flood impacts and enhance resilience (Liu et al., 2020).

The DSR model provides a structured approach to understanding and managing the complex interactions between human activities, environmental states, and responses to flood disasters. However, it has been criticised for not adequately highlighting the underlying reasons for the pressures or drivers and for lacking a measure for response change in the state of the environment (Bowen and Riley, 2003).

(3) DPSIR Model

While initially a comprehensive framework for environmental analysis, the DPSIR model has been further refined by the DSR model, offering a more nuanced understanding of flood management dynamics (EEA, 2015).

Driving forces in the context of floods can encompass climate change, leading to increased frequency and intensity of rainfall and changes in land use, such as urbanisation, which reduce natural water absorption capacity (Liu et al., 2021).

Pressures include deforestation, improper land management, and infrastructure construction in flood-prone areas, all contributing to heightened runoff and reduced infiltration.

State refers to the condition of the environment, exemplified by increased regional vulnerability to flooding due to altered hydrological conditions, including changes in river flows and groundwater levels (Qin et al., 2023).

Impacts denote the consequences of these environmental changes on human, economic, and ecological systems. Floods can result in loss of life, damage to property and infrastructure, and negative impacts on agriculture and ecosystems (Duan et al., 2021).

Responses encompass various actions, such as constructing levees and dams, implementing early warning systems, and formulating land-use planning strategies to discourage development in high-risk areas (Kapetas et al., 2019).

(4) DPSEEA Model

The DPSEEA model extends the DPSIR framework by incorporating the concepts of exposure and effect, which are particularly pertinent to health outcomes and interventions (WHO, 1999).

Driving forces may include population growth, urbanisation, and climate change, all of which can alter precipitation patterns and increase flood risks (Gentry-Shields and Bartram 2014).

Pressure may arise from land-use changes, deforestation, and infrastructure construction that affect natural water flow and drainage patterns (Waheed et al., 2011).

State refers to the environmental conditions resulting from these pressures, such as changes in river flows, soil saturation levels, and the integrity of floodplains and wetlands.

Exposure focuses on the extent to which human populations and ecosystems are exposed to flood risks, considering vulnerable populations in flood-prone areas and the assets that might be affected by flooding.

Effect relates to the consequences of exposure, which in the case of floods can be measured in terms of human health impacts, economic losses, and ecological damage.

Actions are the strategies and measures implemented to manage driving forces, alleviate pressures, maintain or restore desirable states, reduce exposure, and mitigate effects. Actions in flood management can include the development of early warning systems, flood defence, land-use planning, and emergency response plans.

(5) SPRC Model

The SPRC model is a widely used conceptual framework for describing surface water floods. It was utilised to delineate the progression of a flood event from the source through various pathways to potential receptors and its associated consequences, as adopted by the UK Environment Agency (Yan et al., 2016).

The initiation points of the flood risk may include heavy rainfall, sea-level rise, or storm surges. For instance, studies have used the SPRC model to evaluate the impacts of projected flood risks caused by sea-level rise and storm surges in Shanghai, China (Feng et al., 2023).

The pathways through which floodwaters travel include surface water flow, sewer systems, or groundwater movement (Jiang et al., 2020).

Receptors refer to entities at risk from floodwaters and contaminants, such as human populations, ecosystems, or infrastructure. Humans are particularly vulnerable in areas with high population densities (Jiang et al., 2020).

The advantages and disadvantages of the aforementioned conceptual models are summarised in Table 2.3. It is evident that the SPRC model can objectively depict the influence process and the consequence of source impacts on receptors differently (Narayan et al., 2012; Yan et al., 2016). Therefore, based on the principles of the SPRC model, this study established an SPRC model for assessing the vulnerability of road networks under the influence of surface water floods.

Table 2.3 The characteristics of various conceptual models

Model	Advantage	Disadvantage
PSR	The PSR model could present the impacts of human activity on the natural environment, emphasising pressure and response.	The relationship between elements is too simple.
DSR	DSR model could present the impacts of human activity on the natural environment, emphasising driving force, pressure, and response.	Lacking influence process analysis for source impacts on the receptor.
DPSIR	The DPSIR model could present human activity's impacts on the natural environment, emphasising driving force, pressure, impact, and response.	Lacking influence process analysis for source impacts on the receptor.
DPSEEA	The DPSEEA model could present human activity's impacts on the natural environment, emphasising driving force, pressure, effect, and response.	Lacking influence process analysis for source impacts on the receptor.
SPRC	The SPRC model could present human activity's impact on the natural environment, including source, pathway, and consequence.	SPRC model could not directly support multi-criterion decision-making.

2.4.3 Vulnerability assessment methods

According to previous studies, methods for assessing vulnerability can be categorised into four main groups: the vulnerability index-based method, the vulnerability curve method, the historical disaster data-based method, and the scenario simulation method (Huang et al., 2012; Nasiri et al., 2016).

(1) Vulnerability index-based method

The vulnerability index-based method is widely used for assessing flood vulnerability in a specific area (Huang et al., 2012; Zhang and You, 2014). Previous studies have highlighted that indicator-based vulnerability assessments are essential for flood management planning, preparedness, emergency responses, and long-term flood recoveries (Cascini 2008; Špitalar et al., 2014). The vulnerability index-based method involves identifying various indicators that contribute to the vulnerability of a community to floods, such as population density, land use, topography, flood history, and socioeconomic status. Each indicator is assigned a weight based on its relative importance in contributing to flood vulnerability. These weights are then used to calculate an overall vulnerability score, often on a scale of 0 to 1, where a higher score indicates greater vulnerability to surface water flooding.

Several studies have employed the vulnerability index-based method to assess flood vulnerability, establishing various vulnerability index systems to evaluate the impacts of surface water floods on social and economic development (Nasiri et al., 2019; Duan et al., 2022). For instance, Yan et al., (2016) developed a socio-economic vulnerability index system to evaluate the impacts of coastal floods caused by sea-level rise. Aroca-Jiménez et al., (2020) focus on developing and validating an Integrated Socio-Economic Vulnerability Index (ISEVI) for urban areas susceptible to flash floods, highlighting the challenges of validating vulnerability indices in such regions due to data scarcity and the localised nature of flash flooding events. Duan et al., (2022) provided a vulnerability assessment model to analyse the social vulnerability to floods in the countries situated along the Belt and Road region.

Recently, some studies explored the spatial pattern of road infrastructure vulnerability to natural disasters on a large scale (Hu et al., 2016; Liu et al., 2018). For example, Li et al., (2015) assessed physical vulnerability of surface roads to natural disasters in China using provinces as the basic assessment unit. In addition, He et al., (2021a) established a flash flood vulnerability index system and explored the spatial pattern of the flash flood vulnerability of roads in China.

The vulnerability index-based method offers several advantages. Firstly, the vulnerability index-based method can be implemented flexibly locally and often at a low cost, mainly when pre-existing databases are accessible. Additionally, it serves as a helpful communication tool among stakeholders, facilitating discussions at each project stage (Hélène et al., 2022). Third, the method produces a single score based on exposure, sensitivity, and adaptive capacity, providing a comprehensive view of vulnerability. Finally, the method allows for the customisation of models based on area size, available data, scale, time, cost, user needs, and targets (Zare et al., 2022).

The vulnerability index-based method also has some disadvantages. There is subjectivity in selecting parameters, their relationship to vulnerability, and the assignment of ratings and weights (Taghavi et al., 2022). Different methods can yield inconsistent results when applied to the same area. The index system may only apply to specific regions, and some data may be difficult to obtain, limiting the universality of the method (Li et al., 2021; Wang et al., 2018).

(2) Vulnerability curve method

The vulnerability curve method is a quantitative tool used in flood risk assessment to evaluate the potential damage to assets resulting from flood events. This method employs empirical damage or fragility curves that correlate the intensity of flood hazards with the vulnerability or damage to the assets at risk. Vulnerability curves are grounded in empirical data collected from historical records of flood events and their consequent impacts (Abebe et al., 2018). The curves predict potential damage by linking simulated flood depths to expected consequences on exposed populations and assets (Lallemant et al., 2021). The development of vulnerability curves can involve simulations from various models, such as those predicting agricultural impacts, to estimate potential damage under different flood scenarios.

The application of the curve method in flood vulnerability assessment is a critical approach that integrates various data sources and methodologies to evaluate the potential impact of flooding on urban environments. Pall et al., (2011) created a probabilistic event attribution framework to quantify the human-induced contribution to flood risk, using runoff occurrence frequency curves in their analysis. Munoz et al., (2018) examine the amplification of flood hazards due to climatic control and river engineering, which could be relevant to studies using frequency curves to assess flood vulnerability. Kreibich et al., (2022) provide insights into flood and drought risk management, which may include the use of frequency curves to assess flood vulnerability.

The vulnerability curve method allows for the simulation and estimation of disaster losses on a global scale, offering a more comprehensive approach compared to estimation based solely on observations. However, the quality of vulnerability assessments can be affected by the availability and reliability of data, which may not always reflect different degrees of vulnerability accurately (Sorichetta et al., 2011). The vulnerability curve method relies on extensive damage surveys, which consume significant time and resources. Additionally, its reliability is lower than that of other methods as it may not apply to different regions (Nasiri et al., 2016).

(3) Historical disaster data-based method

Historical disaster data-based methods can respond to the combined effects of natural and social vulnerability on data collected from actual flood events (Duan et al., 2022). This method considers factors such as flood frequency, magnitude, duration, and the extent of damage caused by past floods to determine the level of vulnerability. This method uses historical data and statistical analysis to identify the frequency and intensity of past flood events and their effects on infrastructure, property, and people.

By analysing the data, the method identifies vulnerable areas more likely to be affected by future floods.

Historical disaster data-based methods have been applied in various studies. For example, Benito et al., (2004) employed historical flood data and European water level records, integrating geological, historical, hydraulic, and statistical approaches to evaluate extreme floods. Langlois et al., (2023) showcased the application of a global flood monitoring database connected to national disaster databases to assess local flood-related vulnerability in Indonesia. It can be found that the historical disaster data-based method is straightforward to compute when sufficient historical data is available (Li et al., 2023).

However, the historical disaster data-based method demands extensive and continuous historical data, which can be time-consuming to collect and susceptible to errors (Wang et al., 2023). Limited historical events and poor data quality can lead to biased evaluation results, which may not represent the full scope of potential future flood risks (Yao et al., 2023). Moreover, historical data may not always accurately predict future conditions due to changes in climate, land use, and urbanisation, leading to low model accuracy (Li et al., 2023).

(4) Scenario simulation method

The scenario simulation method is constructed on the scenario model for a quantitative prediction. This method uses computer models to estimate the potential impact of a range of flood magnitudes, frequencies, and durations, as well as other factors such as land use and infrastructure (Nasiri et al., 2016). It integrates diverse data types, including geomorphological, topographical, and urban drainage system data, to evaluate flood disaster risk and assess various scenarios across different spatial scales (Zhu et al., 2016; Lin et al., 2020). The simulation approach allows for the assessment of the vulnerability of a community or region to various potential flood events, which can help inform planning and preparedness efforts (Yao et al., 2023). By simulating multiple scenarios, decision-makers can better understand the potential impact of different flood scenarios and prioritise actions to reduce vulnerability and increase resilience.

The application of scenario simulation methods for flood vulnerability assessment is an evolving field that addresses some of the limitations inherent in historical disaster data-based methods. Vamvakeridou-Lyroudia et al., (2020) concentrated on evaluating and visually presenting hazard impacts to improve Critical Infrastructure (CI) resilience to surface water flooding, employing extensive scenario simulations. Li et al., (2021) used scenario simulations based on hydrological models or spatial models to improve the accuracy of vulnerability assessment. Yao et al., (2023) assessed how urban stormwater systems respond and adapt to altered rainfall patterns using CMIP6 projections. They conducted scenario simulations based on future rainfall data. Li et al., (2023) developed an urban rainstorm and flood resilience model using the System Dynamics method. This model simulates the dynamic process of urban rainstorms and flood resilience.

However, high-quality data is essential for setting up and validating models, which can be a limitation in data-scarce areas (Vaddiraju and Talari 2022). The requirement for high data comprehensiveness can be challenging, as the method must accurately simulate the flooding process (Li et al., 2023). Moreover, the results of the scenario simulation model are subject to uncertainty due to issues like index selection, weight allocation, and applicability to the study (Yao et al., 2023).

Table 2.4 summarises the advantages and disadvantages of various vulnerability assessment methods. The index-based approach offers key benefits, including easy data access, straightforward modelling and calculations, and the capacity to depict regional vulnerability trends on a broader scale. This study specifically examined the vulnerability of road infrastructure to surface water floods, thus opting for the index-based methodology.

Table 2.4 The comparison among four vulnerability assessment methods

Methods	Advantages	Disadvantages
Vulnerability index-based method	Providing a clarified vulnerability image in a specified region helps prioritize measures and plan for flood risk management in specified regions.	• Complexities of standardisation, weighting, aggregation, and uncertainty. • Difficulties in the quantification of some social indicators.
Vulnerability curve method	It is founded on real damage investigation and should be precise.	• Taking a lot of time and resources. • Not valid for other areas.
Historical disaster data-based method	Simple method, real damage analysis.	• Taking a lot of time and resources. • Being inapplicable to other regions. • The results may be inaccurate due to unevenly recorded data.
Scenario simulation method	Providing accurate results in a specific region based on detailed data about topographic, hydrographic, and economic information.	• Significant irregularities in lack of sufficient data. • Unable to describe a clear link between the predicted map and real flood damage.

2.5 Flood management in road transport system

2.5.1 Existing practices in China

Currently, different countries have proposed or revised national practices and legislation to improve the protection of road transport from surface water floods. The Chinese National Government has highlighted the necessity for additional measures regarding flood management (Hénonin et al., 2015). Local municipal ministries are tasked with building and upkeeping infrastructure in line with national planning and design guidelines, with particular attention to planning, construction, and operational aspects (Qi et al., 2020). These governance responsibilities can be categorised as follows: the Ministry of Housing and Urban-Rural Development (MHURD) oversees surface water flood control planning and works in conjunction with the Chinese National Government to implement the Sponge City Program in selected cities across the country. These governmental agencies closely cooperate with the Ministry of Water Resources (MWR) to address surface water floods, waterlogging, and flood risk reduction and management. Furthermore, the MHURD collaborates with the Ministry of Finance (MOF) on financial arrangements for construction and operational costs, with the Ministry of Transport (MOT) on reducing urban surface water flood risk, such as road inundation depth, and with the Ministry of Emergency Management (MEM) on reducing emergency response times for on-road services.

Urban flood control planning plays a vital role in overall urban planning, especially in cities prone to high flood risks. The *Code for Urban Planning on Urban Flood Control (GB 51079-2016)*, issued by the MHURD in 2016, serves as a guideline for city authorities to formulate specific flood control plans tailored to the unique characteristics of each city. One of the key considerations in these plans is the surface water flood control standard, which is determined based on factors such as population density, socioeconomic status, and various aspects of flood information, including the types, causes, and potential consequences of floods.

Urban areas generally have a higher surface water flood control standard than rural areas (Ministry of Housing and Urban-Rural Development of the People's Republic of China 2016b). Ensuring a secure layout of urban land, flood control systems, and other necessary measures are essential components of surface water flood control planning. Chinese cities predominantly use structural measures for controlling surface water floods, focusing on managing rainstorm storage and discharge in upstream and middle-lower streams. Non-structural measures for surface water flood control, such as flood warnings and flood insurance, have gained importance in Chinese cities since the 2000s.

The *Sponge City Program (SCP)* is a significant initiative in China to improve water sensitivity and enhance the management of surface water floods (Chan et al., 2018). The program also seeks to change the perception of rainstorm water from being solely viewed as a problem to being seen as a potential resource. SCP pilot cities or areas are mandated to handle runoff from a 30-year, 24-hour rainfall event. The goal is for more than 80% of urban built-up areas to meet SCP requirements by 2030 (Xia et al., 2017; Jiang and Ma, 2018).

The SCP entails transitioning from conventional 'Grey' strategies to more sustainable 'Green' and 'Blue' approaches. It includes measures like expanding green spaces and implementing permeable pavement to enhance SCP development (Kabisch et al., 2017). After a 3-year pilot, pilot cities have executed projects like green roofs, belts, and permeable pavement, offering valuable lessons for future planning and policy scaling.

Enhancing the effectiveness of land drainage systems is a direct method to tackle surface water flooding problems, often caused by the heavy reliance on urban drainage systems (Chan et al., 2018). Currently, the urban drainage protection standards in Chinese cities are relatively low, typically designed for a 1-in-1-year to 1-in-5-year return period. While these standards may be adequate for mild rainstorms, they fall short during intense, cyclone-enhanced rainstorms. To address these challenges, city authorities have examined the practices of other cities in the region. For instance, Tokyo has adopted a 1-in-30-year return period standard, while Singapore has implemented a 1-in-50-year return period standard to mitigate urban surface floods (Chan et al., 2018). To improve the situation, the *Code for Design of Outdoor Wastewater Engineering (GB 50014—2021)* has been updated to address deficiencies in stormwater sewer systems in Chinese cities (Ministry of Housing and Urban-Rural Development of the People's Republic of China 2016b). In the central areas of megacities, stormwater sewer systems are designed to accommodate rainfall events with a 1-in-3-year to 1-in-5-year return period. In contrast, in more critical areas, the design standards extend to a return period of 1-in-5-year to 1-in-10-year.

Economic costs are essential when upgrading land drainage systems. In newly developed areas, enhancing road drainage standards, as outlined in *the Code for Design of Outdoor Wastewater Engineering (GB 50014—2021*), can improve resilience to surface water flooding. However, for existing paved roads in densely built-up areas, meeting these standards would often necessitate substantial reconstruction of road sections, leading to higher economic costs than those incurred from surface water flooding, such as road repair and maintenance (Koks et al., 2019). Upgrading land drainage systems in urban central areas presents challenges due to their long development history, spanning decades or even centuries.

Increasing Blue-Green Infrastructure (BGI) presents an effective solution to the economic challenges associated with upgrading land drainage systems. *The Code for the Design of Urban Green Space (GB 50420—2007)* outlines the establishment of wet basins and stormwater wetlands for rainwater storage and surface runoff reduction (MHURD, 2016). Elements like grass swales, green roofs, gutters, sunken green belts, and open areas are essential for shielding urban assets from rainstorms and floods. Bio-swales and permeable pavements are engineered to soak rapid runoff during heavy rainstorms. Additionally, integrating vegetation can enhance urban hydrological processes by mimicking soil-water interactions and providing urban ecosystem services (Griffiths et al., 2020).

For example, in Shenzhen, the implementation of sponge road designs has significantly increased the capacity to capture stormwater, capturing up to 75% of the annual rainfall volume (Shenzhen Municipal Water Bureau, 2017). Additionally, bio-swales and permeable pavement have been installed in residential areas of the Futian district, boosting the volume capture ratio of annual rainfall from 38% to 62% (see Figure 2.2) (Shenzhen Municipal Water Bureau, 2021). *The Technical Code for Urban Flooding Prevention and Control (GB5122-2017)* states that new areas should have over 40% permeable pavement, while areas at higher risk of waterlogging should have over 50% (MHURD, 2017).

Figure 2.2 Bio-swales on roadsides (left) and permeable pavement (right) in Shenzhen

Addressing and mitigating surface water flood hazards to road transport is a critical priority for urban management in Chinese cities. *The Specifications for Urban Waterlogging Risk Investigation (QX/T 441-2018)* was introduced to assess surface water flood risks and identify potential waterlogging trouble spots. This technical guidance includes ten normative annexes, such as those for urban land use investigation, to aid in identifying these trouble spots (CMA, 2018). In Chinese megacities, *the Technical Code for Urban Flooding Prevention and Control (*GB5122-*2017)* specifies that road inundation depth should not exceed 15 cm during a 1-in-100-year urban flood (MHURD, 2017). By conducting waterlogging investigations and adhering to these standards, cities can propose adaptation and mitigation measures to improve emergency response systems and address potential threats before surface water flooding occurs.

EMS response times are often mandated to meet specific deadlines, although China lacks a national legislative framework for such timeframes. In Beijing and Shanghai, EMS aim to arrive at patients' locations within a 12-minute (People's Government of Beijing City, 2020; Shanghai Municipal People's Government, 2016). Additionally, the average service radius of EMS stations in Shanghai is anticipated to be under 3.5 km (Shanghai Municipal Peoples Government, 2016). Despite this, there is no consistent requirement for EMS response times across Chinese cities. Some cities use the time for dispatch instruction as a quantitative indicator of EMS performance. For instance, in Guangzhou and Shenzhen, dispatch instructions must be issued within 1 minute of receiving the emergency call, and ambulances must depart within 3 minutes of receiving the dispatch instruction (People Government of Guangzhou Province, 2011; Shenzhen Municipal Health Commission, 2018). As a result, Chinese cities still face significant challenges in improving EMS response times, which will be further discussed.

2.5.2 International experiences

Chinese cities can look to Nature-Based Solutions (NBS) and BGI practices from Western and Asian cities for surface water flood management. Since the 1970s, western cities have implemented various ecological programs, such as Best Management Practices (BMPs) and Low Impact Development (LID) in American cities (Matteo et al., 2017; Matos et al., 2019), Sustainable Drainage Systems (SuDs) in the European cities (Gimenez-Maranges et al., 2020), and initiatives such as the ‘Room for the Rivers’ in the Netherlands cities (Böhm et al., 2004; Van and Logtmeijer, 2005; Stokkom et al., 2005) and the ‘Water Sensitive Urban Design’ (WSUD) in Australian cities (Cook et al., 2019). In the past two decades, Asian cities have also adopted BGI solutions, including the ‘Active Beautiful and Clean’ (ABC) water program in Singapore (Lim and Lu, 2016; Liao, 2019), the ‘Urban River Revitalisation’ in Japanese cities (Moor 2020), and the ‘Clean River Scheme’ in Korea cities (Seoul Metropolitan Government, 2021). These initiatives offer valuable insights for Chinese cities seeking to enhance their surface water flood management strategies.

These NBS and BGI initiatives provide cost-effective strategies with various environmental, social, and economic benefits (Kabisch et al., 2017; Debele et al., 2019; Kuriqi and Hysa, 2021). For example, a rainwater harvesting program in New York resulted in savings of $10 million compared to conventional drainage systems (UFCOP, 2016), highlighting the potential for savings. However, Chinese cities predominantly rely on conventional hard-engineering approaches (Qi et al., 2020), indicating a need for a shift towards more sustainable solutions. Implementing a mix of solutions tailored to local social, economic, and environmental contexts is crucial. This could involve BGI design, developing warning systems, and engaging in public education and participation (Lim and Lu, 2016; Liao, 2019). China can learn from Singapore’s experience, especially considering their similarities in high-density urban environments and limited green spaces. BGI, including wetlands, detention ponds, rain gardens, green roofs, and bioswales, controls surface runoff and flooding and enhances public health and well-being. It is essential to conduct systematic performance audits and benchmarking to evaluate the effectiveness of these BGI measures. Looking at the example of Japan, Chinese cities can improve warning and evacuation systems (MILT, 2018). Moreover, enhancing public education and participation is crucial to prepare for extreme weather events and surface water floods.

From the surface water flood management perspective, there is no specific national standard for EMS response times in major Chinese cities. Significant efforts are needed to enhance current EMS practices and meet international standards. For instance, UK legislation mandates that EMS (first responders) should reach 75% of ‘Red 1’ (high-priority, life-threatening) incidents within 10 minutes of receiving the initial report (Coles et al., 2017; Green et al., 2017). However, the average EMS response time in Beijing is 18 minutes (Chaoran and Zhao, 2021), well beyond Beijing City’s requirement of 12 minutes. During road transport disruptions caused by surface water floods, EMS response times could deteriorate further. Studies should assess the spatial accessibility of EMS stations considering road inundation and traffic delays to provide valuable insights for government decision-making. Additionally, government organisations must understand their roles in the urban system’s operation and enhance cooperation to improve overall response efficiency.

2.6 Gaps in the current knowledge

It is widely acknowledged that heavy rainfall poses a significant hazard to road networks. During heavy rainfall and subsequent surface water flooding, road surface friction decreases, vehicle speeds reduce, and visibility is impaired, often leading to increased travel times. Consequently, access to essential facilities such as schools, workplaces, and hospitals may be disrupted. Urban areas, particularly city centres, are more vulnerable than rural areas due to higher road and population densities, as well as the performance of drainage systems. The increasing impact of surface water floods on road transport networks underscores the importance of considering broader experiences and implications in surface water flood management to safeguard urban public infrastructure, including road infrastructure and transportation facilities.

Significant advancements have been made in understanding surface water flooding and its impact on road transportation, such as road inundation, traffic delays, and changes in spatial accessibility. These studies have contributed to academic knowledge and practical improvements in surface water flood management. However, several gaps in research and practice remain, as outlined below (see Figure 2.3):

Most of the previous studies focused on social media data analysis rather than news media data analysis. Social media data, being user-generated, is often subjective. Therefore, using social media data to assess flood damage raises concerns regarding its accuracy and reliability. In contrast, analysing news media data can offer more objective and dependable information. However, most existing studies that utilised news media data did so at a small scale, such as the district level. This limitation is due to the considerable time and data resources required for news media data analysis.

Limited understanding of how news media enhances flood preparedness in the road transport system. Previous research has suggested various non-structural measures (i.e., non-engineering measures) for enhancing flood readiness, including flood forecasting and warning systems, public education, and awareness campaigns. News media plays a vital role in facilitating the implementation of these measures. However, there is still uncertainty regarding the effectiveness of news media coverage during flood events, which is essential for preparedness and early warning efforts.

Few studies have conducted network analysis to explore government agency engagement and collaboration during flood events. Existing approaches to analysing media data related to flood and transport networks only capture public participation and response. Indeed, government agency engagement and collaboration should be investigated as such. Based on the news media data, collaborative network analysis can provide the role of different agencies in flood management and the actual performance of government agency engagement and collaboration. However, existing studies could not answer whether the collaboration is reasonable under surface water flood conditions.

Limited understanding of how to assess flood impacts on complex transport networks by combining news media and vulnerability assessment. Previous studies have confirmed that vulnerability assessment is one of the valuable tools for investigating flood impacts on road infrastructure. However, these studies ignored the impacts of surface water floods on transport performance. With the development of digital media, media data, especially social media data, is becoming a more popular and promising way to fill in the gaps in conventional data. However, social media data is often mined to analyse the characteristics of flood impacts at the event level, making it hard to compare different areas. Few studies have focused on the effects and severity of floods on road infrastructure and transportation at a large scale.

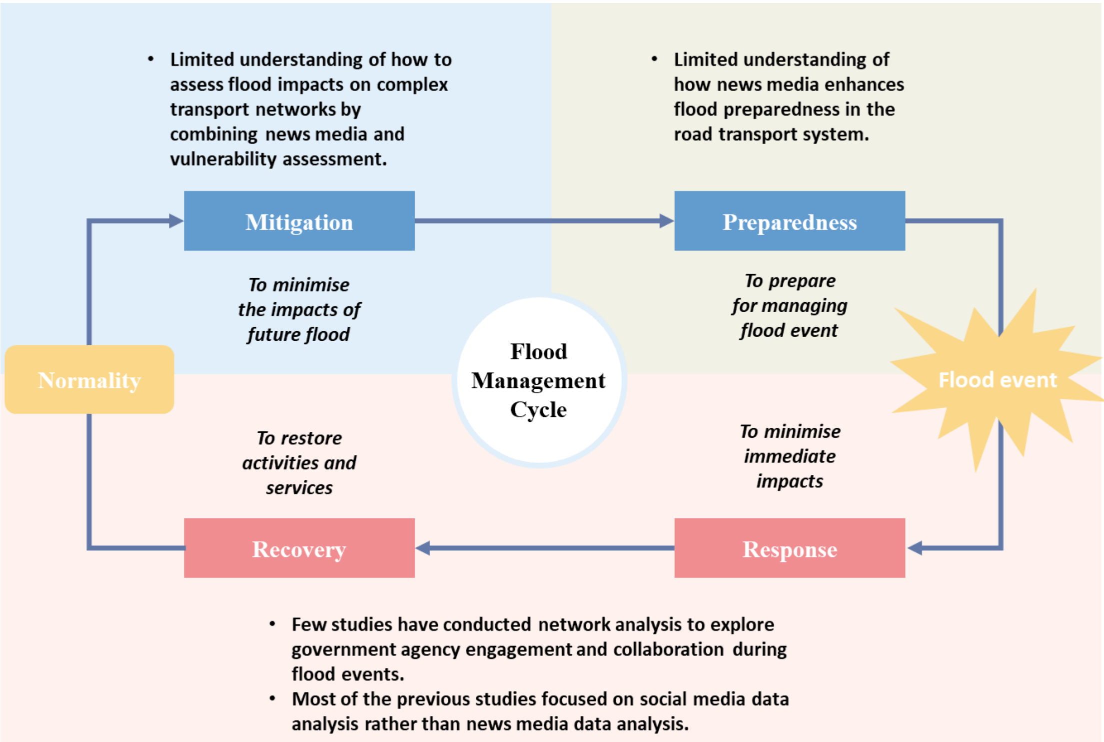

Figure 2.3 Research gaps in existing literature

Motivated by the existing knowledge gaps, an integrated framework was proposed in Chapter 3, including news media activities analysis, government agency collaboration analysis, and potential flood impact assessment, to enhance different phases of flood management in the road transport system. A more detailed analysis of news media activities attempts to enhance the phase of preparedness and early warning from the perspective of news media adoption. Government agency collaboration analysis was conducted to enhance the phase of response and recovery from the perspective of government response. Potential flood impact assessment was used to enhance the phase of mitigation.

Furthermore, the key findings adopting the integrated framework will be presented in Chapters 4-6. Based on the research findings, design recommendations will be proposed for enhancing flood management from the perspective of the transport system in the Discussion Section of Chapters 4-6.

Chapter 3: Research methodology

3.1 Introduction

An overview of the state-of-the-art surrounding flood management was presented in Chapter 2, where current approaches and best practices were reviewed, highlighting limitations and potential areas of development. In order to address the significant gaps mentioned in Chapter 2, this chapter presents an original integrated framework for flood management in the road transport system. The research design is tailored to the context of the Guangdong-Hong Kong-Macao Greater Bay Area (GBA). Moreover, it is also intended to serve as a valuable resource for urban planners working on urban planning projects in other cities facing flood impacts on the road transport system similar to those in the GBA cities.

3.2 Research design

3.2.1 Overview of schematic diagram

The research design is summarised in a flow chart (see Figure 3.1). The initial issue that guided this research was associated with the increase in frequency and intensity of heavy rainfall in the context of climate change and rapid urbanisation. Moreover, heavy rainfall-induced surface water floods often damage road transport networks. A comprehensive literature review of surface water flood management in the road transport system was conducted, covering five parts (see Chapter 2). A quantitative method will be employed to answer the research question and fill the research gaps in the literature.

The proposed framework aims to enhance surface water flood management in the road transport system based on the Source-Pathway-Receptor-Consequence (SPRC) conceptual model. A case study was adopted to develop an in-depth and detailed understanding of the research question covering the three major phases of flood management (Ragini et al., 2018; Qadir and Bukhari 2016), i.e., (a) preparedness and early warning (the first study of this thesis), (b) response and recovery (the second study of this thesis), (c) mitigation, risk and vulnerability modelling (the third study of this thesis). According to the results, the potential of news media and vulnerability analysis to derive flood damage and recommendations for flood management in the road transport system were discussed.

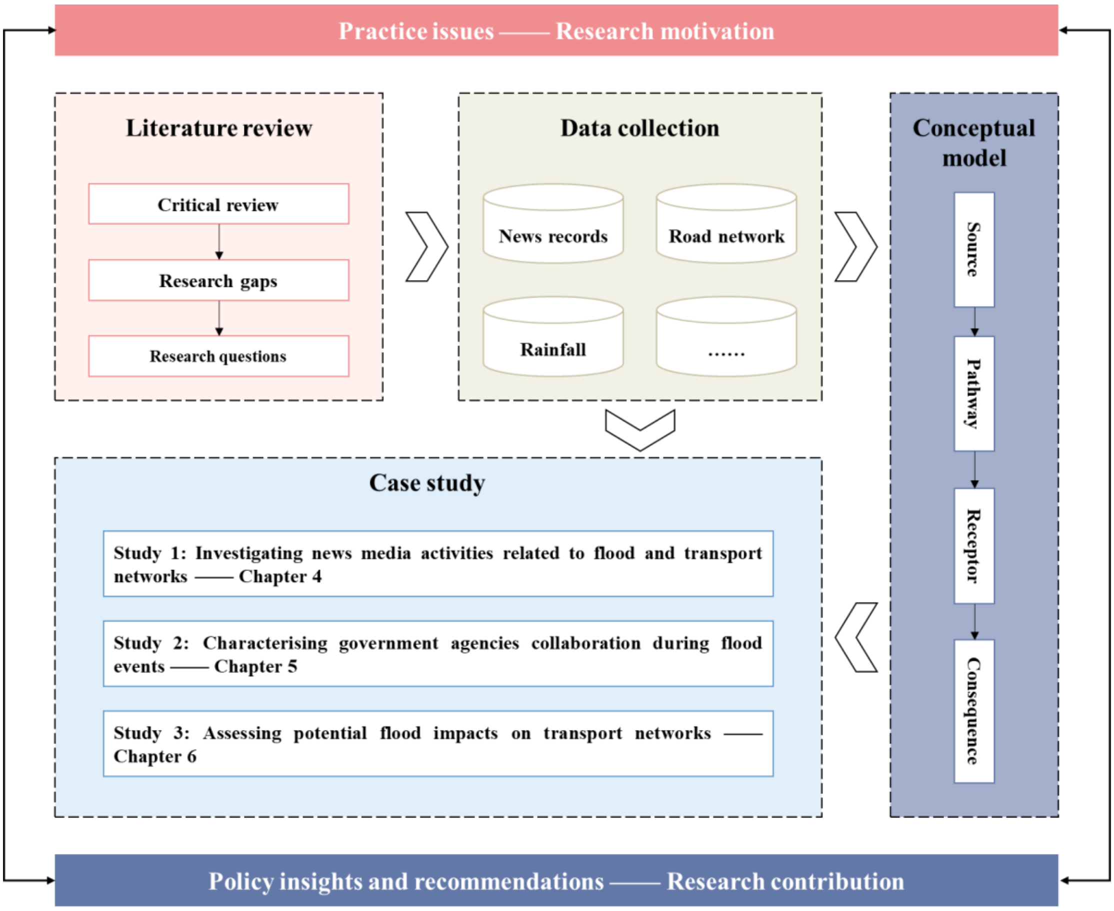

Figure 3.1 Overview of framework to enhance flood management in the road transport system

3.2.2 The conceptual model

A conceptual model, the SPRC model (Narayan et al., 2012; Kandilioti, Makropoulos 2012; Yan et al., 2016), was utilised to explore the action mechanism of surface water floods in the road transport system of the GBA. As shown in Figure 3.2, SRPC was employed to analyse the relationship between the flood trigger (i.e., rainfall), the transmitted pathway (i.e., surface water flow), and the consequences (i.e., impact loss) on the receptor (i.e., surface road).

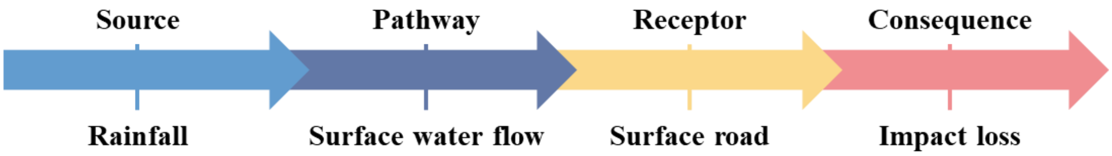

Figure 3.2 Schematic diagram of the SPRC model, modified from (Kandilioti, Makropoulos 2012; Pregnolato 2017)

According to the SPRC model, the projected surface water floods caused by rainfall directly impact the GBA transport system. Climate change is the most significant factor in increasing rainfall and associated surface water floods (Xu et al., 2018; Zhou et al., 2012). Temperature changes intensify the urban hydrological cycle and subsidence, resulting in more frequent high-intensity, short-duration rainstorms (Kendon et al., 2012). From 1990 to 2018, 956 disastrous rainstorms were recorded at 29 meteorological observation stations, making up 22.3% of the total 4286 rainstorms in the GBA during that period (Wang and Zhai et al., 2022). Additionally, there were 299 urban waterlogging disasters and 145 floods recorded in the GBA, making up 46.3% of the total rainstorm-induced disasters (Wang and Zhai et al., 2022). In particular, over 60% of the rainstorm-induced disasters were urban waterlogging disasters in 17 districts, including Dongguan, Zhongshan, seven districts of Guangzhou, five districts of Shenzhen, and three districts of Zhuhai (Wang and Zhai, et al., 2022).

The pathway is the route between the source and the receptor, which identifies how the source affects the receptor. The accumulation of surface water is the first phenomenon and a significant threat of surface water floods to road transport (Lu et al., 2022). If the surface water accumulation increases under conditions of intensive rainfall, the existing drainage systems will be insufficient, resulting in surface water flooding and subsequent consequences of surface roads. The increase in impervious areas has intensified surface water flow and overwhelmed the capacity of existing drainage systems in the GBA.

Rapid urbanisation has been the primary driver of significant land-use changes since economic reform and open-door policies were implemented in 1978 (George et al., 2007). In the GBA, the total population was about 86.7 million in 2021 (Statistia 2022) and is projected to be 120 million by 2050 (Chan and Chen et al., 2021). The increasing population will be concentrated in urban areas. Indeed, the urbanisation rate in the GBA has been more than 85% (Guangdong Provincial Committee of the Chinese People's Political Consultative Conference, 2021).

Due to rapid urbanisation, urban infrastructure has steadily replaced many aquatic ecosystems like lakes and wetlands and artificial water systems (Jiang et al., 2022; Lyu et al., 2019). From the 1980s to the 1990s, more than 26% of green spaces were converted to concrete structures (i.e., impervious surfaces) in the GBA (Chan and Yang et al., 2021). Surface water flow would be worse with the obsolete and dilapidated urban drainage systems in densely populated urban areas of the GBA. For example, the drainage system can only cope with 1-in-1-year to 1-in-5-year return period events in Guangzhou and Shenzhen. Under the condition of further urbanisation, open natural spaces will be transformed into impervious built-up areas, which will disrupt soil-water infiltration and aggravate road infrastructure vulnerability to surface water floods.

Receptor refers to the potential part affected by the source. In this study, the receptor is surface roads, including Expressways, National Highways, Provincial Roads, County-level Roads, and Township-level Roads (see Figure 3.3). The GBA boasts a complex road network spanning approximately 69,091 kilometres in total length. According to the *Technical Standards of Highway Engineering (JTG BOI-2014)* (Ministry of Transport of the People's Republic of China 2015), the concepts and characteristics of various roads can summarised as follows:

-- *Expressways*, denoted with a 'G' for '高速' (high-speed), are high-capacity, controlled-access highways designed for fast and efficient long-distance travel. They are often well-maintained and well-designed, with high-quality road infrastructure, multiple lanes and modern facilities. The total length of expressways is about 13797 kilometres in the GBA.

-- *National Highways* are major road routes connecting major cities and regions. They serve as primary transportation corridors within the country. They are one part of the national road network and are maintained by the national government. The total length of National Highways is about 7123 kilometres in the GBA.

-- *Provincial Roads* are roads within a specific province or administrative region. Provincial Roads are constructed to access the administrative centres, transportation hubs, commercial spines, residential zones, industrial areas, and tourist attractions. Their maintenance and funding often come from provincial governments. The total length of Provincial Roads is about 12245 kilometres in the GBA.

-- *County-level Roads* are roads within a county or district, connecting towns, villages, and rural areas. County-level Roads are smaller in scale compared to national and provincial roads. The total length of County-level Roads is about 13899 kilometres in the GBA.

-- *Township-level roads* serve townships, villages, and local areas. Township-level Roads are constructed to link the county and township-level administrative regions. They are often unpaved or gravel roads in less urbanised areas. The total length of Township-level Roads is about 22027 kilometres in the GBA.

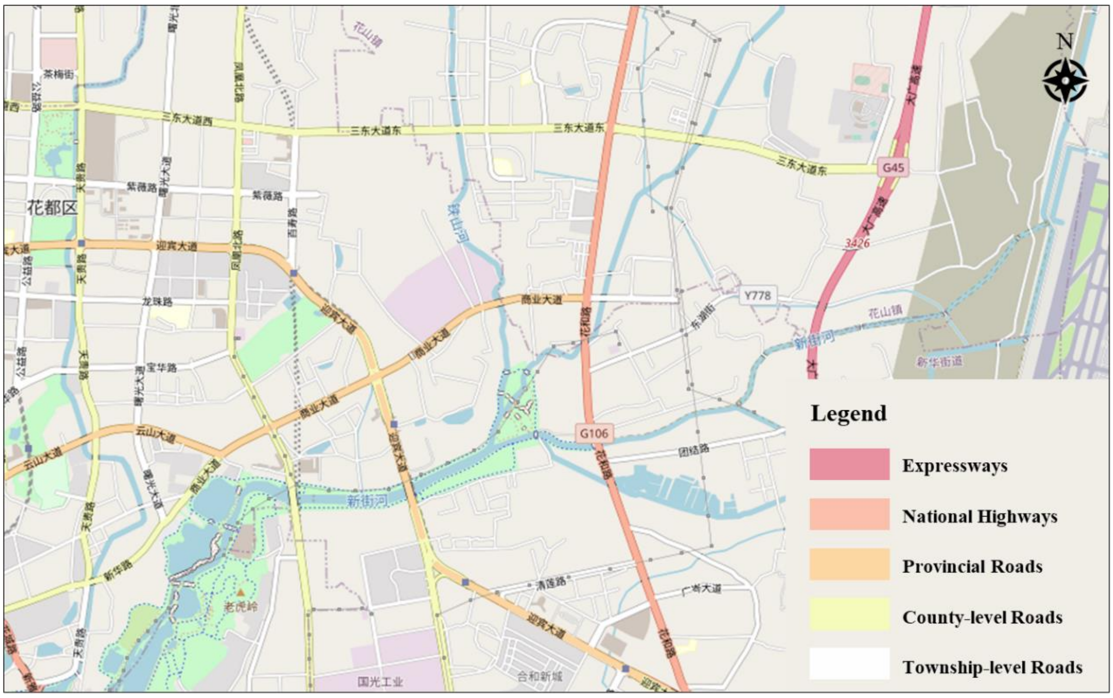

Figure 3.3 An example of the structure of five-grade roads in the GBA. Source: (OSM)

Damage to surface roads from surface water flooding results in economic losses and impacts the transport system. As road construction accelerates and road quality improves, the economic losses from roads damaged by surface water floods are increasing annually (He et al., 2021). In 2018, floods disrupted 28 expressways, 33 national highways, and over 200 provincial roads in China, leading to direct losses of around 42 billion RMB.

As shown in Figure 3.4, the structure of high-grade roads is more complex than that of low-grade roads. For example, expressways consist of a roadway, ramp, auxiliary lane, subgrade, shoulder, and fill slope (see Figure 3.4a). Moreover, expressways need higher-grade safety facilities (e.g., road signs, traffic marking, crash barriers), management facilities (e.g., communication, lighting, maintenance), and green facilities (e.g., vegetation). As shown in Figure 3.4e, township-level roads are paved with cement concrete. The characteristics of township-level roads include simple facilities, narrow roadways, low quality, steep slopes, and sharp bend (Ministry of Transport of the People's Republic of China, 2015).

Hence, different grades of roads have different economic costs and disaster resistance because of road design, material, and structure. Using insights from earlier research (Li et al., 2015; He et al., 2021) and the road construction information, the average value of Expressways, National Highways, Provincial Roads, County-level Roads, and Township-level Roads is 40 million RMB/km, 20 million RMB/km, 15 million RMB/km, 8 million RMB/km, and 4 million RMB/km, respectively. The anti-disaster ability of Expressways, National Highways, Provincial Roads, County-level Roads, and Township-level Roads is 10, 7, 4, 2, and 1, respectively (He et al., 2021; Li et al., 2015).

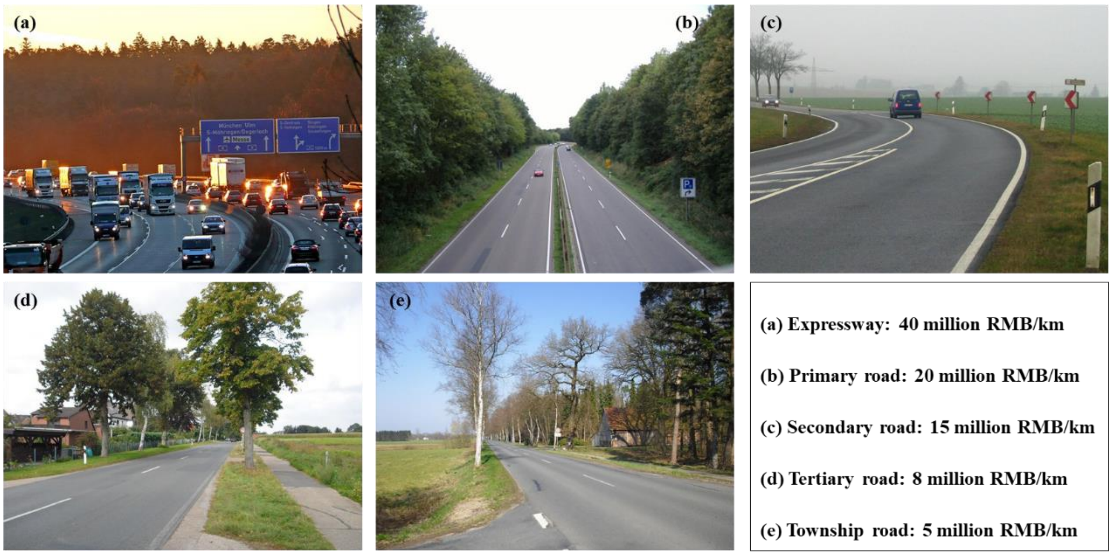

Figure 3.4 Examples and the average value of various roads. Picture source: (OSM)

3.2.3 The methodology framework

Figure 3.5 presents the methodology framework of flood management in the road transport system via combination of news media data and conventional data. It describes (a) the process that computes the historical news activities related to surface water flood and transport networks (see Section 3.3); (b) the process that estimates government agency networks (see Section 0); (c) the process that computes potential impacts of surface water flood on road infrastructure and transport (See Section 3.5). The outputs of this model include the database of news articles related to flooding and transport networks, news responses to floods, government networks and collaboration, and the characteristics of flood impacts on road infrastructure and transport. These can be useful for (1) supporting decision-making about road design and planning, (2) government operation, and (3) news media adoption.

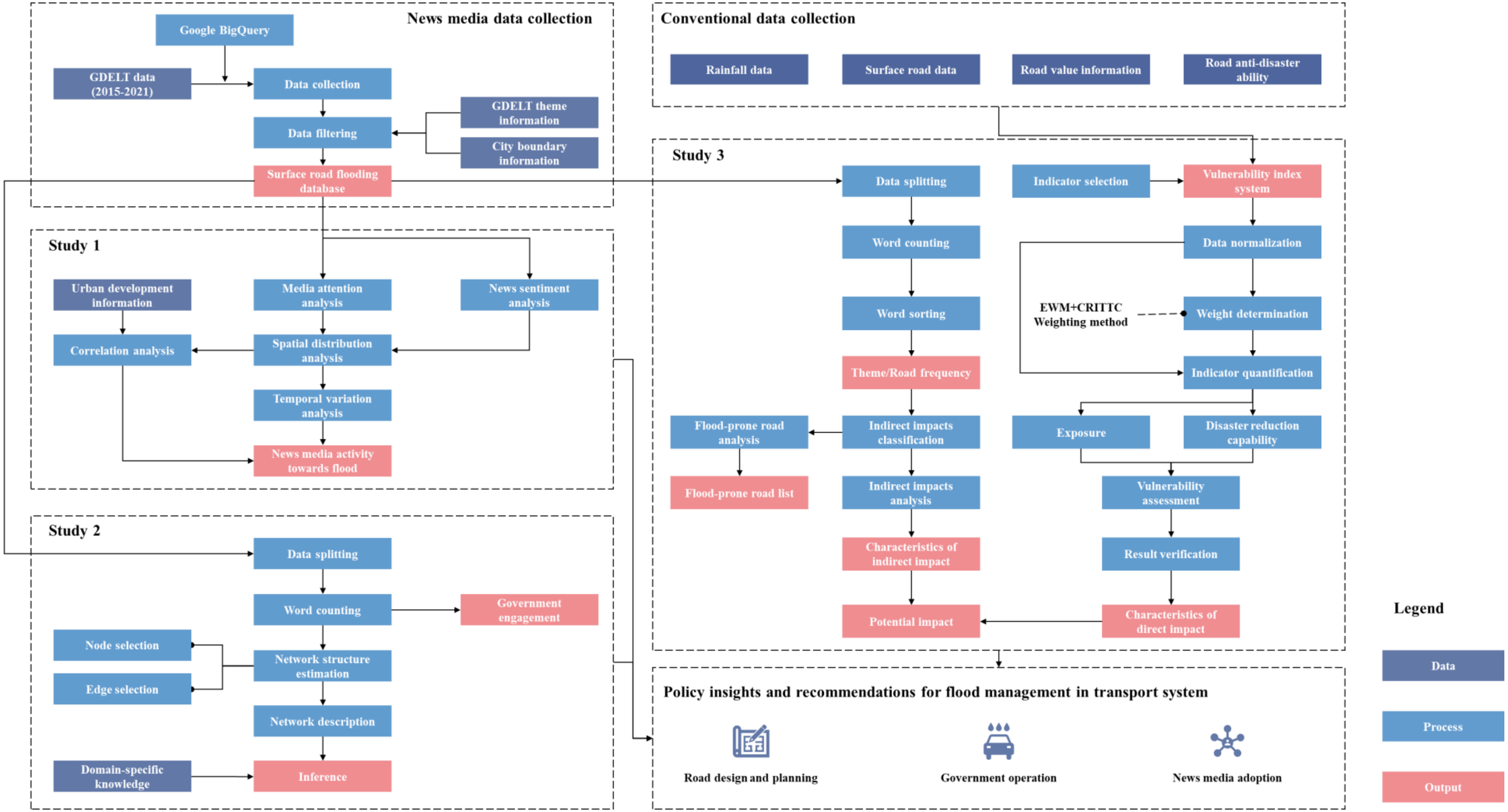

Figure 3.5 The methodology framework

3.3 News media activity analysis

3.3.1 Data collection

News media data was collected from the Global Knowledge Graph (GKG) of the GDELT (Global Database of Events, Language, and Tone) project, a large-scale database and knowledge repository. It is designed to capture, monitor, and analyse news articles, blog posts, and other textual sources worldwide to create a structured and comprehensive representation of global events, entities, and their relationships. The GDELT project uses natural language processing and machine learning techniques to extract events, entities (such as people, organisations, and locations), and other relevant information from the text. The GDELT project associated events with precise timestamps and geographic coordinates, allowing for the tracking of when and where events occur. The extracted information is organised into a structured knowledge graph, where events are linked to related entities and additional contextual data, creating a web of interconnected information. It provides a real-time and historical record of global events, which can be used for event tracking, trend analysis, and early warning systems.

This study collected news media data from the GDELT project via Google BigQuery, providing a convenient and efficient way to access and analyse the GDELT GKG data (Google Cloud, 2020). The steps include: (a) Access Google BigQuery: Users can sign up for a Google Cloud account and enable BigQuery or use the existing Google Cloud account. (b) Navigate to BigQuery Console: Go to the Google Cloud Console and navigate to the BigQuery section. (c) Find the GDELT GKG Dataset: The ‘gdelt-bq’ dataset can be found in the 'Public Datasets' tab. Within the ‘gdelt-bq’ dataset, various GDELT data can be explored, including the GKG. (d) Query the GKG Table: To query the GKG data, find the table named ‘gdelt-bq.gdeltv2.gkg’. This table contains the GDELT GKG data. Click on the table, and SQL queries can be used to retrieve specific data. Finally, more than 10 billion news records have been collected in this study.

Data filtering was applied by employing news article themes to ensure the relevance of the data to surface water floods and road transport in the GBA. The keywords, including ‘Flood’, ‘Road’, ‘Transport’, and ‘Highway’, were used to screen out the news records relating to surface water flood and road transport (Table 3.1). The news article must be related to both 'Flood' themes and 'Transport' themes. In other words, if the news article is only related to the 'Flood' themes or 'Transport' themes, it will be excluded.

Table 3.1 The GDELT themes related to flood and transport

Categories	NO	GDELT Themes
Flood	1	NATURAL_DISASTER_FLOODING
	2	NATURAL_DISASTER_FLOOD
	3	NATURAL_DISASTER_FLOODS
	4	NATURAL_DISASTER_FLOODED
	5	WB_154_FLOOD_PROTECTION
	6	NATURAL_DISASTER_FLOODWATERS
	7	NATURAL_DISASTER_FLASH_FLOOD
	8	NATURAL_DISASTER_FLASH_FLOODS
	9	NATURAL_DISASTER_FLOODWATER
	10	NATURAL_DISASTER_FLOOD_WATER
	11	NATURAL_DISASTER_FLOOD_WATERS
	12	NATURAL_DISASTER_FLOOD_WARNING
	13	NATURAL_DISASTER_FLOODED_ROADS
	14	NATURAL_DISASTER_FLOODED_AREAS
	15	NATURAL_DISASTER_FLOODED_ROAD
Transport	1	WB_168_ROADS_AND_HIGHWAYS
	2	WB_1809_HIGHWAYS
	3	INFRASTRUCTURE_BAD_ROADS
	4	MANMADE_DISASTER_ROAD_ACCIDENT
	5	NATURAL_DISASTER_FLOODED_ROAD
	6	NATURAL_DISASTER_FLOODED_ROADS
	7	ROAD_INCIDENT
	8	ROAD_INCIDENT_BRIDGE_COLLAPSE
	9	ROAD_INCIDENT_BRIDGE_DISASTER
	10	ROAD_INCIDENT_BRIDGE_FAILURE
	11	ROAD_INCIDENT_CAR_ACCIDENT
	12	ROAD_INCIDENT_CAR_CRASH
	13	ROAD_INCIDENT_CAR_PILEUP
	14	ROAD_INCIDENT_COLLAPSED_BRIDGE
	15	ROAD_INCIDENT_FATAL_PILEUP
	16	ROAD_INCIDENT_FREEWAY_PILEUP
	17	ROAD_INCIDENT_HIGHWAY_PILEUP
	18	ROAD_INCIDENT_MOTORWAY_PILEUP
	19	ROAD_INCIDENT_MOTOR_VEHICLE_COLLISION
	20	ROAD_INCIDENT_ROAD_ACCIDENT
	21	ROAD_INCIDENT_TRAFFIC_ACCIDENT
	22	ROAD_INCIDENT_TRAFFIC_COLLISION
	23	ROAD_INCIDENT_VEHICLE_CRASH
	24	ROAD_INCIDENT_VEHICLE_PILEUP
	25	UNGP_TRANSPORTATION_ROADS
	26	WB_1429_ROAD_SAFETY
	27	WB_1801_ROAD_TRANSPORT

Table 3.1 The GDELT themes related to flood and transport (continue)

Categories	NO	GDELT Themes
Transport	28	WB_1816_ROAD_FUNDS
	29	WB_1818_ROAD_TOLLS
	30	WB_784_TRAFFIC_AND_ROAD_SAFETY
	31	WB_785_URBAN_ROADS
	32	WB_786_RURAL_ROADS
	33	MANMADE_DISASTER_TRAFFIC_ACCIDENT
	34	MANMADE_DISASTER_TRAFFIC_COLLISION
	35	SOC_TRAFFICACCIDENT
	36	TRAFFIC
	37	WB_1810_TRAFFIC_CONTROL_AND_MONITORING
	38	WB_2458_HUMAN_TRAFFICKING
	39	WB_2461_TRAFFICKING_NATURAL_RESOURCES
	40	CRISISLEX_C04_LOGISTICS_TRANSPORT
	41	ECON_TRANSPORT_COST
	42	MANMADE_DISASTER_TRANSPORTATION_DISASTER
	43	MANMADE_DISASTER_TRANSPORT_DISASTER
	44	PUBLIC_TRANSPORT
	45	TAX_FNCACT_TRANSPORTATION_SECURITY_OFFICER
	46	WB_1172_TRANSPORT_INTEGRATORS
	47	WB_1173_TRANSPORT_LOGISTICS_PROVIDERS
	48	WB_135_TRANSPORT
	49	WB_162_TRANSPORT_ECONOMICS
	50	WB_1630_TRANSPORT_SUBSIDIES
	51	WB_163_LOW_EMISSIONS_TRANSPORT
	52	WB_164_MODES_OF_TRANSPORT
	53	WB_1725_INTELLIGENT_TRANSPORT_SYSTEMS
	54	WB_1728_URBAN_TRANSPORT_POLICY_AND_PLANNING
	55	WB_1802_MULTIMODAL_TRANSPORT
	56	WB_1803_TRANSPORT_INFRASTRUCTURE
	57	WB_1808_TRANSPORT_SAFETY
	58	WB_1812_TRANSPORT_EQUIPMENT
	59	WB_1819_TRANSPORT_EFFICIENCY
	60	WB_1820_TRANSPORT_EMPLOYMENT
	61	WB_1823_TRANSPORT_GOVERNANCE
	62	WB_1825_TRANSPORT_INSTITUTIONS
	63	WB_1826_TRANSPORT_POLICY
	64	WB_1827_RURAL_TRANSPORT_POLICY_AND_PLANNING
	65	WB_536_ENERGY_EFFICIENT_TRANSPORT
	66	WB_551_GAS_TRANSPORTATION_STORAGE_AND_DISTRIBUTION
	67	WB_686_TRANSPORT_INFORMATION_SYSTEMS
	68	WB_787_NON_MOTORIZED_TRANSPORT
	69	WB_788_URBAN_TRANSPORT
	70	WB_789_RURAL_TRANSPORT
	71	WB_790_TRANSPORT_AND_SUSTAINABLE_DEVELOPMENT
	72	WB_791_TRANSPORT_IMPACT_ON_THE_ENVIRONMENT
	73	WB_793_TRANSPORT_AND_LOGISTICS_SERVICES
	74	WB_976_TRANSPORT_LAW_AND_REGULATION

The GDELT project provides both location (e.g., China-Guangdong-Shenzhen) and longitude-latitude information (114.07, 22.62). Sometimes location information does not correspond to longitude-latitude information. This study found that longitude-latitude information is more accurate than location information. Hence, administrative boundary information was used to select news articles published in the cities of the GBA based on the longitude-latitude information (see Figure 3.6). Administrative boundary information was acquired from DataV.GeoAtlas (https://datav.aliyun.com/portal/school/atlas/area_selector). QGIS was used to determine whether the point (i.e., news article location) is within the city boundary. This process successfully identified 157 thousand news data records directly related to road flooding across the 11 GBA cities. Data pre-processing filters for relevant keywords remove duplicates and missing values and transform semi-structured data into a structured format.

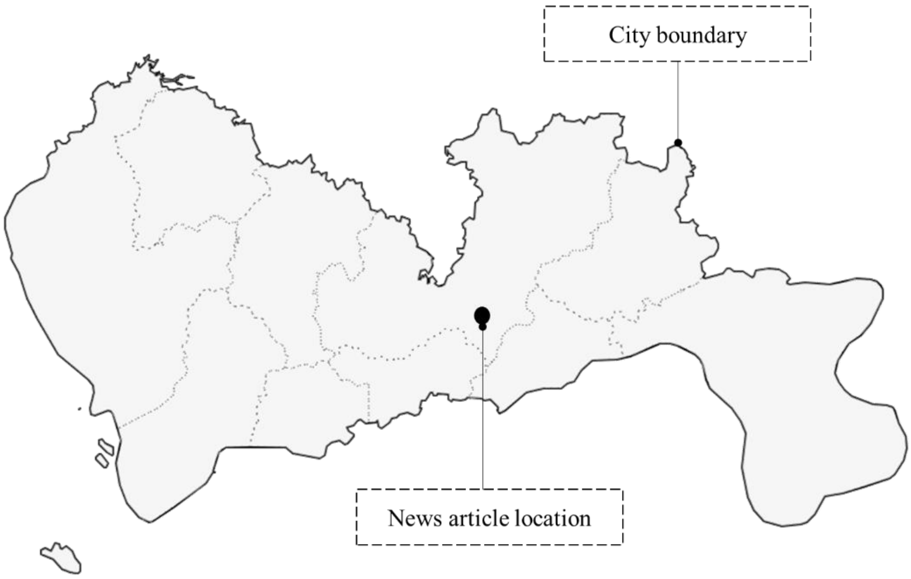

Figure 3.6 Schematic diagram of the relationship between news article location and city boundary.

3.3.2 Measuring index

Descriptive analysis was conducted to summarise and describe the characteristics of news media data. The news media data was analysed by two indexes: media attention and news sentiment.

Media attention refers to the level of coverage, visibility, or focus that surface water flooding receives from various forms of news media. It represents the degree to which the media reports, discusses or features surface water flooding, and it is a critical factor in shaping public awareness, perception, and discourse on that subject. Media attention is defined as the number of news records related to surface water floods and road transport in a city (or during a year/month/day interval). Flooding events that receive high media attention often significantly impact public perception and behaviour.

News sentiment refers to the emotional tone, attitude, or subjective opinion expressed in news articles, reports, or media coverage of surface water flooding. It reflects whether the news conveys a positive, negative, or neutral perspective, and it can influence how readers or viewers perceive and interpret the information presented in the news. News sentiment is the average tone of articles across all news about floods and road transport in a city (or during a year/month/day interval).

The ‘article tone’ is provided by the GDELT project. It refers to the emotional or sentiment characteristics associated with news articles and media content, providing insights into how these surface water flood events are portrayed. The score ranges from -100 (highly negative) to +100 (highly positive), with most scores falling between -10 and +10, with 0 indicating neutrality. It is derived by subtracting the Negative Score from the Positive Score. A score near zero suggests either a mild emotional response or a balance between positive and negative sentiments. This can be confirmed by reviewing the Positive and Negative scores individually or by checking the Polarity variable. Both the Positive Score and Negative Score are provided below for reference.

-- *Positive Score* is the proportion of all words in the news article that convey positive emotions, such as ‘good’ or ‘active response’.

-- *Negative Score* is the proportion of all words in the news article that convey negative emotions, such as ‘injury,’ ‘death,’ or ‘kill’.

3.3.3 Correlation analysis

GDP and City population are key drivers in city structure development (Leong Glastris 2013). Cities with larger populations and GDP are often the centres of politics, economy, culture, and society, and their developments and changes have a greater impact and influence. Usually, news media pays more attention to these cities. This attention may result in a higher likelihood of negative news being reported and disseminated. Therefore, this study hypothesised:

Hypothesis 1: The media attention trend to concentrate in the city with more population and GDP.

Hypothesis 2: The news sentiment trend to be more negative in the city with more population and GDP.

Correlation analysis was adopted to explore the measure the strength and direction of the relationship between GDP and media attention, the relationship between population and media attention, the relationship between GDP and news sentiment, and the relationship between population and news sentiment. Table 3.2 shows four types of Correlation Coefficient. According to the definition of different Correlation Coefficients, the Pearson Correlation Coefficient is used to detect linear relationships between two variables (Benesty et al., 2009). In this study, there would be a linear relationship between GDP and media attention, a linear relationship between population and media attention, a linear relationship between GDP and news sentiment, and a linear relationship between population and news sentiment.

Table 3.2 Comparison of various Correlation Coefficients

Correlation Coefficient	Definition	References
Pearson Correlation Coefficient	Used to detect linear relationships between two variables, assuming the data comes from a normally distributed population	(Benesty et al., 2009)
Spearman Rank Correlation Coefficient	Assesses monotonic relationships between two continuous or ordinal variables	(Zar 2005)
Kendall Correlation Coefficient	Reflects the correlation between categorical variables, especially for ordinal variables	(Hervé Abdi 2007)
Multiple Correlation Coefficient	Reflects the correlation between a dependent variable and a set of independent variables (two or more)	(Herve Abdi 2007)

Hence, the Pearson Correlation Coefficient was utilised to identify patterns and associations of news media activities. Population and GDP data were collected from the Statistical Yearbook of 11 GBA cities (see Table 3.3). The Pearson Correlation Coefficient is computed by dividing the covariance of two variables by the product of their standard deviations. The equation is as follows:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \quad 3.1$$

Where X_i and Y_i are data points, $\bar{X}$and $\bar{Y}$ are the means of X and Y. If r is close to +1, it suggests a strong positive linear relationship. If r is close to -1, it indicates a strong negative linear relationship. If r is close to 0, there is little to no linear relationship.

Table 3.3 Data for correlation analysis

City	Year	Population	GDP (Trillion RMB)
Dongguan	2015	999.6	0.67
Dongguan	2016	1,016.6	0.73
Dongguan	2017	1,038.2	0.81
Dongguan	2018	1,043.8	0.88
Dongguan	2019	1,045.5	0.95
Dongguan	2020	1,048.4	0.98
Dongguan	2021	1,053.7	1.09
Foshan	2015	864.3	0.81
Foshan	2016	874.8	0.88
Foshan	2017	900	0.94
Foshan	2018	926	1
Foshan	2019	943.1	1.07
Foshan	2020	951.9	1.08
Foshan	2021	961.3	1.22
Guangzhou	2015	1,595	1.73
Guangzhou	2016	1,678.4	1.86
Guangzhou	2017	1,746.3	1.99
Guangzhou	2018	1,798.1	2.1
Guangzhou	2019	1,831.2	2.38
Guangzhou	2020	1,874	2.51
Guangzhou	2021	1,881.1	2.82
Hong Kong	2015	729.13	2.12
Hong Kong	2016	733.66	2.20
Hong Kong	2017	739.32	2.34
Hong Kong	2018	745.26	2.48
Hong Kong	2019	750.79	2.49
Hong Kong	2020	748.1	2.37
Hong Kong	2021	741.31	2.54
Huizhou	2015	550.4	0.31
Huizhou	2016	562.7	0.34
Huizhou	2017	572.2	0.37
Huizhou	2018	584.7	0.40
Huizhou	2019	591.2	0.42
Huizhou	2020	605.7	0.43
Huizhou	2021	606.6	0.50
Jiangmen	2015	458	0.23
Jiangmen	2016	461.8	0.25
Jiangmen	2017	465.1	0.27
Jiangmen	2018	470.4	0.30
Jiangmen	2019	475.3	0.32

Table 3.3 Data for correlation analysis (continue)

City	Year	Population	GDP (Trillion RMB)
Jiangmen	2020	480.4	0.32
Jiangmen	2021	483.5	0.36
Macao	2015	61.52	0.31
Macao	2016	62.6	0.31
Macao	2017	63.86	0.35
Macao	2018	65.1	0.38
Macao	2019	66.37	0.38
Macao	2020	67.63	0.18
Macao	2021	68.66	0.21
Shenzhen	2015	1,408	1.84
Shenzhen	2016	1,495.4	2.07
Shenzhen	2017	1,587.3	2.33
Shenzhen	2018	1,666.1	2.53
Shenzhen	2019	1,710.4	2.7
Shenzhen	2020	1,763.4	2.78
Shenzhen	2021	1,768.2	3.07
Zhaoqing	2015	400.3	0.17
Zhaoqing	2016	401.8	0.187
Zhaoqing	2017	403.9	0.20
Zhaoqing	2018	406.6	0.21
Zhaoqing	2019	409.2	0.23
Zhaoqing	2020	411.7	0.23
Zhaoqing	2021	413	0.27
Zhongshan	2015	397	0.31
Zhongshan	2016	407.7	0.32
Zhongshan	2017	418	0.34
Zhongshan	2018	428.8	0.36
Zhongshan	2019	438.7	0.31
Zhongshan	2020	443.1	0.32
Zhongshan	2021	446.7	0.36
Zhuhai	2015	189.8	0.22
Zhuhai	2016	196	0.25
Zhuhai	2017	207	0.29
Zhuhai	2018	220.9	0.32
Zhuhai	2019	233.2	0.34
Zhuhai	2020	245	0.35
Zhuhai	2021	246.7	0.39

3.4 Government agency network analysis

3.4.1 Government engagement estimation

Government engagement refers to the level of government presence or involvement during surface water flooding events. Word frequency analysis was conducted to estimate government engagement, identifying and quantifying the frequency of government-related words, terms, or phrases within the surface water flooding database. A government-related word list was created based on the organisation information of the GDELT project. This list includes terms associated with government institutions, policies, departments, officials, and other related terms.

MapReduce word count was also conducted to calculate the mentioned frequency of government agencies in the GBA (see Figure 3.7). There are three critical phases in the word count process.

Firstly, the Map function tokenises the input text and generates key-value pairs. Here, the key represents a government agency, and the value is set to 1. The Map phase generates a set of intermediate key-value pairs like (government agency A, 1), (government agency B, 1), (government agency C, 1), and so on.

After the Map phase, the framework performs a shuffle and sort operation. This reorganises the intermediate key-value pairs so that all pairs with the same key are grouped. This prepares the data for the Reduce phase.

Thirdly, the Reduce function accepts the key along with the list of values linked to that key and processes them to derive the ultimate count for each government agency. Finally, the result provides the word counts for the entire input dataset.

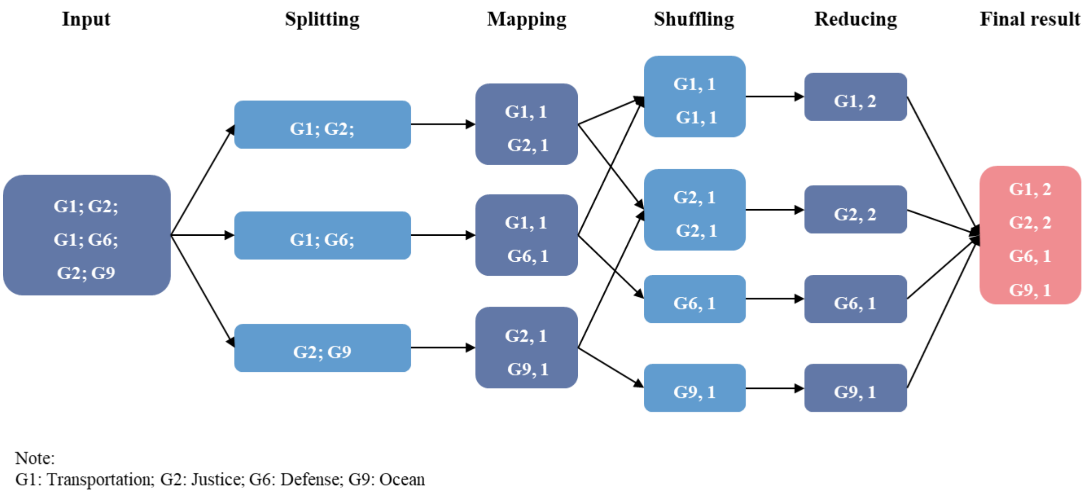

Figure 3.7 An example of the overall MapReduce word count process

3.4.2 Descriptive statistics of network

Descriptive statistics was adopted to quantify various characteristics and attributes of the government agency network, exploring valuable insights into its structure and behaviour. A range of critical metrics and measures is considered in Table 3.4. These measures collectively provide a comprehensive understanding of a network topology, connectivity, and characteristics. They help reveal how nodes are interconnected, the presence of communities or clusters, the spread of influence or information, and the overall efficiency of communication or interaction within the network. In flood management networks, these statistics can aid in identifying critical nodes or agencies, understanding the network resilience, and optimising strategies for better response and recovery. This study used the Gephi algorithm (Bastian et al., 2009) to calculate and visualise the government agency network.

Table 3.4 Key measures for descriptive statistics of government agency network

Measures	Descriptions
Network size	· The number of nodes and edges in the network · Provides an overview of the network's scale.
Node degree	· Indicates the number of connections (edges) each node has. · It helps identify the most connected nodes.
Network density	· Quantifies how connected the network is by measuring the proportion of actual connections to the total possible connections. · High density indicates a highly connected network.
Clustering Coefficient	· Measures the degree to which nodes in the network tend to cluster together. · It helps identify local substructures or communities within the network.
Network Diameter	· Represents the longest shortest path between any two nodes. · Indicates the network's overall size and potential for information transfer.
Centralisation	· Measures of centralisation assess the extent to which network centrality is concentrated in a few nodes. · High centralisation suggests that power or influence is concentrated in a few key individuals or agencies.
Average Path Length	· The average distance (number of edges) between pairs of nodes in the network. · Reflects how easily information or influence can travel through the network.
Node Attributes	· Consider descriptive statistics related to node attributes, such as government department budgets, tenure of government officials, or any other relevant characteristics. · Includes means, medians, and standard deviations.

3.4.3 Network centrality analysis

Network centrality analysis involves examining the significance of individual nodes within a network (Derr 2021). It is a fundamental concept in network and graph theory (Metcalf and Casey 2016), which helps identify the most important or influential nodes within a network. Centrality analysis can be used to identify critical agencies that play pivotal roles in coordination, resource allocation, and information dissemination during flood response and recovery. Identifying these influential nodes helps optimise strategies and improve the efficiency of flood management networks. Degree centrality, betweenness centrality, and closeness centrality were considered in this study.

Degree centrality in the government agency network refers to the number of connections a node (i.e., agency) has (Golbeck 2015, p.21). Nodes with a higher degree of centrality indicate more connections or interactions with other nodes within the network. This could represent agencies that collaborate extensively with multiple other entities in flood management. Higher centrality suggests that these nodes have more significant influence and a broader reach in the network. Agencies with more connections might significantly coordinate efforts, share information, or provide resources during floods. While high-degree nodes have more connections, they might also become critical points of failure. If these agencies fail to function or coordinate effectively, it can significantly impact the overall network's functionality. Degree centrality is calculated by dividing the number of connections a node has (its degree) by the total number of nodes minus one (to normalise the value).

$$DC_i = \frac{K_i}{N - 1} \quad 3.2$$

Where K_i is the number of connections, N is the number of nodes.

Betweenness centrality measures the extent to which a node (i.e., agency) lies on the shortest paths between other nodes in the government agency network (Copestake 2018). Nodes with high between centrality might act as bridges or intermediaries between different agencies or departments, fostering collaboration and information flow across the network. These nodes are critical for disseminating crucial information and mobilising resources across different parts of the network. Agencies identified with high betweenness centrality can influence decision-making processes during floods. Their centrality positions them as influential actors in orchestrating flood mitigation and response strategies, policies, and actions. The identification of critical nodes via betweenness centrality analysis can also highlight vulnerabilities in the network. If a node with high centrality fails or faces challenges during a flood event, it could significantly disrupt the overall response and management efforts. Mathematically, the betweenness centrality of a node *v* is calculated as the number of shortest paths between pairs of nodes that pass through *v* divided by the total number of shortest paths between those pairs.

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \qquad 3.3$$

Where $C_B(v)$ is the betweenness centrality of node *v*, σ_{st} is the total number of shortest paths from node *s* to node *t*, and $\sigma_{st}(v)$ is the number of those paths that pass-through node *v*.

Closeness centrality measures how quickly and efficiently information or resources can spread from a particular node (i.e., agency) to all other nodes in the government agency network (Golbeck 2013). Agencies with high closeness centrality can quickly communicate and share information with other agencies involved in flood management. This ability to disseminate information rapidly across the network is crucial during emergencies, enabling timely responses and coordinated actions. The high closeness centrality of specific nodes signifies that they are well-connected within the network, making the overall flood management system more efficient. These nodes serve as hubs that can efficiently coordinate efforts, reducing delays in decision-making and response times during flood events. Agencies with high closeness centrality can act as focal points for collaboration. They have the potential to bridge different segments of the network, fostering cooperation and information exchange between otherwise disparate parts of the flood management system. Analysing closeness centrality can also reveal vulnerabilities in the network. Suppose a highly central node fails or gets disrupted during a flood event. In that case, it might significantly hamper the flow of information and resources, impacting the overall response capacity of the network.

$$C_C(v) = \sum\nolimits_{s \neq v \neq t} \frac{N-1}{\sum_{i=1}^{N-1} d(v,i)} \qquad 3.4$$

Where $C_C(v)$ is the closeness centrality of node v, N is the total number of nodes in the network, and $d(v, i)$ represents the shortest path distance between node v and all other nodes i in the network.

3.4.4 Co-occurrence analysis

Co-occurrence refers to the simultaneous appearance or presence of two or more items within a specific context, time frame, or dataset (Cohen et al., 2005; Freilich et al., 2010). This study used co-occurrence analysis to identify patterns of association or co-occurrence between government agencies. Analysing the co-occurrence of collaborations or interactions between these government agencies could identify which departments tend to work together more frequently, providing insights into effective coordination and potential gaps in collaboration. Term Frequency (TF) (Ganesan 2019), a fundamental concept in co-occurrence analysis, was used to measure the frequency of government agencies. TF is essential for understanding how often specific terms appear together or in proximity in the context of co-occurrence analysis. A step-by-step process for calculating TF in the context of co-occurrence analysis is as follows:

Step 1 Term Frequency Calculation

Calculate the TF for each term (i.e., government agency) within the pre-processed dataset. This is done by counting how often each government agency appears. The equation for TF is straightforward:

$$TF(t) = \frac{f_{t,d}}{n_d} \qquad 3.5$$

Where $f_{t,d}$ is the number of times 'term' appears in 'article', and n_d is the total number of terms in 'article'.

Step 2 Creating a co-occurrence Matrix

After calculating TF, this information can be used to create a co-occurrence matrix. In this matrix, rows and columns represent terms, and the cells contain the TF values for how often terms co-occur in the same news article.

Step 3 Pairwise co-occurrence

Examine the corresponding cells in the co-occurrence matrix to assess the co-occurrence of pairs of terms. The value in the cell (i, j) represents how often term i and term j co-occur in the same news article.

Step 4 Interpretation and visualisation

Use the co-occurrence matrix to visualise and interpret relationships and patterns between government agencies. It allows us to identify which government agencies tend to appear together more frequently, providing insights into term associations within the dataset. The Gephi was used to visualise the government agency network.

3.5 Potential flood impact analysis

3.5.1 Data collection

Surface road network data was collected from OpenStreetMap (OSM) (https://www.openstreetmap.org/), a collaborative, open-source mapping project. Unlike traditional mapping initiatives, OSM relies on contributions from individuals and organisations worldwide, who share their geographic knowledge and data to build a comprehensive and up-to-date map. OSM captures various types of geographic data, including roads, buildings, parks, rivers, land use, transport networks, and points of interest. The map data is continually updated and expanded, reflecting real-world changes, new developments, and improvements made by contributors.

OSM provides vast road network data, including detailed and up-to-date information about streets, highways, paths, and other navigable routes. OSM classifies roads into various types, each with its attributes. Common road types include motorways, trunk, primary, secondary, and tertiary roads. These classifications help users understand road hierarchies and functionality. OSM road network data is continuously updated by contributors worldwide, making it a valuable resource for end-users and developers seeking reliable and detailed information for various applications.

Moreover, several studies have been conducted to evaluate completeness, positional accuracy, attribute accuracy, and semantic accuracy of OSM road networks. Researchers have consistently held a positive attitude toward OSM road networks (Zhao et al., 2015; Minaei 2020; Zhang and Malczewski 2018). Zhao et al., (2015) conducted a statistical examination of the development of OSM road networks in Beijing. Their findings indicated a similarity between the expansion patterns of OSM road networks and actual road networks. Zhang and Malczewski (2018) explored the spatial pattern of road density and type diversity in China based on OSM road networks.

This study exported OSM road network data from the Geofabrik website (http://download.geofabrik.de). Geofabrik provides pre-compiled extracts of OSM data for various regions and countries in different formats, including PBF and Shapefile. Table 3.5 shows the correlation between China's and OSM's road grades. QGIS (https://www.qgis.org/) was used to calculate the length of OSM road networks in the GBA combined with administration boundary information. Finally, there are 290,413 data records for vulnerability assessment.

Administration boundary data was collected from Alibaba Cloud DataV.GeoAtlas (https://datav.aliyun.com/portal/school/atlas/area_selector). DataV.GeoAtlas data refers to geospatial information and datasets, such as maps, spatial boundaries, topography, and land use data, which are the foundational layer for geospatial analysis and visualisation. DataV.GeoAtlas data serves diverse applications, from business intelligence and urban planning to environmental monitoring and logistics optimisation. The data export options include formats such as CSV, GeoJSON, shapefiles, or other geospatial data formats. This study selected the GeoJSON format to download the geospatial boundary information of the GBA cities.

Table 3.5 Corresponding between China's road grades and OSM's road grades

Rank	China's road classification	OSM's road classification	Description from OSM
1	Expressway	Motorway	A controlled-access, high-capacity road typically has two or more lanes and an emergency lane in each direction. Similar to a freeway or autobahn.
		Motorway Link	The roads connecting a motorway to another motorway or a lower-grade highway are usually subject to the same restrictions as the motorway.
2	National Highway	Trunk	The most important roads in a country's network are not always motorways and may not necessarily be divided highways.
		Trunk Link	The connecting roads (slip roads/ramps) that lead to or from a trunk road to another trunk road or a lower-grade highway.
3	Provincial Road	Primary	The following roads are essential after the main trunk roads in a country's system. These roads typically connect larger towns.
		Primary Link	The roads connecting to or from a national highway include slip roads or ramps, which also connect to lower-grade highways.
4	County-level Road	Secondary	The roads are of intermediate importance in a country's road system, typically connecting towns.
		Secondary link	The roads that connect provincial roads, or lower-grade highways, with slip roads or ramps.
5	Township-level Road	Tertiary	The following roads are in a country's network, typically connecting smaller towns and villages.
		Tertiary Link	The roads connecting county-level or lower-grade highways are part of the country's network.

3.5.2 Index system development

In this section, more attention will be given to the physical properties of the transport system that could suffer damage or harm from surface water floods. Table 3.6 shows the computational process of road infrastructure vulnerability. Firstly, based on the previous study conducted for road vulnerability assessment (He et al., 2021), an indicator system for road infrastructure vulnerability assessment was established to analyse the potential impacts of surface water floods on surface roads (see Table 3.6). Then, indicators were quantified based on the data normalisation and weight determination. Finally, the assessment of exposure, disaster reduction capability, and vulnerability were conducted, and the output is the vulnerability map.

Road infrastructure vulnerability assessment indexes were categorised into exposure and disaster reduction capability. The concepts of road infrastructure vulnerability, exposure, and disaster reduction capability are as follows:

-- *Road infrastructure vulnerability* refers to the degree of physical losses of surface roads caused by a surface water flood event.

-- *Exposure* refers to the degree of various road exposed to surface water flood hazards. Greater exposure leads to increased vulnerability of road infrastructure.

-- *Disaster reduction capability* refers to the ability of surface roads to reduce losses under surface water flood events. The greater the disaster reduction capability, the lower the vulnerability of road infrastructure.

Table 3.6 The explanations of indicators for the road infrastructure vulnerability index system

Index	Indicators	Abb.	Units
Exposure	Surface road value	SRV	millions RMB/km^2
	Rainfall amount	AR	mm/year
Disaster reduction capability	Surface road density	SRD	km/km^2
	Road bridge density	RBD	km/km^2
	Road culvert density	RCD	km/km^2
	Road anti-disaster ability	RAA	

The vulnerability model was adopted using Equation 3.6 based on previous studies. Road infrastructure vulnerability (V) was determined by combining the exposure (E) and the disaster reduction capability (R) value.

$$V = E(1 - \sqrt{R}) \qquad 3.6$$

Where *E* is the exposure index, and *R* is the disaster reduction capability index.

Surface water floods result in more significant losses in regions with increased exposure, which considers the economic impact of surface road damage. Annual rainfall and surface road value were used to determine the exposure of surface roads to surface water floods. The higher the annual rainfall, the higher the exposure (Cho and Chang 2017; Nasiri et al., 2019). If there is no rainfall in the area, the exposure is 0. Areas with a higher value for surface roads are assumed to suffer heavier damage from surface water flood events (Li et al., 2015; He et al., 2021). If there are no roads in the area, the exposure is 0. Hence, the exposure can be calculated using the following equation:

$$E = \sum_{i=1}^{2} U_i W_i \qquad 3.7$$

Where U_i is the scores of *ith* exposure factors (i.e., SRV, AR), and W_i is the weight of *ith* factors.

Surface road value (SRV) refers to the total value of road construction, ancillary facilities, road repair, and reconstruction costs, which contains expressways, national highways, provincial roads, county-level roads, and township-level roads. The surface road value can be calculated using the following equation:

$$SRV = \sum_{i=1}^{n} L_i V_i \tag{3.8}$$

Where L_i is the length of the *ith* road, and V_i is the average value of the *ith* road.

QGIS calculated the total length of various roads in different districts based on the OSM and administrative boundary data. The high-grade roads have higher construction, maintenance, repair, and reconstruction costs than the low-grade roads. The economic cost of expressways, national highways, provincial roads, county-level roads, and township-level roads is 40 million RMB/km, 20 million RMB/km, 15 million RMB/km, 8 million RMB/km, and 4 million RMB/km, respectively (He et al., 2021; Li et al., 2015).

More excellent disaster reduction capability leads to reduced road infrastructure losses during surface water flood events. Disaster reduction capability was determined by surface road density, road bridge density, road culvert density, and road anti-disaster ability. Surface water floods lead to fewer losses in areas with higher surface road density, road bridge density, road culvert density, and road anti-disaster ability. Hence, the disaster reduction capability can be calculated using the following equation:

$$R = \sum_{i=1}^{3} U_i W_i \tag{3.9}$$

Where U_i is the score of the *ith* disaster reduction capability factors, and W_i is the weight of *ith* factors.

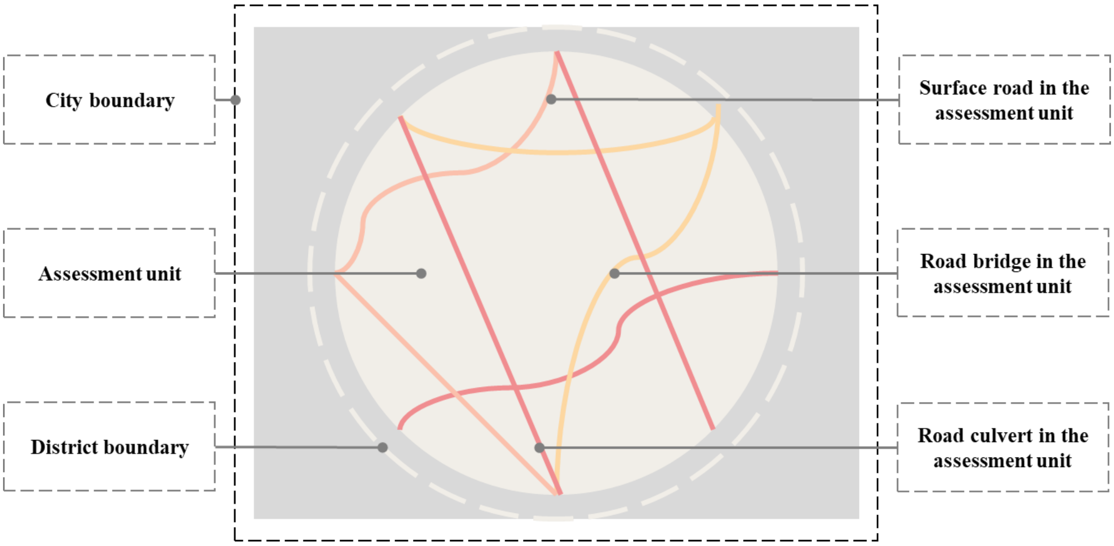

Figure 3.8 Schematic diagram of surface road density, road bridge density, and road culvert density calculation

Surface road density (SRD) is defined as the total length of surface roads per assessment unit (see Figure 3.8). A higher SRD indicates a greater capacity of emergency rescue services for road protection during surface water flood events (Duan et al., 2022). The SRD can be calculated using the following equation:

$$SRD = \sum_{i=1}^{n} L_i/S \tag{3.10}$$

Where L_i is the total length of the ith road (km), and S is the area of the assessment unit (km^2).

Road bridge density (RBD) refers to the total length of road bridges per assessment unit (see Figure 3.8). A higher RBD indicates a greater capacity for flood water discharge (Li et al., 2015; He et al., 2021). The RBD can be calculated using the following equation:

$$RBD = L_{br}/S \tag{3.11}$$

Where L_{br} is the total length of the road bridges (km), and S is the area of the assessment unit (km^2).

Road culvert density (RCD) refers to the total length of culverts per assessment unit (see Figure 3.8). A higher RCD indicates a greater capacity for flood water discharge

(Li et al., 2015; He et al., 2021). The RCD can be calculated using the following equation:

$$RCD = L_{cu}/S \tag{3.12}$$

Where L_{cu} is the total length of the road culverts (km), and S is the area of the assessment unit (km^2).

Road anti-disaster ability (RAA) has been considered during road design and construction. The higher the road grade, the higher the anti-disaster ability. The anti-disaster ability of expressways, national highways, provincial roads, county-level roads, and township-level roads is 10, 7, 4, 2, and 1, respectively (He et al., 2021; Li et al., 2015). The RAA can be calculated using the following equation:

$$RAA = \sum_{i=1}^{n} \beta_i R_i \tag{3.13}$$

Where β_i is the anti-disaster ability index, and R_i is the ratio of the *ith* road length in the study area.

Given that each indication contribution to the results varies, determining each indicator weight is necessary (Peng and Zhang 2022). The weighting method was categorised into two groups: subjective weighting and objective weighting.

-- *Subjective weighting* is a method that assigns the weights of the indicator based on personal preferences and judgments (Sahoo et al., 2016). The weights are often determined through discussions or surveys with experts or stakeholders. This method is relatively easy to implement and provides flexibility to the decision-makers (Dandapat and Panda 2017). However, the results may be biased and subjective due to individual differences in perceptions and preferences (Duan et al., 2022). There are several subjective weighting methods, such as Simple additive weighting (SAW) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Setyani and Saputra 2016; Pathan et al., 2022).

-- *Objective weighting* is a method that uses mathematical or statistical techniques to objectively determine the weights of the indicator (Peng and Zhang 2022). This method is based on quantitative data and can provide more accurate and consistent results. Several objective weighting methods exist, such as Equal Weighting, Entropy Weighting Method (EWM), Analytic Hierarchy Process (AHP), and Criteria Importance Though Intercrieria Correlation (CRITIC) (see Table 3.7).

This study compared the EWM and CRITIC methods according to the data characteristics. We found that the CRITIC method is superior to the EWM weighting method, consistent with previous studies (Peng and Zhang, 2022). Hence, the results shown in this study were conducted based on the CRITIC method.

Table 3.7 Comparison of various objective weighting methods

Method	Description	Advantage	Disadvantage	References
Equal Weighting	All indicators are given equal weightage in the decision-making process.	It is a simple and easy-to-use method.	It does not account for the relative importance of different criteria.	(James 2022)
EWM	This method uses the concept of entropy to calculate the weightage of each indicator. It considers the degree of diversity in the decision-making process and assigns higher weightage to indicators with greater diversity.	It can provide a more objective and accurate weightage.	It may require more data.	(Kumar et al., 2021; Sarkar et al., 2022)
AHP	This approach simplifies a complex decision problem into smaller, more manageable sub-problems. It assigns weights to indicators through pairwise comparisons using a scale of relative importance.	It is a flexible method that can incorporate different opinions and preferences.	It may be subjective and time-consuming.	(Wu et al., 2022; Dung et al., 2022)
CRITIC	This method uses inter-criteria correlations to determine the weightage of each indicator. It considers the interactions and relationships between indicators and assigns weightage accordingly.	It can provide a more accurate and objective weightage.	It may require more data and computation.	(Diakoulaki et al., 1995; Peng, Zhang 2022)

CRITTIC method was proposed to indicate that the weight is determined by the divergence and the contradiction (Diakoulaki et al., 1995). The standard deviation reflects divergence. Contradiction is assessed based on the correlation between two evaluation indicators. A strong positive correlation between indicators indicates low contradiction, while a robust negative correlation suggests high contradiction. The calculation steps of the CRITTIC are as follows:

(1) Normalisation

Normalisation is the first step for weight determination. The min-max normalisation method was used to normalise the data from websites and yearbooks. Normalisation of positive and negative indicators was conducted using the following equations:

.

$$Y_{ij} = \frac{X_{ij} - X_{jmin}}{X_{jmax} - X_{jmin}} \tag{3.14}$$

$$Y_{ij} = \frac{X_{jmax} - X_{ij}}{X_{jmax} - X_{jmin}} \tag{3.15}$$

Where X_{ij} is the original value of the *ith* sample under the *jth* indicator, X_{jmax} and X_{jmin} are the maximum and minimum values of the *jth* indicator, respectively.

(2) Calculate divergence

$$S_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(Y_{ij} - \overline{Y_j})^2}, (i = 1, \dots, n), (j = 1, \dots, m) \tag{3.16}$$

Where S_j is the divergence of the *jth* indicator.

(3) Calculate contradiction

$$R_j = \sum_{i=1}^{n}(1 - r_{ij}) \tag{3.17}$$

Where R_j is the contradiction value between the *jth* indicator and the rest indicators, and r_{ij} is the correlation coefficient between the *ith* indicator and the *jth* indicator using the Pearson correlation coefficient.

(4) Calculate the information-carrying capacity

$$C_j = S_j R_j \tag{3.18}$$

(5) Calculate the weight of each indicator

$$W_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \tag{3.19}$$

SPSS was used to normalise the data and determine weight. The indicators were firstly normalised to account for the varying magnitudes among them. Then, the weights of various indicators were superposed for calculating exposure and disaster reduction capability. Table 3.8 presents the results of indicator weights.

Table 3.8 The weight of various indicators for road infrastructure vulnerability assessment

Index	Indicator	Weight
Exposure	Surface road value	0.3894
	Rainfall amount	0.6106
Disaster reduction capability	Surface road density	0.2078
	Road bridge density	0.1995
	Road culvert density	0.1755
	Road anti-disaster ability	0.4171

3.5.3 Word frequency analysis

Word frequency analysis was adopted to determine the media-mentioned frequency of indirect tangible impacts and roads in the GBA. MapReduce word count was also conducted to calculate the frequency of indirect impacts and roads.

The classification method used in the indirect tangible impact information classification was to develop indirect intangible impact dictionaries. 19 GDELT themes relating to road transport were divided into four indirect impacts, including public transport, logistics transport, road traffic, and traffic accidents. Then, the characteristics of indirect impacts were analysed, including the proportion of different impacts in each city and the proportion of each impact in different cities.

Generally, if an event significantly impacts some roads, these roads often arouse much attention and discussion on news media platforms. Entity Alignment was adopted to find the roads with different names that refer to the same road. For instance, roads in these texts, such as *Shennan Road*, *Shenan Avenue,* and *Shen Nan Road,* can be unified as Shennan Avenue in Shenzhen. Word Cloud (https://www.weiciyun.com) was used to present the counts of different roads and identify flood-prone roads in the GBA.

3.6 Study area

3.6.1 The physical geographical feature of the GBA

The Guangdong-Hong Kong-Macao Greater Bay Area (GBA), located in Southern China, is a rapidly developing region known for its economic vitality and dense population (see Figure 3.9). Surrounded by mountains on three sides and facing the South China Sea, the area benefits from the flat terrain and complex coastline of the Pearl River Delta (PRD), which has facilitated convenient traffic conditions (Li et al., 2021). The GBA covers 56,000 km^2 of land area, with a population of 86.7 million people (Statistia 2022). It comprises the two Special Administrative Regions (SARs) of Hong Kong and Macao and nine municipalities in Guangdong Province: Guangzhou, Shenzhen, Zhuhai, Foshan, Zhongshan, Dongguan, Huizhou, Jiangmen, and Zhaoqing, comprising 77 districts or counties. Additional details on these 11 GBA cities can be found in Table 3.9.

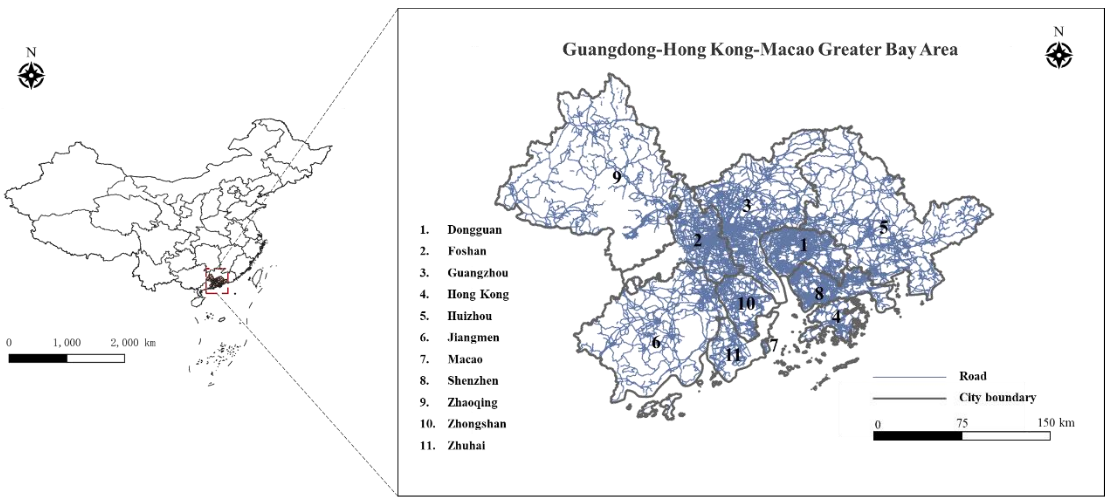

Figure 3.9 The location of the GBA

As early as 1994, the Shenzhen-Hong Kong Bay area was proposed by Wu Jiawei (Song et al., 2022). In 2016, the Chinese government proposed the *13th Five-Year Plan* to build the Greater Bay Area (National Development and Reform Commission 2016). The GBA has been designated a key development area and a world-class city cluster. Nowadays, the GBA is a hub for international trade and commerce, with the ports of Hong Kong and Shenzhen among the busiest in the world. It is also a hub for innovation and technology, with the establishment of technology parks and the promotion of research and development. Moreover, the GBA is a crucial part of China's 'Belt and Road' initiative and is seen as a significant driver of economic growth in the country.

Table 3.9 Facts of the GBA

NO.	City	Land area (km^2)	Population (million)	Annual rainfall (mm)
1	Dongguan	2,465	10.54	1,578
2	Foshan	3,843	9.61	1,500
3	Guangzhou	7,434	18.81	1,724
4	Huizhou	1,691	6.07	1,700
5	Jiangmen	9,464	4.84	1,649
6	Shenzhen	1,997	17.68	1,750
7	Zhaoqing	7,403	4.13	1,500
8	Zhongshan	1,784	4.47	1,700
9	Zhuhai	1,726	2.47	1,818
10	Hong Kong	1,106	7.41	2,400
11	Macao	30.3	0.68	2,058

Data source: (Constitutional and Mainland Affairs Bureau 2022)

The GBA experiences a subtropical monsoon climate, featuring four distinct seasons and an average annual rainfall of approximately 1800 mm (Wang and Zhai, et al., 2022). The climate is heavily influenced by the East Asian monsoon, which brings abundant rainfall in the summer and dry, cool weather in the winter. From May to September, the summer season is characterised by hot and humid weather with frequent typhoons and heavy rainstorms. The average temperature during this period ranges from 25 to 30 degrees celsius, with high humidity levels. Indeed, more than 85% of the annual rainfall occurs from May to September (Yang et al., 2014). The winter season is relatively dry and cool from December to February, with occasional cold fronts from the north. The average temperature during this period ranges from 10 to 15 degrees Celsius, and it is generally sunny and comfortable. Spring and autumn are transitional seasons with mild temperatures and moderate rainfall.

3.6.2 The economic development in the GBA

The GBA is one of the most dynamic and rapidly growing regions in the world, with a GDP of over 1.6 trillion USD (i.e., 12% of GDP in China) in 2020 (see Table 3.10). By 2030, the GDP is expected to amount to 4.62 trillion USD in the GBA (Hui et al., 2020). The area has undergone significant social and economic development in recent decades, driven by its strategic location, robust infrastructure, and favourable government policies. The development of the GBA can be traced back to the 1980s when China began to implement its policy of 'reform and opening up'. This policy led to a significant increase in foreign investment and trade in the region, particularly in the manufacturing and electronics industries.

Table 3.10 The GDP of the GBA

NO.	City	GDP (RMB billion)	GDP per capita (RMB/individual)
1	Dongguan	1,085.5	103,000
2	Foshan	1,215.7	126,000
3	Guangzhou	2,823.2	150,000
4	Huizhou	497.7	82,000
5	Jiangmen	360.1	75,000
6	Shenzhen	3,066.50	174,000
7	Zhaoqing	265	64,000
8	Zhongshan	356.6	80,000
9	Zhuhai	388.2	157,000
10	Hong Kong	2524.1	340,401
11	Macao	204.4	1,610,945

Data source: (Constitutional and Mainland Affairs Bureau 2022)

In recent years, the Chinese government has taken steps to integrate further the GBA, including establishing the *Outline Development Plan for the Guangdong-Hong Kong-Macao Greater Bay Area* in 2019 (The State Council 2019a). The plan outlines a range of measures to promote the economic, social, and environmental development, including the development of transport infrastructure, the promotion of innovation and technology, and the strengthening of collaboration between cities in the region. To further promote social and economic development, the governments of Guangdong Province, Hong Kong, and Macao have launched a series of initiatives and policies to foster collaboration and innovation across the region.

3.6.3 The urbanisation in the GBA

Urbanisation has been a driving force for the socio-economic development of the GBA. Over the past few decades, the region has experienced rapid urbanisation and has transformed from a primarily rural area to an urbanised region with a high level of economic activity (Sun et al., 2020; Yang et al., 2020). The urbanisation rate in the GBA has increased from 19% in 1978 to 86% in 2020. The urbanisation has been shaped by various factors in the GBA, including the geographic location, natural resources, infrastructure, and policy support. The strategic location of this region has become an important international trade and commerce gateway. At the same time, its rich natural resources have supported the growth of critical industries such as manufacturing, finance, and logistics. Also, the GBA has benefited from significant investment in infrastructure.

Table 3.11 The urbanisation of the GBA

NO.	City	Urbanisation Rate (%)	Density (person/km^2)
1	Dongguan	90.7	4,274.56
2	Foshan	87.5	2,501.17
3	Guangzhou	91.4	2,530.35
4	Huizhou	78.8	3,587.23
5	Jiangmen	75.5	510.89
6	Shenzhen	100	8,854.08
7	Zhaoqing	65.2	557.84
8	Zhongshan	75.3	2,503.87
9	Zhuhai	81.4	1,429.14
10	Hong Kong	100	6,702.62
11	Macao	100	22,547.85

Data source: (Constitutional and Mainland Affairs Bureau 2022)

In recent years, the population growth in the GBA has slowed down due to ageing, declining fertility rates, and government policies to control population growth. However, the region still attracts many young professionals and skilled workers, especially in the technology and finance sectors. In addition to urbanisation, the GBA is also experiencing a trend of suburbanisation, as people move to satellite cities and towns for better living conditions and lower living costs. This trend has led to the development of new urban centres and the expansion of the transport network in the GBA.

3.6.4 The development of surface roads in the GBA

The development of surface roads in the GBA has been an essential part of the regional transport infrastructure. The construction of surface roads in the GBA can be traced back to the 1980s when the Chinese government started investing in the development of the PRD region. Since then, the surface roads in the GBA have undergone significant changes and improvements. In the early stages of development, the surface roads in the GBA mainly consisted of national highways and provincial roads, which were built to connect major regional cities. As the economy and population grew, the demand for transportation increased, leading to the construction of more high-grade surface roads. In recent years, the construction of various surface roads has further improved the connectivity of the road network in the GBA. The Hong Kong-Zhuhai-Macao Bridge, for example, is the longest sea-crossing bridge (i.e., 55 km) in the world, connecting Hong Kong, Zhuhai, and Macao (Transport and Logistics Bureau 2022).

Today, the road network in the GBA is well-developed and plays a vital role in the economic development of the region. By the end of 2021, the traffic mileage of the GBA expressway has reached 4972 km (National Development and Reform Commission 2022). Surface roads connect major cities and ports, facilitating the movement of goods and people and promoting the integration and development of the region. Cities in the GBA can be reached within one hour. For example, travelling from Zhuhai can reach Zhongshan (or from Guangzhou to Dongguan) within one hour, and from Shenzhen can reach Zhongshan within only two hours (The Education University of Hong Kong 2022).

Looking forward, the GBA will continue to focus on enhancing its road network to accommodate the growing demand for transportation. The GBA plans to expand and upgrade its existing road network, including constructing new expressways and expanding existing surface roads. According to the *Guangdong Province's expressway network planning (2020-2035),* the GBA will preliminarily have an expressway network with a total length of 15000 km by 2035 (Department of Transport of

Guangdong Province 2020). Moreover, the GBA aims to improve the quality of its roads by adopting advanced construction techniques and materials.

3.6.5 Floods in the GBA

Rapid urbanisation and climate change led to various challenges in the GBA, including surface water flooding. Since 1980, the urbanisation of the GBA has progressed rapidly, making it one of the fastest-growing urban areas globally (Sun et al., 2020). Many natural water bodies and vegetation have been replaced by impervious built-up areas in the urban area, which led to difficult rainfall infiltration (Li et al., 2021). Furthermore, urbanisation has profoundly altered the hydrological dynamics of urban regions. Consequently, the occurrence of intense rainfall has markedly risen due to the combined influence of urbanisation and global climate change (Xu et al., 2019; Qiang et al., 2020), increasing surface water floods.

Surface water floods significantly threaten the urban infrastructure, economy, and residents in the GBA. Heavy rainfall events and typhoons have caused flooding in many parts of the region, leading to property damage, traffic disruptions, and even loss of life. Surface water floods have been particularly problematic in low-lying areas with poor drainage systems and inadequate flood prevention measures. The Chinese government has recently introduced various policies and measures to tackle these issues, including developing flood management systems, improving drainage infrastructure, and promoting sustainable urban development.

Despite these efforts, surface water floods continue to threaten the GBA significantly. The climate is expected to become more extreme due to climate change, leading to more frequent and severe rainfall events. In addition, the rapid urbanisation is expected to continue, further straining the urban infrastructure and drainage systems in the GBA. With the continuous urban road expansion, the impacts of frequent and intensive surface water floods on physical assets are becoming increasingly severe in the next few decades in GBA cities.

3.7 Summary

Chapter 2 analysed the current methods of media data analysis and vulnerability assessment separately, identifying the primary gaps. Surface water floods are a significant threat to the road transport system. An increasing body of evidence recognises that media data analytics are crucial to the different phases of flood management, such as flood impact analysis for flood management. However, previous studies mainly focused on social media data analysis. Additionally, the analysis perspective is relatively single, with most of the focus on the patterns of flood damages/impacts. The role of the news media itself and the exploitable network relationships are often overlooked.

To tackle this, Chapter 3 presented a novel framework for flood management in the road transport system, integrating multiple information sources, such as news media data, road network data, and socioeconomic data. The methodology is coupled with the significant phases of flood management: 'preparedness and early warning—response and recovery—mitigation, risk and vulnerability modelling'. According to the logic of this integrated framework, this chapter also provides detailed information on the case (i.e., 11 GBA cities) selected in this study. In summary, this chapter provides fundamental information on the methodologies in this study.

The next chapter focuses on news media activities related to surface water flood and transport networks and how to adopt news media for better preparedness and early warning efficiency. In Chapter 5, central agencies and government agencies collaborate on flood management in transport systems was explored based on the network analysis, which can contribute to enhancing the performance of flood response and recovery. Finally, potential flood impacts on road infrastructure and transportation were assessed, and recommendations for future road design and transport operation were discussed in Chapter 6.

Chapter 4: Investigating news media activities related to flood and transport networks

4.1 Introduction

As surface water floods increase in frequency and severity, relying solely on engineering measures may not be adequate for effective flood management in the face of uncertainties. News media is one of the most important channels to timely convey rainstorm information, including the intensity, scope, and possible consequences of rainstorms. Moreover, news media is responsible for reporting rainstorm-induced flood disasters fairly and objectively. City authorities can obtain disaster information via news articles, which is useful for making the right decision to help the affected people with their needs. In such situations, news media data analytics is useful for effectively handling chaotic and disorganised flood situations. However, there is limited knowledge and understanding of adopting news media data for flood management.

According to the flood management cycle, this chapter focused on the phase of preparedness and early warning. Based on the methodological framework proposed in Chapter 3 (see Section 3.3), this chapter aims to investigate news media activities related to flood and transport networks and to fulfil the following objectives:

(a) Explore the spatial pattern of media attention and news sentiment and analyse the correlation between news media activities and urban development.

(b) Investigate the temporal evolution of news media activities, including yearly, monthly, and daily variations.

(c) Compare news media activities among different flood events, including non-typhoon and typhoon-induced floods.

4.2 Spatial distribution of news media activities

4.2.1 Media attention

From 2015 to 2021, there are about 440 thousand news articles on floods in the GBA. The 74 GDELT themes (e.g., WB_168_ROADS_AND_HIGHWAYS) related to transport networks are used to narrow the focus of news articles. As a result, 157 thousand news articles are related to transport networks, accounting for 35.7% of the total flood news articles. Moreover, the proportion of news articles related to transport networks in the total flood news articles has shown an increasing pattern in the past seven years (see Figure 4.1). In 2021, the proportion of news articles related to transport networks was higher than 40% in most cities of the GBA. The highest one occurred in Jiangmen (47.24%), followed by Shenzhen (47.21%) and Zhongshan (47.01%).

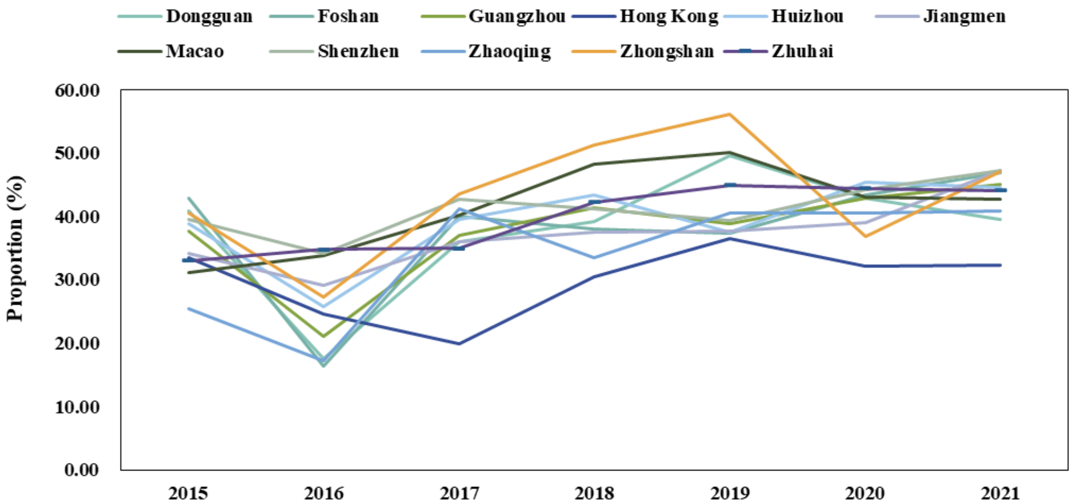

Figure 4.1 The proportion of news articles related to transport networks in GBA cities

The annual number of news articles on surface water floods and transport networks in the past seven years was 18,304 in 2015, 30,957 in 2016, 23,379 in 2017, 24,576 in 2018, 22,633 in 2019, 18,526 in 2020, and 18,295 in 2021. It can be found that the number of news articles has shown a decreasing trend year by year since 2018. The phenomenon is significant in Shenzhen, with 7,369 news articles in 2018, 6,205 in 2019, 6,103 in 2020, and 5,586 in 2021. This may be attributed to the progress of flood management in the GBA cities in recent years. For example, the Water Authority of

Shenzhen Municipality has been constructing a sponge city and flood-prone point management since 2016 (Water Authority of Shenzhen Municipality 2016a; Water Authority of Shenzhen Municipality 2016b).

News media attention is concentrated in densely populated and economically developed cities of the GBA (e.g., Guangzhou, Shenzhen, Hong Kong). The media attention on surface road floods is uneven among GBA cities (see Figure 4.2). The city with the most significant number of news articles is Guangzhou (53,579), followed by Shenzhen (47,887), Jiangmen (24,237) and Hong Kong (10,644). Notably, the total number of news articles in Guangzhou and Shenzhen is more than 100000, accounting for 65% of total news articles on surface water floods in the GBA. Zhongshan has the lowest number of news articles (702). It can be found that the maximum number of news articles is about 77 times the minimum number of news articles. The cities with less than 2 thousand news articles include Dongguan (1,459) and Zhuhai (1,417). In Zhaoqing, Huizhou, and Foshan, the number of news articles on surface water floods and transport networks is less than 5 thousand.

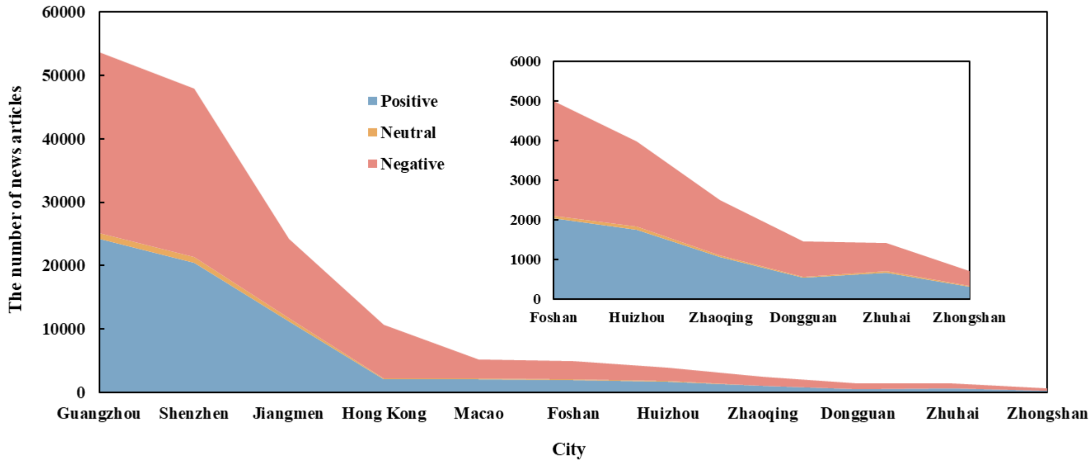

Figure 4.2 The distribution of news media attention in GBA cities

As shown in Table 4.1, news media attention and population show a positive relationship significantly ($p<0.01$). News media tend to pay more attention to surface water flood events and transport networks that affect a more significant number of people. Guangzhou has the highest population (about 18.8 million), followed by

Shenzhen, with a population of 17.7 million. As shown in Figure 4.2, Guangzhou and Shenzhen are the top two cities with the highest number of news articles on surface water floods and transport networks. In the two cities with the lowest number of news articles on surface water floods and transport networks (i.e., Zhongshan and Zhuhai), the population is less than 4.5 million. Generally, the media may prioritise covering surface water flood events and transport networks in the cities with more population and influence. Notably, the population is 4.84 million and 10.54 million in Jiangmen and Dongguan, respectively. However, the number of news articles is 24,237 and 1,459 in Jiangmen and Dongguan, respectively. Compared to Dongguan, Jiangmen is located in the coastal areas. Jiangmen may suffer more frequent and intense rainstorms than Dongguan, leading to more severe surface water flood hazards (Yujie Wang et al., 2022).

Table 4.1 The correlation between population and news media attention, GDP, and media attention

Pearson correlation analysis		
		Media attention
Population	Correlation coefficient	0.763**
	P value	0.000
GDP	Correlation coefficient	0.657**
	P value	0.000
*p<0.05 **p<0.01		

News media attention and GDP also show a positive relationship significantly (p<0.01) (see Table 4.1). A higher GDP indicates a more developed and prosperous city with more significant economic activity, which may have more news media outlets. As mentioned in Chapter 3, the highest GDP exists in Shenzhen (i.e., 3.066 trillion RMB), followed by Guangzhou (i.e., 2.82 trillion RMB) and Hong Kong (i.e., 2.52 trillion RMB). On the contrary, the GDP is less than 500 billion RMB in Zhuhai, Zhongshan, Zhaoqing, and Huizhou. Although Macao has the lowest population and GDP values, it ranks fifth in news media attention. It may be attributed to its highest GDP per capita (i.e., 1.61 million RMB/person) and 100% urbanisation. Moreover, residents tend to have greater access to technology and social media in more developed cities, which can increase the spread of news and information about surface water floods.

4.2.2 News sentiment

Figure 4.3 shows the variation of news sentiment to surface water floods and transport networks in different cities of the GBA. The average value of a news sentiment is less than 0 in all cities. Indeed, more than half (i.e., 102,028) of news articles on surface road floods are negative (i.e., tone<0). Only 2% (i.e., 3,597) of the news articles are neutral (i.e., tone=0). The three most negative cities include Hong Kong (-3.45), Macao (-1.24), and Dongguan (-1.16). In particular, Hong Kong had the lowest news sentiment value (-5.83) in 2019. It can be attributed to the heavy rainstorm in March and August. Besides, Hong Kong protests may affect news sentiment in 2019. The three most positive cities include Zhuhai (-0.26), Jiangmen (-0.40), and Huizhou (-0.55). Notably, cities receiving significant media attention may not necessarily have high news sentiment. During the past seven years, the top values of news sentiment are -0.709 (Macao, 2015), -0.439 (Zhongshan, 2016), -0.330 (Zhaoqing, 2017), -0.376 (Jiangmen, 2018), 0.131 (Guangzhou, 2019), 0.056 (Zhuhai, 2020), and 1.769 (Zhuhai, 2020).

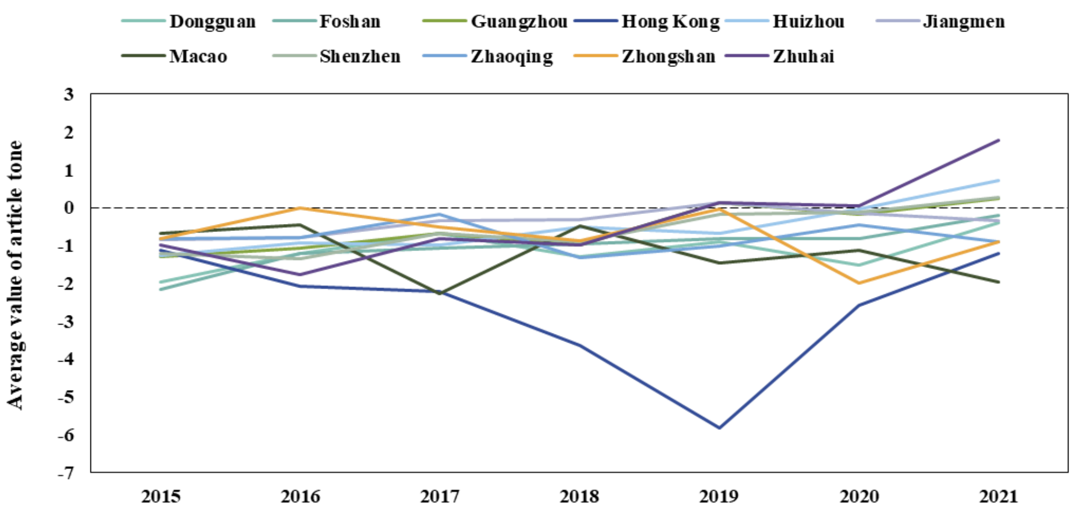

Figure 4.3 The news sentiment in different cities of the GBA

There is no significant relationship between news sentiment and urban development (see Table 4.2). The Pearson correlation analysis was conducted to examine the relationship between news sentiment and two key variables, i.e., population and GDP. The correlation coefficients for population and news sentiment yielded a coefficient of 0.061, indicating a very weak positive correlation. However, this relationship was not statistically significant, with a p-value of 0.598 ($p>0.05$). On the other hand, the correlation between GDP and news sentiment showed a coefficient of -0.207, suggesting a weak negative correlation. While this negative relationship was observed, it approached but did not reach statistical significance with a p-value of 0.071 ($p>0.05$, but $p<0.1$).

The results of correlation analysis show that there is no obvious pattern of news sentiment in different cities. Although the correlation between news sentiment and GDP exhibited a negative trend, neither relationship proved statistically significant. This absence of a clear pattern is potentially linked to the variation of news sentiment, a fluctuation primarily influenced by specific occurrences of surface water flood events in the respective city. It indicates that these news media have no significant bias in various cities, which can objectively reflect the information on transport networks during surface water flood events.

Table 4.2 The correlation between population and news sentiment, GDP, and news sentiment

Pearson correlation analysis		
		News sentiment
Population	Correlation coefficient	0.061
	P value	0.598
GDP	Correlation coefficient	-0.207
	P value	0.071
*p<0.05 **p<0.01		

4.3 Temporal evolution of news media activities

4.3.1 Yearly variation

Over seven years, a significant shift in news sentiment dynamics has become evident, characterised by an increasing prevalence of positive articles and a declining trend in negative ones, as visually depicted in Table 4.3. Generally, news articles have consistently featured a substantial proportion of negative sentiment regarding surface water floods, a pattern that persisted until 2021. The highest percentages of negative sentiment (62.65%) and positive sentiment (52.70%) were observed in 2015 and 2021, respectively. Notably, a noticeable shift in sentiment occurred in 2017, with a decrease in negative articles to 53.49% and a concurrent increase in positive articles to 44.23%. By 2019, this trend toward a more balanced sentiment continued, with negative articles decreasing to 53.15% and a notable increase in positive articles to 45.61%. This increase signifies an overall improvement in public perception of the GBA during these years.

Table 4.3 The proportion of negative, neutral, and positive news articles in the GBA

Year	Negative articles (%)		Neutral articles (%)		Positive articles (%)	
	Whole year	Wet season	Whole year	Wet season	Whole year	Wet season
2015	62.65	64.79	1.72	1.64	35.63	33.57
2016	60.97	63.81	2.38	2.48	36.65	33.71
2017	53.49	56.28	2.28	2.28	44.23	41.44
2018	60.16	67.43	1.60	1.50	38.24	31.07
2019	53.15	60.59	1.24	1.20	45.61	38.20
2020	50.83	52.15	1.28	1.19	47.88	46.66
2021	45.98	52.43	1.32	1.18	52.70	46.39

During the wet season, the GBA has generally maintained a substantial proportion of negative sentiment toward road flooding, with the highest recorded in 2018 at 67.43% (as detailed in Table 4.3). This surge in negativity can be primarily attributed to the widespread flooding and numerous water-related incidents resulting from the impact of Typhoon Mangkhut in September 2018. Notably, the peak in news articles coincides with September 16th, 2018. Moreover, the news sentiment was as low as -5.16 on that day. Neutral sentiment remains relatively consistent at a low level throughout the observed years, indicating a limited presence of indifference or neutrality in media response. Positive sentiment has exhibited a fluctuating trend, with the highest recorded in 2020 at 46.66%. Notably, 2020 and 2021 saw a significant increase in positive sentiment, reaching 46.66% and 46.39%, respectively. The increase indicates an overall improvement in public perception within the GBA during these years.

4.3.2 Monthly variation

News media activities about surface water floods exhibit strong seasonality (see Figure 4.4). The monthly distribution of news articles mirrors rainfall, with concentrations typically occurring from May to September during the wet season. The number of news articles of the wet season is 81,285, accounting for 52.4% of the total news articles. The highest number of news articles occurs consistently in July and August each year from 2015 to 2021. In 2018, the peak of news articles (5,814) was recorded in September. That is attributed to the heavy rainstorm caused by Super Typhoon Mangkhut from September 15 to 18. Besides, the number of news articles in September 2018 is the highest monthly number of news articles in the past seven years.

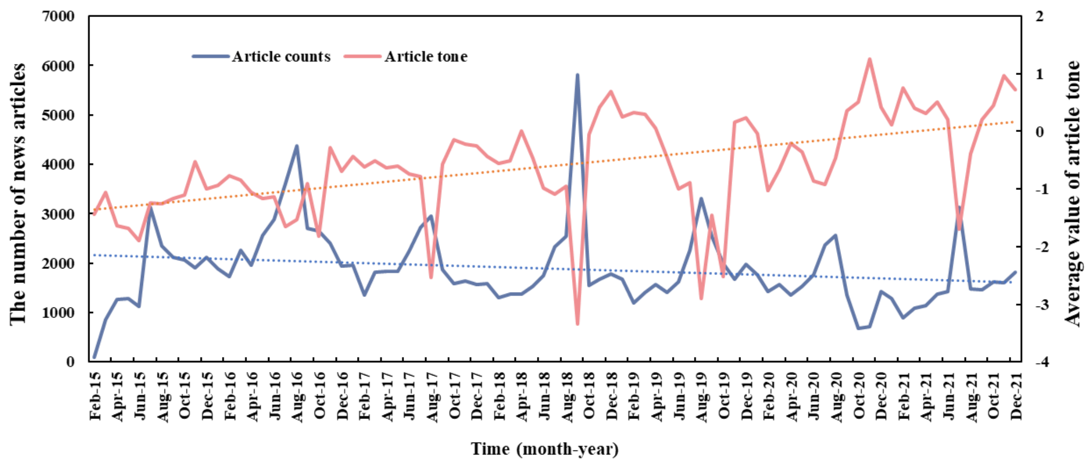

Figure 4.4 The monthly variation of news media attention and news sentiment in the GBA

News sentiment to surface road floods in the wet season is more negative than in the dry season (i.e., from January to April and from October to December). The lowest values of news sentiment are recorded in June 2015 (-1.90), October 2016 (-1.82), August 2017 (-2.53), September 2018 (-3.33), August 2019 (-2.89), July 2020 (-0.92) and July 2021 (-1.70). On the contrary, positive sentiments are recorded from January to April and October to December. The highest monthly value of a news sentiment is recorded in November 2020 (1.26), followed by November 2021 (0.97) and February 2021 (0.75).

4.3.3 Daily variation

There was an increasing trend of news media activities and a decreasing pattern of news sentiment from the Dragon Boat Rain season (the intensive rainstorm that occurred during the Dragon Boat Festival period during 1st May to 30th June) to the Tropical Cyclonic season (1st July to 31st September) (see Figure 4.5). There was a notable surge in news media activities in July, August, and September, surpassing that of other months. Notably, the article tone curve exhibited more pronounced fluctuations during these three months, consistently reflecting the most negative news sentiment. Notably, there is no substantial discrepancy in the frequency of news articles and news sentiment on different days within the Dragon Boat Rain season, which typically transpires from 21st May to 20th June annually. This phenomenon can be attributed to the localised nature of the impacts associated with the Dragon Boat Rain season, which are relatively limited in scope compared to the extensive and regionally widespread heavy rainfall events associated with typhoons. In essence, Dragon Boat Rains tend to affect specific areas within the GBA. At the same time, heavy rainfall events caused by typhoons have the potential to encompass a broader geographical expanse, thus resulting in a more widespread impact zone.

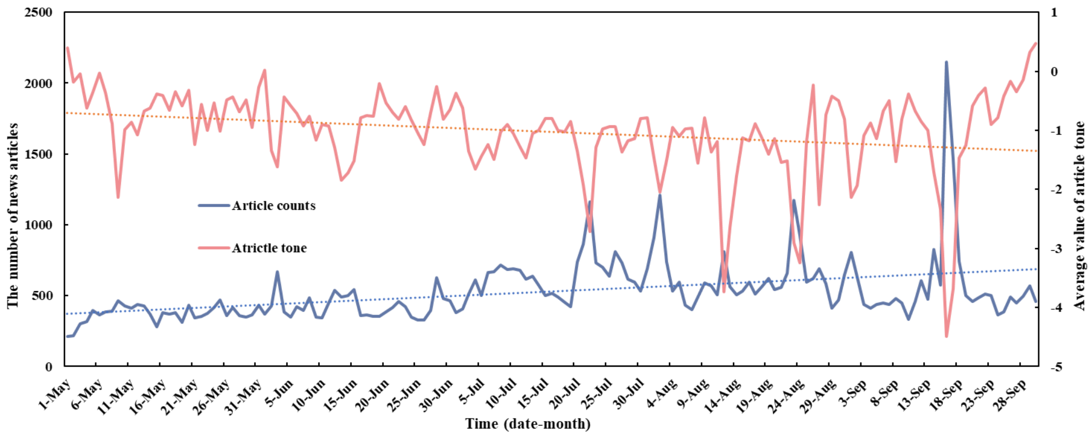

Figure 4.5 Daily variations of news media attention to surface water floods during summer and autumn in the GBA

4.4 News media activities during specific flood events

In the GBA, there are two main types of rainstorms: those not caused by typhoons (i.e., non-typhoon rainstorms) and those induced by typhoon (i.e., typhoon-induced rainstorms) (Cheng et al., 2024). Non-typhoon rainstorms occur independently of tropical cyclones and are caused by various atmospheric conditions such as convective instability, frontal systems, orographic lifting, or monsoonal influences. These rainstorms typically have localised or regional impacts and can result in urban inundation due to intense and prolonged rainfall within a short period. They are not associated with the structure or influence of a typhoon. On the other hand, typhoon-induced rainstorms are directly linked to tropical cyclones, particularly typhoons or hurricanes. These storms originate over warm ocean waters and are characterised by low-pressure systems with powerful winds. Typhoons often bring heavy rainfall to large areas over an extended period due to their vast circulation and slow movement. The intense rainfall associated with typhoons can cause widespread flooding and storm surges.

4.4.1 Flooding caused by non-typhoon rainstorms

According to the Guangdong-Hong Kong-Macao Greater Bay Area Climate Bulletin, there were 17, 15, 14, and 14 heavy precipitation processes in 2018, 2019, 2020 and 2021, respectively. Table 4.4 presents the flood events caused by non-typhoon rainstorms since the establishment of the GBA. There were 3, 5, 2, and 6 serious flood events caused by non-typhoon rainstorms in 2018, 2019, 2020, and 2021, respectively. Five of them did not lead to significantly severe consequences, i.e., flooding in 12-13 June 2018, 22-23 August 2018, 27 April 2019, 1 August 2021, and 14 August 2021. During the five flood events, less than half of the GBA cities were affected (Guangdong Meteorological Service et al., 2018; Guangdong Meteorological Service et al., 2019; Guangdong Meteorological Service et al., 2021).

Generally, the greater the rainfall, the more news articles there are. Figure 4.6 shows the relationship between media attention and rainfall. The lowest number of news articles is five on 14 August 2021, with a maximum daily rainfall of 118.4 mm in Jiangmen. Heavy rainstorms occurred in some areas of Jiangmen, Zhuhai, and Zhongshan but did not cause severe damage. The second lowest number of news articles is 39 on 18 August 2021. During this non-typhoon rainstorm, the maximum daily rainfall is 118.1 mm in the Conghua District of Guangzhou. The direct economic loss of this flood was 78 thousand RMB.

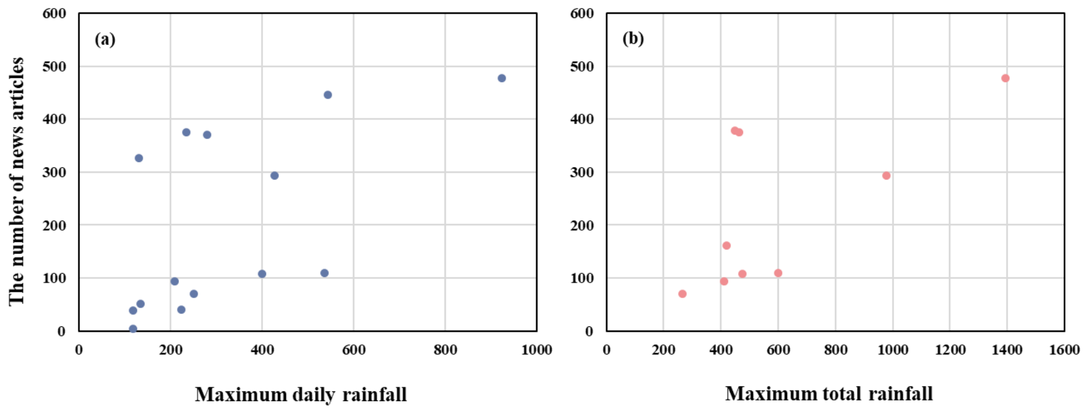

Figure 4.6 The relationship between media attention and rainfall

The highest number of news articles was 478 between 27 August and 1 September 2018 (i.e., the third non-typhoon rainstorm flood in 2018). It can be attributed to its maximum total rainfall (i.e., 1394.6 mm), which refreshed the historical extreme value of total rainfall of the GBA (i.e., 1,330.3 mm during 18-24 June 2005). The number of news articles (i.e., 446) during the 23-30 May 2019 (i.e., the fourth non-typhoon rainstorm flood in 2019) was closely followed due to its maximum daily rainfall (i.e., 543.3 mm). The direct economic losses of the third non-typhoon rainstorm flood in 2018 and the fourth non-typhoon rainstorm flood in 2019 were 790 million RMB and 140 million RMB, respectively. Besides, there were no deaths or injuries during the two flood events.

Low media attention may lead to higher economic losses, especially in situations with higher rainfall (see Figure 4.6 and Table 4.4). The number of news articles is only 294 during 5-9 June 2020, while the maximum total rainfall and maximum daily rainfall are 978.4 mm and 426.6 mm, respectively. Extraordinary heavy rainstorms occurred in

Guangzhou, Huizhou, Shenzhen, and Zhuhai. Consequently, the direct economic losses were 2.78 billion RMB. The direct economic losses of the non-typhoon rainstorm flood in 21-22 May 2020 closely followed, which was 892 million RMB. Besides, this flood event led to three deaths and two injuries. It is the first non-typhoon rainstorm flood in 2020, with a maximum total rainfall of 474.4 mm and a maximum daily rainfall of 399.5 mm. However, the number of news articles about this rainstorm flood was 108.

A predominant observation is that most news articles were published during the flood periods rather than preceding them. For example, the number of news articles was 38 on 26 August 2018, one day before the rainstorm (see Figure 4.7). During the rainstorm (i.e., 27 August-1 September 2018), the number of articles reached 478. On the day after the rainstorm, the number of articles was 69. The number of articles was 33, 446, and 48 before, during, and after the rainstorm flood in 23-30 May 2019. Such findings further justified that the number of news articles tends to peak during flood events, primarily owing to impacts on transportation activities.

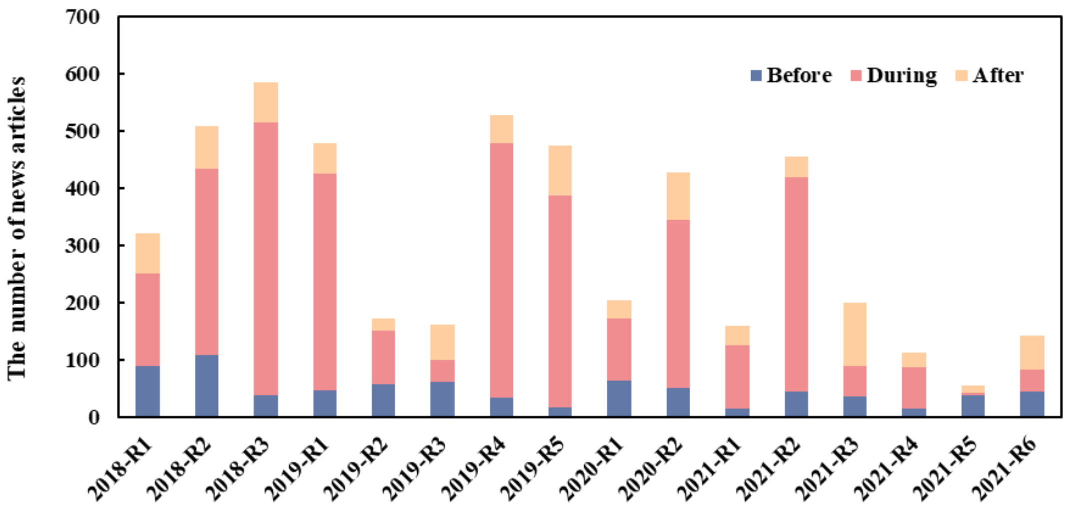

Figure 4.7 Media attention before, during, and after flood events caused by non-typhoon rainstorms

Table 4.4 Flood events caused by non-typhoon rainstorms (Guangdong Meteorological Service et al., 2018; Guangdong Meteorological Service et al., 2019; Guangdong Meteorological Service et al., 2020; Guangdong Meteorological Service et al., 2021)

Year	Num	Date	Affected city	Maximum rainfall	Consequence
2018	2018-R1	12-13 June	Jiangmen, Zhuhai, Zhongshan	Total rainfall: 421 mm.	N/A
	2018-R2	22-23 August	Guangzhou, Dongguan, Zhuhai	Daily rainfall: 131.7 mm.	N/A
	2018-R3	27 August – 1 September	Huizhou, Shenzhen, Jiangmen, Zhongshan, Zhuhai	Total rainfall: 1,394.6 mm. Hourly rainfall: 103.5 mm.	Affected people: 352 thousand. Direct economic losses: 790 million RMB.
2019	2019-R1	11-16 April	Zhaoqing, Shenzhen	Total rainfall: 448 mm. Half-hour rainfall: 73.4 mm.	Death: 11.
	2019-R2	19-20 April	Huizhou, Guangzhou, Hong Kong, Shenzhen, Foshan, Zhaoqing	Total rainfall: 411.1 mm. Daily rainfall: 209.5 mm.	Affected people: 8.5 thousand. Death: 2. Direct economic losses: 150 million RMB.
	2019-R3	27 April	Guangzhou	Daily rainfall: 224.4 mm. Hourly rainfall: 94.3 mm.	N/A
	2019-R4	23-30 May	Zhuhai, Jiangmen, Zhaoqing	Daily rainfall: 543.3 mm.	Affected people: 56 thousand. Direct economic losses: 140 million RMB.
	2019-R5	10-13 June	Guangzhou, Huizhou, Zhaoqing, Dongguan	Daily rainfall: 280.6 mm.	Affected people: 15 thousand. Direct economic losses: 70 million RMB.
2020	2020-R1	21-22 May	Guangzhou, Dongguan, Huizhou, Shenzhen	Total rainfall: 474.4 mm. Daily rainfall: 399.5 mm. Hourly rainfall: 167.8 mm.	Affected people: 294.3 thousand. Death: 3. Injury: 2. Direct economic losses: 892 million RMB.
	2020-R2	5-9 June	Guangzhou, Huizhou, Zhuhai, Shenzhen, Hong Kong	Total rainfall: 978.4 mm. Daily rainfall: 426.6 mm.	Affected people: 221.4 thousand. Direct economic losses: 2.78 billion RMB.

Table 4.4 Flood events caused by non-typhoon rainstorms (continue) (Guangdong Meteorological Service et al., 2018; Guangdong Meteorological Service et al., 2019; Guangdong Meteorological Service et al., 2020; Guangdong Meteorological Service et al., 2021)

Year	Num	Date	Affected city	Maximum rainfall	Consequence
2021	2021-R1	31 May – 1 June	Huizhou, Zhongshan, Zhuhai, Macao, Hong Kong	Total rainfall: 599.6 mm. Daily rainfall: 537.2 mm. Hourly rainfall: 156.4 mm.	Affected people: 20.2 thousand. Direct economic losses: 35 million RMB.
	2021-R2	22-28 June	Zhuhai, Dongguan, Guangzhou, Hong Kong, Macao, Zhaoqing, Shenzhen	Total rainfall: 463.4 mm. Daily rainfall: 234.9 mm. Hourly rainfall: 124.4 mm.	Affected people: 31. Direct economic losses: 160 thousand RMB.
	2021-R3	1 August	Huizhou, Foshan, Jiangmen, Hong Kong, Macao	Daily rainfall: 134.8 mm. Hourly rainfall: 93.4 mm.	N/A
	2021-R4	9-10 August	Guangzhou, Zhuhai, Hong Kong, Huizhou, Zhaoqing	Total rainfall: 266.8 mm. Daily rainfall: 250.6 mm. Hourly rainfall: 97.2 mm.	Affected people: 32. Direct economic losses: 1.20 million RMB.
	2021-R5	14 August	Jiangmen, Zhuhai, Zhongshan, Hong Kong	Daily rainfall: 118.4 mm. Hourly rainfall: 71.1 mm.	N/A
	2021-R6	18 August	Guangzhou, Zhongshan, Shenzhen, Foshan, Huizhou, Zhaoqing	Daily rainfall: 118.1 mm. Hourly rainfall: 86.5 mm.	Affected people: 5. Direct economic losses: 78 thousand RMB.

4.4.2 Flooding caused by typhoon-induced rainstorm

According to the Guangdong-Hong Kong-Macao Greater Bay Area Climate Bulletin, there were 6, 2, 5, and 6 typhoons in 2018, 2019, 2020 and 2021, respectively. The GBA was less affected by typhoons in 2019 and 2020. Typhoons caused a total of approximately 15.08 billion RMB and 240 million RMB in direct economic losses in 2018 and 2021, respectively. Table 4.5 presents the flood events caused by typhoons since the establishment of the GBA. There were 4, 2, 3, and 5 serious flood events caused by typhoons in 2018, 2019, 2020 and 2021, respectively. Five of them did not lead to significantly severe consequences, i.e., flooding caused by Typhoon Son-Tinh in 2018, Yingwu and Sinlaku in 2020, and Xiaoxiong and Lupit in 2021.

The highest number of news articles was 2,936 related to Typhoon Mangkhut (see Figure 4.8). Typhoon Mangkhut was a powerful tropical cyclone that struck in September 2018. It was characterised by exceptionally heavy rainstorms with a maximum total rainfall of 254.1 mm and a maximum daily rainfall of 173.5 mm. Besides, some areas experienced rainfall rates exceeding 100 mm per hour. Typhoon Mangkhut led to widespread flooding and numerous water-related incidents in the GBA. Low-lying areas, streets, and urban districts experienced waterlogging, impacting transportation and daily life. In Hong Kong, the typhoon led to the closure of schools, businesses, and transport systems and caused significant flooding in low-lying areas. Typhoon Mangkhut caused at least 460 injuries and affected over 1.66 million people, with flooding reported in several cities. Many businesses in the GBA experienced disruptions in their operations due to power outages, transportation difficulties, and property damage. Consequently, the direct economic losses caused by Typhoon Mangkhut were 11.75 billion RMB, including 3.02 billion RMB in Hong Kong, 440 million RMB in Macao, and 8.29 billion RMB in 9 mainland cities.

Direct economic losses caused by Typhoon Ewiniar in 2018 (i.e., 2.6 billion RMB) and Typhoon Higos in 2020 (i.e., 779 million RMB) closely followed those caused by Typhoon Mangkhut. However, the number of news articles was 372 and 400 during

Typhoon Ewiniar and Higos, respectively. The event with the second highest media attention (i.e., 1,191 news articles) was Typhoon Cempaka during 18-22 July 2021. The maximum total rainfall caused by Typhoon Cempaka was 400 mm in the Longgang District of Shenzhen. Typhoon Cempaka led to 1 death and 8.86 million RMB directed economic losses. The media attention on Typhoon Bebinca followed, with 613 news articles during 10-17 August 2018. The maximum total rainfall and maximum daily rainfall caused by Typhoon Bebinca were 672.5 mm and 477.9 mm, respectively. The directed economic losses were 270 million RMB, which is significantly higher than that caused by Typhoon Cempaka. These findings also justified that low media attention may lead to higher direct economic losses.

Figure 4.8 also shows the media attention before, during, and after flooding caused by typhoon-induced rainstorms. The difference in the number of news articles before, during, and after were more significant. Media attention on road transport damages displayed an inverted V-shaped pattern. Before the surface water flood events, the number of news articles remained conspicuously low. For example, the number of news articles was 233 on 15 September 2018, which was one day before the flood caused by Typhoon Mangkhut. On 18 September 2018, the volume of news articles dwindled to 333.

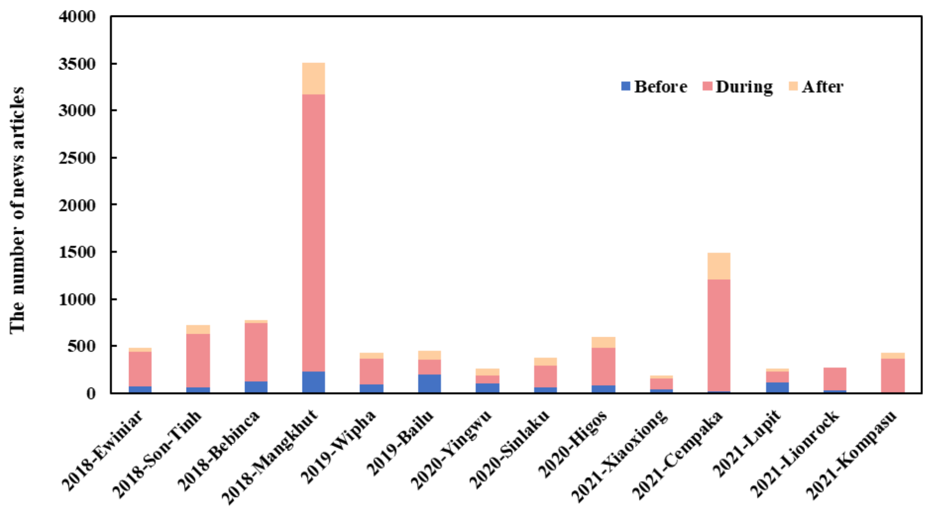

Figure 4.8 Media attention before, during, and after different flood events caused by typhoon-induced rainstorms

Table 4.5 Flood events caused by typhoon-induced rainstorms (Guangdong Meteorological Service et al., 2018; Guangdong Meteorological Service et al., 2019; Guangdong Meteorological Service et al., 2020; Guangdong Meteorological Service et al., 2021)

Year	Typhoon	Date	Affected city	Maximum rainfall	Consequence
2018	Ewiniar	5-9 June	Jiangmen, Guangzhou, Huizhou, Dongguan, Zhaoqing, Zhongshan, Hong Kong, Macao	Total rainfall: 785 mm. Daily rainfall: 286.4 mm.	Death: 1. Direct economic losses: 2.6 billion RMB
	Son-Tinh	17-24 July	Shenzhen, Zhuhai, Zhongshan, Jiangmen, Guangzhou, Zhaoqing	Daily rainfall: 124.5 mm.	N/A
	Bebinca	10-17 August	Jiangmen, Zhuhai	Total rainfall: 672.5 mm. Daily rainfall: 477.9 mm. Hourly rainfall: 112.3 mm.	Affected people: 140 thousand. Direct economic losses: 270 million RMB.
	Mangkhut	16-17 September	Huizhou, Shenzhen, Guangzhou, Dongguan, Hong Kong, Macao, Zhuhai	Total rainfall: 254.1 mm. Daily rainfall: 173.5 mm.	Affected people: 1.66 million. Death: 4. Direct economic losses: 11.75 billion RMB.
2019	Wipha	31 July – 2 August	Jiangmen, Zhuhai, Hong Kong, Zhaoqing, Huizhou, Shenzhen, Macao	Total rainfall: 354.9 mm. Daily rainfall: 190.3 mm.	Injury: 20. Direct economic losses: 52.12 million RMB.
	Bailu	25-26 August	Zhaoqing, Hong Kong	Total rainfall: 266.7 mm. Daily rainfall: 178.3 mm.	Direct economic losses: 10 million RMB.
2020	Yingwu	13-14 June	Jiangmen, Foshan, Zhongshan, Shenzhen, Hong Kong	Total rainfall: 71 mm.	N/A
	Sinlaku	31 July – 2 August	Jiangmen, Zhuhai, Zhongshan, Shenzhen, Huizhou	Total rainfall: 192 mm.	N/A
	Higos	18-20 August	Hong Kong, Macao, Shenzhen, Zhuhai, Huizhou, Zhongshan, Jiangmen, Guangzhou, Foshan, Dongguan, Zhaoqing	Total rainfall: 150 mm.	Affected people: 61.3 thousand. Direct economic losses: 779 million RMB.

Table 4.5 Flood events caused by typhoon-induced rainstorms (continue) (Guangdong Meteorological Service et al., 2018; Guangdong Meteorological Service et al., 2019; Guangdong Meteorological Service et al., 2020; Guangdong Meteorological Service et al., 2021)

Year	Num	Data	Affected city	Maximum rainfall	Consequence
2021	Xiaoxiong	11-13 June	Zhuhai, Hong Kong, Macao	Total rainfall: 214.3 mm. Hourly rainfall: 100.2 mm.	N/A
	Cempaka	18-22 July	Shenzhen, Jiangmen, Hong Kong, Macao	Total rainfall: 400 mm.	Death: 1. Direct economic losses: 8.86 million RMB.
	Lupit	3-5 August	Shenzhen, Zhuhai, Jiangmen, Hong Kong, Macao	Total rainfall: 249.4 mm. Hourly rainfall: 76.4 mm.	N/A
	Lionrock	7-10 October	Hong Kong, Macao, Zhuhai	Total rainfall: 718.3 mm. Daily rainfall: 377.3 mm.	Death: 2. Injury: 20. Direct economic losses: 189 million RMB.
	Kompasu	12-14 October	Jiangmen, Zhuhai, Zhongshan, Shenzhen, Huizhou, Zhaoqing, Hong Kong, Macao	Total rainfall: 100 mm.	Affected people: 75.9 thousand. Injury: 20. Direct economic losses: 41 million RMB.

4.5 Discussion

News media data analytics offers valuable insights into the temporal evolution of historical flood damage on transport networks. There has been an increasing pattern of news sentiment and a decreasing pattern of media attention in the GBA over the past seven years (see Table 4.3 and Figure 4.4). The variation indicates an overall improvement in flood management and public perception within the GBA during these years. According to the Meteorological Development Plan for the Guangdong-Hong Kong-Macao Greater Bay Area (2020-2035), the casualties caused by flood disasters in the GBA have been decreasing yearly. Moreover, 'zero casualties' were achieved during strong typhoons such as Typhoon Wilson, Seagull, Nida, and Haima (The China Meteorological Administration 2020). It can be attributed to the effective implementation of national (see Table 4.6) and local-specific measures in the GBA. For example, the GBA was the first to establish a system for suspension of classes, work, and business operations led by typhoons and rainstorm warning signals.

City authorities are inevitably stretched thin during sudden floods. During flood times, the authorities are severely disadvantaged by a shortage of personnel and a lack of information. Hence, effective and successful preparedness helps city authorities respond to the flood better. News media analytics may provide answers regarding the optimal timing for comprehensive preparedness efforts. Our research findings clearly illustrate that news media activities peak during the wet season, while news sentiments exhibit a more negative tone in this period compared to the dry season (see Figure 4.4). The wet season in the GBA typically occurs during the summer months, from May to September. This period corresponds with the monsoon season, characterised by increased rainfall and higher humidity levels. The wet season is influenced by the southwest monsoon winds, which bring moisture from the South China Sea, leading to heavier precipitation across the region. During this time, the GBA experiences frequent rain showers, thunderstorms, and occasional typhoons or tropical storms. These weather phenomena contribute significantly to the accumulation of annual rainfall, support agricultural activities, and replenish water reservoirs. However, substantial rainfall can also lead to challenges such as localised flooding, which affects infrastructure, transport, and urban areas in the region.

Table 4.6 National measures for flood management adopted by (Lu et al., 2022)

Year	Measures	Description
2016	Code for Urban Planning on Urban Flood Control (GB 51079 –2016)	• The standard for flood control often varies based on factors such as population density, socioeconomic status, and flood characteristics (e.g., types, causes, consequences, etc.).
2017	Sponge City Program (SCP)	• Cities or areas must manage runoff from a rainfall event with a 30-year return period and a duration of 24 hours. • By 2030, over 80% of urban built-up areas are expected to comply with SCP requirements.
2017	Technical Code for Urban Flooding Prevention and Control (GB5122-2017)	• The permeable pavement should constitute more than 40% and 50% of new areas and areas at higher risk of waterlogging, respectively. • The road inundation depth should not exceed 15 cm during a 100-year urban flood.
2018	Specifications for Urban Waterlogging Risk Investigation (QX/T 441–2018)	• It offers ten types of standard annexes, such as one for urban land use investigation and risk assessment to identify areas prone to waterlogging.
2021	Code for Design of Outdoor Wastewater Engineering (GB 50014–2021)	• The stormwater sewer systems in central areas of megacities were designed to meet a 3-year to 5-year return period standard. • In areas of higher importance, the stormwater sewer systems were designed for a return period ranging from 5 years to 10 years.

Within the wet season, there was an increasing trend in media attention and a decreasing trend in news sentiment (see Figure 4.5), particularly from the Dragon Boat Rain season to the Tropical Cyclonic season. It can be found that media attention on typhoon-induced floods was more significant than that on non-typhoon floods, even if they did not lead to severe consequences. For example, the number of news articles related to Typhoon Son-Tinh was 564, which is higher than those related to any non-typhoon flood. According to the Guangdong-Hong Kong-Macao Greater Bay Area Climate Bulletin 2018, no significant economic losses and casualties occurred during Typhoon Son-Tinh (Guangdong Meteorological Service et al., 2021). Previous studies identified that the rainfall of typhoon rainstorms is large, and the rainfall intensity is high (Chen et al., 2019; Lin et al., 2017).

Moreover, the disaster phenomena caused by typhoons include not only rainstorms but also gales and storm surges (Wang and Yin et al., 2022). Therefore, the number of news articles related to the typhoon-induced flood was higher than that related to non-typhoon floods. Hence, city authorities should enhance awareness of information disclosure during Dragon Boat Rain season. Media attention needs to be increased during the Dragon Boat Rain season.

Media attention focused on situations with higher rainfall or severe casualties. This phenomenon was notably evident during the non-typhoon floods. For example, the number of news articles related to the non-typhoon from 27 August to 1 September 2018 was 478 due to its maximum total rainfall of 1394.6 mm. The number of news articles related to rainstorms during 23-30 May 2019 and 11-16 April 2019 was closely followed. They can be attributed to a maximum daily rainfall of 543.4 mm and a casualty of 11 deaths, respectively. Low media attention sometimes leads to serious economic consequences, such as the rainstorm from 5-9 June 2020. Hence, city authorities should provide more information on the coming rainstorms to the public and news organisations.

Media attention was paid to surface water flood damage on transport networks, which displayed an inverted V-shaped pattern (see Figure 4.9). There is less media attention before surface water floods. Hence, this study recommended that more news articles should be released before the flooding rather than only during the flooding. Furthermore, integrating the consequences of past floods, such as traffic disruptions and vehicle flooding, with early warning signals can enhance public awareness of flood preparedness.

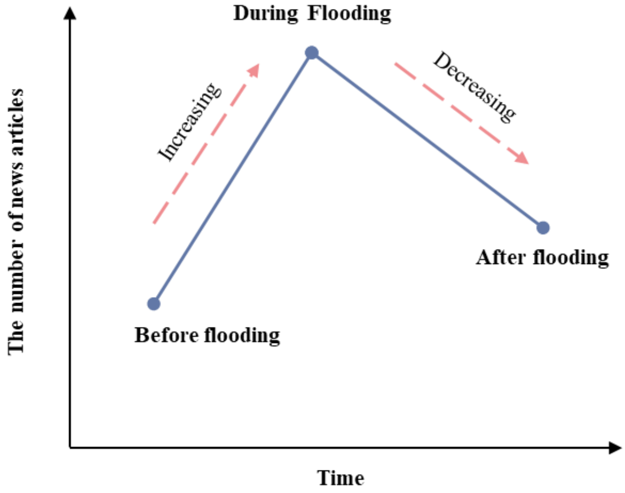

Figure 4.9 The inverted V-shaped of media attention during surface water flood events

4.6 Summary

This chapter implemented the news media activity analysis outlined in Chapter 3 (see Section 3.3). An analysis of media attention and news sentiment related to flood and transport networks was undertaken from a spatial and temporal perspective. In summary, the results showed that:

(a) News media activities related to flood and transport networks are uneven among GBA cities. It can be found that media attention is concentrated in densely populated and economically developed cities of the GBA, such as Guangzhou, Shenzhen, and Hong Kong. As for the news sentiment, there is no such significant phenomenon. This indicates that these news media outlets have no significant biases in the various cities of the GBA. These news media can objectively reflect the information on transport networks during surface water flood events.

(b) From the perspective of temporal evolution, there was a decrease in media attention and an increase in news sentiment over the past seven years. The monthly distribution of news articles mirrors that of rainfall, with concentrations typically occurring from May to September during the wet season. News sentiment to surface water floods and transport networks in the wet season was more negative than that in the dry season.

(c) During the wet season, there was an increasing trend in media attention and a decreasing trend in news sentiment, particularly from the Dragon Boat Rain season to the Tropical Cyclonic season. It can be found that media attention on typhoon-induced floods was more significant than that on non-typhoon floods, even if they did not lead to serious consequences. Consequently, low media attention may lead to higher economic losses, especially in situations with higher rainfall.

(d) A predominant observation is that most news articles were published during the flood periods rather than preceding them. Media attention on road transportation damages displayed an inverted V-shaped pattern. Before the surface water flood events, the number of news articles remained conspicuously low.

According to the results of news media activities related to flood and transport networks, the effective implementation of both national and local-specific measures in the GBA was reviewed in this chapter. Then, some recommendations were proposed to answer the question of how to adopt news media for better preparedness and early warning.

Next, Chapter 5 focuses on response and recovery based on the network analysis proposed in Chapter 3 (see Section 3.4).

Chapter 5: Characterising government agency collaboration during flood events

5.1 Introduction

Government agency collaboration plays a crucial role in flood management in transport systems. Inadequate coordination among agencies can result in avoidable casualties and harm to economies. The emphasis on flood management should shift from individual agencies to collaborative partnerships, especially during the initial stages of the flood management process, such as preparedness and response (Abdeen et al., 2021). However, collaborating between government agencies is often difficult due to several factors, including cultural, procedural, and systemic differences, varying motivations and incentives, competition for limited resources, and a lack of coordination among the agencies. Hence, it is essential to explore the role of different agencies in flood management and the actual performance of government agency collaborations.

Previous studies often measure government agency networks through multiple sources of data, such as interviews and questionnaires. Currently, event data coded by humans from content analysis of news and published reports is utilised. The limitation of this approach is the requirement for a lot of time and resources. As mentioned in Chapter 3, the GDELT database includes a vast network of interconnected events, organisations, locations, and themes, offering an additional data source to assess the effectiveness of flood governance networks in adhering to their established policies and plans.

Based on the methodological framework proposed in Chapter 3 (see Section 3.4), this chapter aims to explore the government agency collaboration for flood management in the transport system. More specifically, this chapter analyses the performance of government agency networks during flood response and recovery, using representative annual flood events from 2017 to 2021 as cases. To achieve the aim, specific objectives are as follows:

(a) Investigate the engagement of different government agencies during the five flood events.

(b) Identify the position of different agencies within the government agency collaborative network.

(c) Discuss and compare the government agency collaboration during the five flood events.

5.2 Government agency categorisation

According to China's administrative relationships and functions (The State Council 2023), the government categories for capturing the government agency collaboration analysis during the flood response and recovery are presented in Table 5.1. There are 26 national-level agencies and 50 local-level agencies according to their responsibilities. Table 5.1 also presents the keywords of GDELT related to government agencies. According to the roles or objectives of these agencies during the floods, some of the key agencies involved include agencies responsible for water resources, meteorology, emergency management, natural resources, finance, transport, civil affairs, public security, and environmental protection.

Table 5.1 Government agency list sorted alphabetically

NO	National level	Roles/Objectives	Local level	GDELT related keywords
1	Agriculture and Rural Affairs	Safeguarding agricultural production, supporting rural communities, and ensuring food security during and after flood events.	Agriculture and Rural Affairs	Agriculture, Farm, Fisheries
			Animal Husbandry Affairs	Animal Husbandry
2	Audit	Ensuring that resources are used efficiently, funds are allocated properly, and operations are conducted in compliance with regulations during flood response and recovery phases.	Audit Affairs	Audit
3	Civil Affairs	Providing humanitarian aid, shelter, and support for displaced individuals and affected communities.	Civil Affairs	Home Affairs, Civil Affairs
4	Commerce	Facilitating economic recovery, ensuring business continuity, and mitigating the economic impacts of floods on local businesses and industries.	Trade Affairs	Trade
			Commerce Affairs	Commerce, Business
5	Culture and Tourism	Safeguarding cultural heritage, preserving tourism sites, and ensuring visitor safety during flood events.	Culture and Tourism Affairs	Culture, Cultural, Tourism
6	Customs	Expediting the clearance of humanitarian aid and essential supplies, while also maintaining regulatory compliance and preventing misuse of the situation for illegal activities during floods.	Customs Affairs	Customs
7	Defense and Military Affairs	Leveraging their manpower, resources, and expertise to provide swift and effective assistance to affected regions.	Armed Forces Department	Armed Forces Department
			China Military Commission	China Military Commission
			Defense Affairs	Defense
			People's Liberation Army	People's Liberation Army
8	Development and Reform Commission	Aligning economic development goals with flood risk reduction strategies, ensuring that developmental initiatives are resilient to potential flooding, and contributing to the overall disaster risk reduction efforts.	Development and Reform Affairs	Development, Reform
9	Education	Ensuring the well-being of students and educators, maintaining educational continuity, and facilitating the recovery of educational facilities affected by flooding.	Education Affairs	Education
10	Emergency Management	Coordinating disaster response and managing emergency operations, including flood relief efforts and rescue operations.	Disaster Reduction Affairs	Disaster Reduction
			Emergency Management	Emergency

Table 5.1 Government agency list sorted alphabetically (continue)

NO	National level	Roles/Objectives	Local level	GDELT related keywords
11	Ecology and Environment	Safeguarding the environment, ensuring the resilience of ecosystems, and minimizing the long-term environmental impact of floods on natural resources and communities.	Ecology and Environment Affairs	Sanitation, Environmental Protection, Environment
12	Finance	Allocating funds for flood management, relief, and recovery efforts, supporting infrastructure repair and rehabilitation.	Finance Affairs Revenue Affairs	Finance, Economy, Economic Revenue, Tax
13	Foreign Affairs	Leveraging international relations, cooperation, and resources to support the country's efforts in managing and recovering from the flood while ensuring a positive global perception of the country's response and resilience.	Foreign Affairs	Foreign
14	Health	Preventing the outbreak of diseases, ensuring access to healthcare services, and addressing health concerns that arise during and after flooding to safeguard public health.	Health Affairs Hospital International Committee A Red Cross Medical Products Affairs	Health Hospital International Committee A Red Cross Drug
15	Housing and Urban-Rural Development	Ensuring safe and sustainable urban development, minimising the vulnerability of urban areas to flooding, and facilitating recovery and reconstruction efforts in affected regions.	Housing Affairs Buildings Affairs Construction Affairs Urban management Affairs	Housing Buildings Construction Urban Management, City management, City Administration
16	Human Resources and Social Security	Providing assistance, support, and necessary resources to help affected individuals recover from the impact of a flood, safeguarding their well-being, and facilitating their return to normalcy as swiftly as possible.	Human Resources Affairs Family Planning Affairs	Human, Labour, Personnel Family Planning
17	Industry and Information Technology	Supporting industries, maintaining operational continuity, and fostering recovery efforts to reduce the economic impact of flooding on businesses and infrastructure.	Industry Affairs Information Affairs	Industry, Industrial Information
18	Justice	Ensuring legal compliance, protecting rights, and providing legal support contribute significantly to the overall management and recovery efforts during and after flooding events.	Justice Affairs Regulation Affairs Legislative Affairs	Justice Regulations Legislative
19	Meteorology	Providing timely and accurate information to support decision-making, enhance preparedness, and mitigate the impacts of floods	Meteorology Affairs	Meteorology, Weather, Meteorological

Table 5.1 Government agency list sorted alphabetically (continue)

NO	National level	Roles/Objectives	Local level	GDELT related keywords
20	Natural Resources	Focusing on land and water resources management, including flood risk assessment and land-use planning.	Natural Resources and Planning Affairs	Planning, Land Resources, Land
			Ocean Affairs	Ocean, Oceanic, Sea
			Forestry Affairs	Forest, Forestry
21	Power Supply	Maintaining continuous electricity supply, ensuring public safety, and facilitating the recovery of affected communities during and after flood events.	Power Supply Affairs	Power Supply
22	Public Security	Maintaining public order, enforcing evacuations if necessary, and managing security during flood events.	Public Security Affairs	Public Security, Police
			Fire Brigade	Fire
23	Science and Technology	Leveraging scientific research, technological innovations, and data analysis to enhance flood prediction, response, and mitigation strategies, contributing significantly to effective disaster management efforts.	Science and Technology Affairs	Science
24	Statistics	Providing accurate, up-to-date information and analysis essential for informed decision-making, resource allocation, and policy formulation during and after a flood event.	Statistics Affairs	Statistics
25	Transportation	Ensuring the safety and functionality of transport networks during floods, enabling the efficient movement of people, goods, and emergency services while contributing to the overall emergency response and recovery efforts.	Transportation Affairs	Transportation, Traffic, Transport
			Port Affairs	Port
26	Water Resources	Encompassing both proactive measures to prevent flooding and reactive actions to manage and minimize the impact of floods., including flood control, reservoir operations, and river management.	Water Resources Affairs	Water, Irrigation, Hydrological, Drainage
			River and Lake Affairs	River, Lake

5.3 Description of flooding events

According to the flood events presented in Table 4.4 and Table 4.5, this chapter selected representative annual flood events from 2017 to 2021 as case studies. They are Typhoon Hato-induced flood during 23-24 August 2017, Typhoon Mangkhut-induced flood during 16-17 September 2018, non-typhoon flood during 19-20 April 2019, non-typhoon flood during 5-9 June 2020, Typhoon Lionrock-induced flood during 7-10 October 2021. These floods led to severe damage in the GBA. Hence, these floods were selected to explore government agency collaboration for flood management in the transport system.

5.3.1 Typhoon Hato-induced flood in 2017

Typhoon Hato, an intense tropical cyclone, resulted in widespread damage in Vietnam and Southern China during August 2017 (Takagi et al., 2018). Beginning as a tropical depression east of Luzon on 19 August, it strengthened into a tropical storm on the next day. On 23 August, Hato made landfall near Macao and Zhuhai, with maximum sustained winds near its centre reaching 14 levels (45 meters/second) and a minimum central pressure of 950 hPa (ESCAP/WMO Typhoon Committee 2017). The typhoon intensity decreased as it passed through Guangxi the next day (Macau SMG 2017).

When Typhoon Hato made landfall, it coincided with an astronomical high tide, leading to severe storm surges. Many stations recorded record-high sea levels. For instance, Zhuhai station reported a maximum storm surge of 2.79 meters and a maximum sea level of 6.14 meters. A-Ma station in Macao recorded a maximum sea level of 5.58 meters, the highest since records began in 1925. This storm was the most powerful to strike Macao in 53 years and was the first time in 18 years that the Macao authorities raised a No. 10 tropical cyclone signal. Some areas of the GBA experienced extremely heavy rain, with Taishan in Jiangmen recording a maximum hourly rainfall of 126.3 mm, setting a record for a 1-in-50-year period of rainfall. Total rainfall between 22 August and 25 August ranged from 100 to 473 mm (Wang et al., 2019).

Hato caused significant damage to the GBA, particularly Zhuhai, Hong Kong, and Macao. In particular, coastal areas in Zhuhai, including underground car parks, have experienced flooding. In Hong Kong, at least 129 individuals sustained injuries due to the typhoon. The estimated economic impact was around HK$4 billion (Hong Kong Observatory 2017). Macao suffered extensive damage, with severe flooding leading to at least ten deaths and over 240 injuries. Direct losses amounted to MOP 8.31 billion, with indirect losses reaching MOP 3.16 billion (Government of Macao Special Administrative Region Statistics and Census Service 2018).

5.3.2 Typhoon Mangkhut-induced flood in 2018

Typhoon Mangkhut, a potent and destructive tropical cyclone, inflicted significant damage in Guam, the Philippines, and South China in September 2018. It originated over the western North Pacific east of Guam on 7 September. It made landfall near Taishan in Jiangmen, Guangdong, on 16 September, with maximum sustained winds of 14 levels (45 meters/second) near its centre and a minimum central pressure of 955 hPa (Guangdong Meteorological Service et al., 2018). Subsequently, Mangkhut lost strength as it advanced into the western region of Guangdong (Hong Kong Observatory 2018) and eventually dissipated into a low-pressure area over Guangxi the next night (Choy et al., 2020).

During the period affected by Typhoon Mangkhut, the GBA experienced heavy rainstorms, particularly in Huiyang and Shenzhen. The average rainfall of 26 observation stations in the area reached 153.9 mm, with the highest total rainfall in Taishan (254.1 mm) and the highest daily rainfall in Shenzhen (173.5 mm) on 16 September. On that day, 24 (92.3%) observation stations recorded rainfall above the rainstorm threshold, with 18 (69.2%) stations experiencing rainfall above the heavy rainstorm threshold. On 17 September, 13 (50%) observation stations recorded rainfall above the rainstorm threshold. Typhoon Mangkhut also triggered a storm surge, causing high tide levels with a 1-in-100-year return period at major tidal stations in Guangdong, Dongguan, and Shenzhen. This broke historical extreme records and led to seawater backflow in many coastal areas. For example, tide levels at Guangzhou Nansha Station, Huangpu Station, and Zhongda Station exceeded historical extreme records, reaching 3.19 meters, 3.07 meters, and 3.28 meters, respectively.

On 16-17 September, nine mainland cities initiated a Level I Emergency Response for wind prevention, implementing the suspension of work, business, markets, classes, and operations. Shenzhen issued its longest effective Red Warning (24 hours) since its warning signal was introduced in 1994. The Hong Kong Observatory raised Hurricane Signal No. 10, which remained in effect for 10 hours. Additionally, on 16 September, the observatory issued a Red Rainstorm Warning and a Special Announcement regarding flooding in the Northern New Territories. The Macao Meteorological Bureau suspended Hurricane Signal No. 10 for 9 hours, the longest suspension since 1968.

Despite the warnings, the impact of the rainstorm, storm surge, and high waves from Mangkhut was severe in the GBA. Coastal areas in Hong Kong, Macao, Guangzhou, Shenzhen, and Zhuhai were significantly inundated. In Hong Kong, for instance, seawater submerged many private vehicles in Hung Fa Chuen and Tseung Kwan O South. Cycling paths near the Shing Mun River in Shatin, the coastal region of Tolo Harbour, and the Lam Tsuen River in Tai Po were also flooded. Road transportation was severely disrupted, with sections of significant roads remaining closed, and public transport services were unable to resume the following day due to flooding. Most public bus services were halted, and at least 458 people sustained injuries during Mangkhut's passage in Hong Kong.

5.3.3 Non-typhoon flood during 19-20 April 2019

During 19-20 April, the GBA encountered widespread torrential to heavy torrential rainstorms. The average cumulative precipitation recorded at 26 stations in the region was 90.9 millimetres. Among these, 13 stations reported torrential rainstorms, and six stations experienced heavy torrential rainstorms. Longcheng Town, Longmen County, Huizhou, registered the highest processed rainfall of 411.1 millimetres. On the 19 April, the highest daily rainfall of 209.5 millimetres occurred in Zhongluotan Town, Baiyun

District, Guangzhou. The Hong Kong Observatory issued its first Red Rainstorm Warning Signal of 2019 on the 20 April. The torrential rainstorm impacted 8,500 individuals in Shenzhen, Foshan, and Zhaoqing, leading to 2 fatalities due to flooding and direct economic losses amounting to 150 million yuan. Additionally, in Hong Kong, one hiker died from a lightning strike, and two individuals drowned after a sampan capsized (Guangdong Meteorological Service et al., 2019).

5.3.4 Non-typhoon flood during 5-9 June 2020

From 5-9 June, the GBA witnessed its most intense rainfall event of 2020, with precipitation levels surpassing those of torrential rainstorms in many regions. Cities such as Guangzhou, Huizhou, Shenzhen, and Zhuhai experienced exceptionally heavy torrential rainstorms. This event stood out for its prolonged duration, extensive coverage of heavy torrential rainstorms, and significant cumulative rainfall in specific areas. Huangbu Town in Huidong County of Huizhou recorded the highest daily rainfall of 426.6 millimetres on 8 June, while Longtan Town in Longmen County reported the highest total rainfall of 978.4 millimetres. Hong Kong also saw heavy showers from 6 June to 8 June, with most areas receiving over 250 millimetres of rainfall during this period. The morning of 6 June experienced particularly heavy rainfall, leading to the Hong Kong Observatory issuing its first black rainstorm warning signal since May 2017, resulting in severe flooding in the Kwun Tong area of Kowloon (see Figure 5.1c).

This heavy rainfall disaster affected approximately 221,400 people across 16 counties (districts) and 122 towns in five cities of the GBA, including Guangzhou, Zhuhai, Foshan, Huizhou, and Zhaoqing. Emergency relocations were required for 38,200 people. Secondary geological disasters caused one death and three injuries. The affected agricultural area covered 30.28 thousand hectares, with 341 houses collapsing and a direct economic loss amounting to 2.787 billion RMB. The direct economic loss was estimated at around 37 million Hong Kong dollars in Hong Kong (Guangdong Meteorological Service et al., 2020).

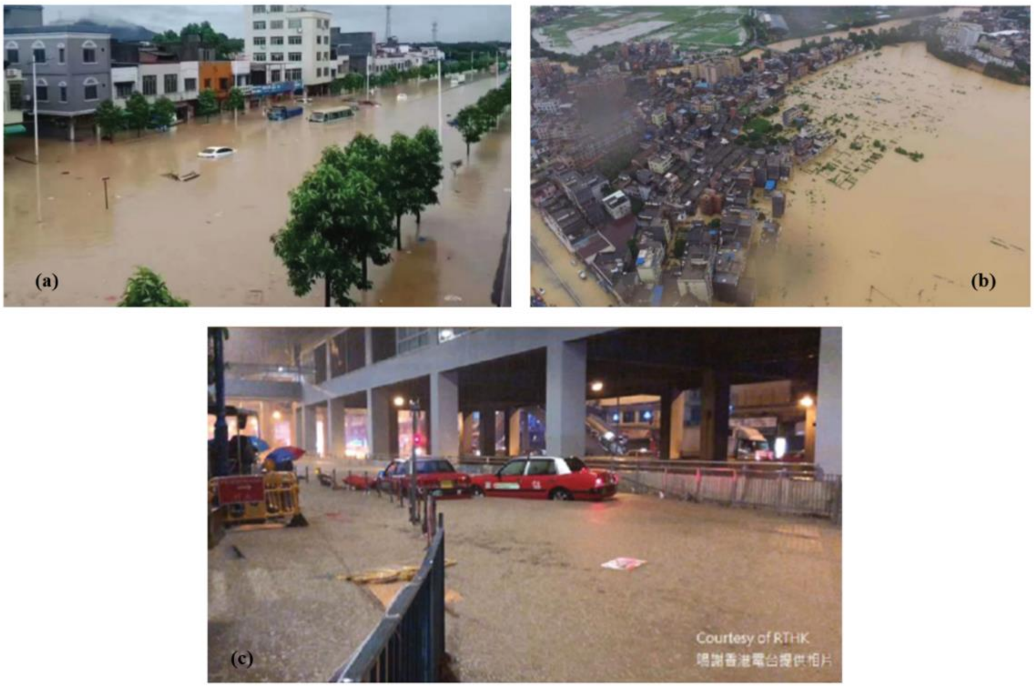

Figure 5.1 Heavy rainstorms led to surface road flooding in Gaoping County in Conghua (a), Tangtang County in Fogang (b), and Kowloon Kwun Tong in Hong Kong (c). Source: (Guangdong Meteorological Service et al., 2020)

5.3.5 Typhoon Lionrock induced flood in 2021

On 8 October, the thermal low pressure in the South China Sea developed into the 17th typhoon of 2021, named Lionrock (Wu et al., 2021). It made landfall as a tropical storm along the coast of Hainan in Qionghai City at 22:55 on the 8 October. At the time of landfall, the maximum wind force near the centre was at level 8 (20 meters/second), and the central minimum pressure was 990 hPa (Yue et al., 2021).

As Typhoon Lionrock, combined with natural precipitation from cold air and artificial rain enhancement operations, affected the GBA, the region experienced prolonged heavy torrential rainstorms, with some areas facing extremely heavy rainstorms from 7 October to 10 October. Wanshan Town in Xiangzhou District, Zhuhai, recorded a maximum total rainfall of 718.3 millimetres and a maximum daily rainfall of 377.3 millimetres on 10 October. On average, Hong Kong received over 400 millimetres of rainfall, with parts of Hong Kong Island exceeding 700 millimetres. 8 October saw particularly intense and sustained rainfall, setting a record daily rainfall for October at the Hong Kong Observatory with 329.7 millimetres. The Macao Datanshan

Meteorological Station recorded a total rainfall of 471.6 millimetres, with some stations recording over 550 millimetres. On 10 October, Macao experienced several hours of torrential rainstorms, with a daily rainfall of 244.4 millimetres, breaking the highest daily rainfall record for October since 1952.

Due to the influence of Typhoon Lionrock, Hong Kong reported two fatalities and at least 14 injuries. There were more than 1100 instances of fallen trees, six cases of flooding, and three reports of landslides. Approximately 300 hectares of agricultural land in the New Territories were affected. The direct economic loss for Hong Kong is estimated to be around 189 million RMB. Widespread flooding occurred in Macao, with the highest water level reaching 0.25 meters, resulting in injuries to six individuals.

5.4 Government agency network analysis

5.4.1 Network statistics

Table 5.2 shows network statistics of five flood events. The flood event with the most agency engagement was in 2017, followed closely by the flood event in 2018. There are 377 and 178 undirected ties in the 2017 flood and 2018 flood, respectively. On average, each agency has about 16 and 8.9 ties in the 2017 flood and 2018 flood, respectively. It can be found the agencies had a close collaboration during the 2017 and 2018 floods. The network with the lowest number of nodes and edges is the 2019 flood network. That means the engagement and collaboration of government agencies were low in the 2019 flood. It can be attributed to the consequences of the 2019 flood were lower than the other four floods (see Table 4.4 and Table 4.5).

The diameter of the network is 3, 4, 5, 4, 4 in the 2017, 2018, 2019, 2020, and 2021 flood (see Table 5.2), respectively. It indicated that the two agencies are furthest apart in terms of the shortest path between them, which is connected through about four other agencies. The mean geodesic distance (i.e., average path length) is about 2, which means that agencies in the network are situated two ‘degrees of separation’ away from one another (Wasserman, Faust 1994). Hence, the five networks are closely connected networks. Generally, the spread of ideas, propagation of behaviours, and sharing of resources and information are effective up to two degrees of separation.

The density of the five networks ranges from 0.228 to 0.349. Network density measures the degree of completeness of the network. In other words, a network that is complete has a density of 1 and every conceivable tie between its nodes. Network density is calculated by summing the number of ties and dividing it by the total number of all possible ties (Wasserman, Faust 1994). It means that the network has 34.9%, 22.8%, 23.8%, 29.9% and 25.9% of all possible ties in the 2017, 2018, 2019, 2020, and 2021 floods, respectively.

Average clustering coefficient measures the degree to which nodes are situated in clusters or neighbourhoods of higher connectivity (Latapy 2008). Networks with a high degree of clustering but a low average path length demonstrate ‘small world’ properties such as faster diffusion of ideas and behaviour (Milgram 1967; Watts, Strogatz 1998). The five networks were highly clustered but had a lower average path length. For example, the average clustering coefficient and average path length of the 2017 flood network were 0.713 and 1.789, respectively. It can be found that ‘small world’ properties, such as faster diffusion of ideas and behaviour, are significantly exhibited in the five flood events.

Table 5.2 Network statistics during five flood events

Metrics	Value				
	2017	2018	2019	2020	2021
Number of Nodes	47	40	22	27	27
Number of Edges	377	178	55	105	91
Average Degree	16.043	8.9	5	7.778	6.741
Network Diameter	3	4	5	4	4
Network Density	0.349	0.228	0.238	0.299	0.259
Modularity	0.156	0.238	0.42	0.143	0.385
Connected Components	1	1	2	1	1
Average Clustering Coefficient	0.713	0.558	0.628	0.675	0.708
Average Path Length	1.789	2.065	2.099	1.942	2.06

5.4.2 Most active and central agencies

The agencies with higher centrality were also more active, such as the ‘Public Security Department’, ‘Finance Department’, ‘Natural Resources Department’, ‘Meteorology

Department', and 'Transportation Department'. These agencies shoulder distinct responsibilities to ensure an efficient response and recovery process. Each agency plays a vital role in addressing specific aspects of flood management, aiming to minimise damage, ensure public safety, and facilitate recovery efforts. The list of the most active agencies in the five events can be found to be consistent (see Table 5.3).

Table 5.3 Ranking of engagement levels of active agencies in different events sorted alphabetically

National categories	2017	2018	2019	2020	2021
Commerce	12	5	1	11	2
Defense and Military Affairs	3	3	13	12	4
Finance	7	8	5	5	1
Housing and Urban-Rural Development	9	11	7	4	8
Meteorology	4	2	12	1	6
Natural Resources	6	7	4	10	7
Public Security	2	1	2	2	3
Transportation	5	4	6	3	5

The 'Public Security Department' was one of the most prominent agencies in the government agency network during the most floods. This agency cooperated the most with other agencies due to having the highest degree of centrality score (see Figure 5.2). According to the closeness centrality score, the 'Public Security Department' had the highest efficiency in communicating or spreading information to all other agencies. Moreover, the 'Public Security Department' was active during the five flooding events.

The 'Finance Department' played an influential role in the multi-agency collaboration network, especially during the 2017, 2020 and 2021 floods. The 'Finance Department' likely controls the flow of financial resources, allocating funds to different agencies involved in flood relief and recovery. They might distribute budgets for emergency response, infrastructure repair, relief supplies, or other critical needs. Table 5.2 presents that the 'Finance Department' had a high engagement during the five floods, and its ranking rose from 2017 to 2021.

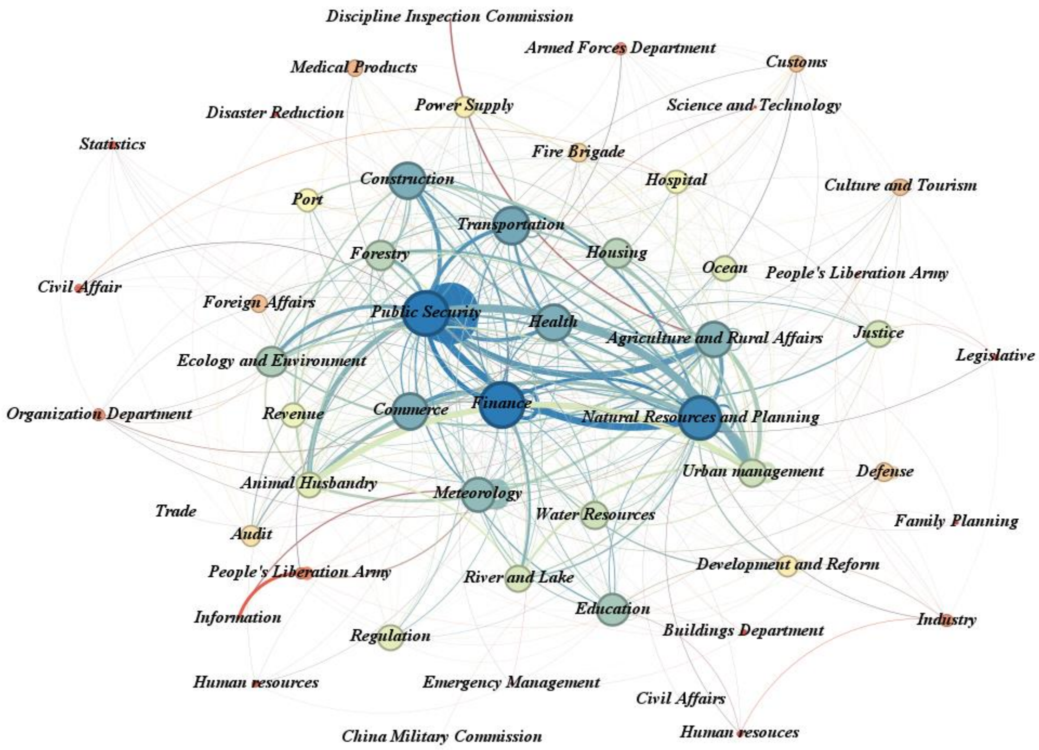

Figure 5.2 Government agency network during the five floods. The size of the circle represents the *Degree* of the node. The colour represents the *Closeness Centrality* of the node, with the *Closeness Centrality* value increasing from red to blue. The thickness of the edge represents the weight between two nodes

The ‘Transportation Department’ was also actively engaged in the five flooding events. The ‘Transportation Department’ plays a crucial role in managing and ensuring the safety and functionality of transport systems. The agency manages traffic flow, reroutes vehicles away from flooded areas, and implements traffic control measures to ensure public safety. It needs to provide real-time updates to the public about road closures, alternate routes, and transportation disruptions. During and after flood events, this agency inspects, maintains, and repairs roads, bridges, and tunnels to ensure their structural integrity.

It can be found that the ‘Defense and Military Affairs Department’ was more active during the typhoon-induced flood than the non-typhoon flood. The ‘Defense and Military Affairs Department’ mobilises military resources, personnel, and equipment to support relief efforts, including deploying specialised teams for rescue missions, providing medical aid, and distributing essential supplies to affected areas. The

‘Defense and Military Affairs Department’ also assists in reinforcing critical infrastructure like levees, dams, or other flood control structures to minimize damage and prevent further flooding.

In addition to these core agencies, some agencies occasionally exhibited very high levels of engagement during the flood event. For example, the ‘Industry and Information Technology Department’ had the highest number of times mentioned in news articles during the 2017 flood. That can be attributed to the seriously damaging communication infrastructures during 2017 Typhoon Hato. In Guangdong province, 10276 base stations have been decommissioned, and 338.5 kilometres of communication lines were damaged on 23 August 2017. According to the overall deployment and requirements of the Ministry of Industry and Information Technology, the communication management bureaus of Guangdong provinces actively organise the local communication industry to make every effort to prevent flood risks.

‘Industry and Information Technology Department’ is responsible for ensuring the protection and continuity of critical information technology infrastructure, such as communication networks, data centres, and essential utilities like electricity and water supply. During flood events, the ‘Industry and Information Technology Department’ disseminates real-time updates, warnings, and safety instructions to the public using information technology channels. This agency facilitates recovering and restoring information technology services and infrastructure after flood events. However, the ‘Industry and Information Technology Department’ was inactive during the other flood events. Besides, the ‘Culture and Tourism Department’ and ‘Education Department’ had the same phenomenon, with a high engagement in the 2019 and 2020 floods, respectively. However, they had no significant engagement in the other three floods.

5.4.3 Government agency collaboration

Collaboration among multiple government agencies is crucial for an effective and comprehensive response to flooding events. Before flooding, agencies collaborate in planning response strategies, setting priorities, and making decisions. Different agencies should exchange information about weather forecasts, flood extent, affected areas, and infrastructure damage during flooding. Then, they pool resources like human resources, equipment, and supplies to optimise their utilisation. After flooding, agencies conduct joint assessments to evaluate the damage, identify immediate needs, and plan for long-term recovery efforts.

The government agency collaboration during typhoon-induced floods (i.e., the 2017, 2018, and 2021 floods) was closer than during non-typhoon floods (i.e., the 2019 and 2020 floods). 47, 40, and 27 agencies were engaging in the 2017, 2018, and 2021 floods, respectively. The total agency connections in the three floods were 377, 178, and 91, respectively. The number of agencies in the 2019 and 2020 floods was 22 (55 connections) and 27 (105 connections), respectively. It can be found that the number of agencies involved during typhoon-induced floods is greater than during non-typhoon floods. Typhoon-induced floods are often challenging to predict because of the significant variability in ion budgets linked to typhoons (Chang et al., 2018). Non-typhoon floods might exhibit a more predictable correlation between stream discharge and ion budgets. Moreover, typhoon-induced floods are more complex than non-typhoon floods. Hence, more agencies with different functions need to participate during typhoon-induced floods. In the GBA, various agencies have effectively played their roles in flood control and management.

In emergency practice, agencies with regular connections may collaborate more efficiently, while it might be difficult for unfamiliar agencies (Fan et al., 2022). The 'Public Security Department' was one of the most collaborative agencies during the five floods (see Figure 5.2). The collaboration between the 'Public Security Department' and other agencies ensures comprehensive disaster response, as the 'Public Security Department' often acts as the backbone for emergency management. It can be found that if the 'Public Security Department' fails or gets disrupted during the flood events, it might significantly hamper the flow of information and resources, affecting the overall response capability of the government agency collaboration network. By collaborating with various agencies, the ‘Public Security Department’ ensures efficient coordination of resources, response strategies, and information dissemination. Its partnership with agencies like the ‘Natural Resources and Planning Department’ and ‘Transportation Department’ strengthens response mechanisms, enabling effective evacuation, resource allocation, and public safety measures. For example, the ‘Public Security Department’ coordinated with the ‘Transportation Department’ for traffic flow management, especially in affected areas prone to congestion or road closures due to flooding, to ensure smooth movement of emergency vehicles and the public. There was a substantial collaboration between the ‘Public Security Department’ and ‘Natural Resources and Planning Department’ during the 2020 flood.

The ‘Transportation Department’ worked closely with the ‘Public Security Department’, ‘Natural Resources and Planning Department’, ‘Finance Department’ and ‘Health Department’ (see Figure 5.2 and Table 5.4). The role of the ‘Transportation Department’ during flood events is multifaceted and critical for ensuring public safety, maintaining accessibility to essential services, and facilitating recovery efforts. The collaboration between the ‘Transportation Department’ and ‘Public Security Department’ is sought to provide alternative medical facilities, helicopter services, and communication channels during floods (Dame et al., 2019). This is crucial when infrastructure is damaged and accessibility to essential services is compromised. When public health officials need to transport medical supplies, the ‘Transportation Department’ provides critical information on route accessibility and collaborates with state highway patrol and other agencies to ensure delivery (White 1993). Moreover, the ‘Transportation Department’ is involved in initiating construction, maintenance, and rehabilitation programs with the ‘Finance Department’ to enhance network structure and incorporate low-impact development measures to reduce runoff volume and peak discharge rates (Yang et al., 2019).

Table 5.4 The top five agencies in collaboration with the transportation department

Year	Agency 1	Agency 2	Weight
2017	Public Security	Transportation	61
	Natural Resources and Planning	Transportation	57
	Urban management	Transportation	52
	Agriculture and Rural Affairs	Transportation	44
	Animal Husbandry	Transportation	41
2018	Public Security	Transportation	12
	Education	Transportation	7
	Health	Transportation	7
	Culture and Tourism	Transportation	5
	Meteorology	Transportation	4
2019	Commerce	Transportation	8
	Finance	Transportation	2
	River and Lake	Transportation	1
	Ecology and Environment	Transportation	1
2020	Finance	Transportation	6
	Public Security	Transportation	5
	Forestry	Transportation	4
	Natural Resources and Planning	Transportation	4
	Housing	Transportation	2
	Construction	Transportation	2
	Health	Transportation	2
	Agriculture and Rural Affairs	Transportation	2
	Revenue	Transportation	2
	Justice	Transportation	2
	Education	Transportation	2
	Audit	Transportation	2
	Port	Transportation	2
2021	Ecology and Environment	Transportation	2
	Power Supply	Transportation	1
	Meteorology	Transportation	1
	Public Security	Transportation	1
	Education	Transportation	1
	Culture and Tourism	Transportation	1

Conversely, collaboration between the ‘Transportation Department’ and ‘Meteorology Department’ was notably limited (see Table 5.4). There was no co-occurrence between the two agencies during the 2019 and 2020 floods. The co-occurrences were 2, 4, and 1 in the floods in 2017, 2018, and 2020, respectively. The integration of meteorological data with transport management is essential. Meteorological systems that monitor and forecast extreme weather events provide valuable data for transport management during floods (Yu et al., 2023; Balogun et al., 2020). Historical events have shown the importance of meteorological input in transport and hydraulic governance, leading to significant changes in landscape management and government policy (Williamson 2016). Hence, the collaboration between the ‘Transportation Department’ and the ‘Meteorology Department’ needs to be improved in the GBA.

Given the intricate and unpredictable nature of floods, city authorities should adopt a comprehensive approach and an inclusive stance toward cooperation. They should also emphasise occasional yet critical collaborations that significantly impact the overall flood management efforts. Institutional designers should strive to optimise the system network structure and establish mechanisms that ensure various departments, despite their differences, collaborate effectively during extreme conditions. This proactive approach enhances the efficiency of resource allocation, facilitating better response and management strategies during flood events.

5.5 Summary

This chapter implemented the government agency network analysis outlined in Chapter 3 (see Section 3.4). An analysis of agency engagement and collaboration during flood response and recovery was undertaken in the case study of representative annual flood events from 2017 to 2021. In summary, the results showed that:

(a) The agencies with higher centrality were also more active, such as the 'Public Security Department', 'Finance Department', 'Natural Resources Department', 'Meteorology Department', and 'Transportation Department'. These agencies were the key agencies involved in flood management in the road transport system, with distinct responsibilities to ensure an efficient response and recovery process. Hence, the disruption of these core agencies would significantly affect the overall response and recovery capability during the flood events.

(b) The government agency collaboration during typhoon-induced floods was closer than during non-typhoon floods. Moreover, the more severe the flood, the closer the collaboration will be. Various agencies have collaborated in the GBA to cope with floods and waterlogging.

(c) Agencies with regular connections may collaborate more easily, while it might be difficult for unfamiliar agencies. If these core connections fail or get disrupted during flood events, it might significantly hamper the flow of information and resources, affecting the overall response capability.

According to the results of the government agency collaboration analysis, some recommendations were proposed to answer how to enhance the government agency collaboration network for better flood response and recovery. Next, Chapter 6 applied vulnerability assessment and news media analysis to explore the potential impacts of the surface water flood on road infrastructure and transport.

Chapter 6: Assessing potential flood impacts on transport networks

6.1 Introduction

The adaptations of the joint multiple models have already been investigated to analyse potential flood impacts on road transport networks (Ouyang et al., 2022; Pyatkova et al., 2019). For example, Pregnolato et al., developed a modelling framework combining flood simulation, transport network model, and vulnerability curve. The effects of flood-related disruptions on the urban transportation network were analysed through a case study conducted in Newcastle upon Tyne, United Kingdom (Maria Pregnolato et al., 2017). An integrated framework was developed to determine road network vulnerability, integrating meteorological information, land use functions, hydrodynamic model, and safety speed function (Singh et al., 2018). Their study contributed to analysing the potential impacts of surface water floods on the performance of transport networks. These multivariate approaches provide valuable information to better understand transport resilience to surface water flooding, yet such complex approaches can be challenging to apply in standard flood impact assessments.

Media data is becoming a more popular and promising way to fill in the gaps in conventional data by examining the effects of floods and modifying disaster management (Fang et al., 2019; Wang et al., 2020a). For example, social media data (Weibo) was adopted for rapid damage classification using a surface water flood in Chongqing from 18 to 20 August 2020 (Tan, Schultz 2021). Moreover, media data has been integrated with the traditional model for flood assessment. For example, Ouyang et al., employed a hydraulic model and social media data to explore flood inundation impacts (Ouyang et al., 2022). Most applied studies of the road transport impacts of surface water flooding rely upon social media data (Ahmad et al., 2019; Tan, Schultz 2021). However, social media data is often characterised by user-generated content that may be subjective compared to the more reliable and objective news articles. Besides, social media data is often mined to analyse the characteristics of flood impacts at the event level, making it hard to compare different areas. Hence, few studies have focused on the effects and severity of floods on road infrastructure and transportation at a large scale.

This chapter aims to address the identified issues to mitigate flood impacts in road transport systems via integrating news media analysis and vulnerability assessment. Compared with social media data, the application of news media data can help extract flood hazard information and analyse the distribution in space and time (Liu et al., 2018). Based on the methodological framework proposed in Chapter 3 (see Section 3.5), this chapter fulfils the following objectives:

(a) Explore the potential direct tangible impact of surface water floods on road infrastructures via the vulnerability index system developed in Chapter 3.

(b) Investigate the potential indirect tangible impact of surface water floods on road transport through news media analytics.

(c) Discuss the potential of news media and vulnerability analysis to derive flood damage and recommendations for flood management in the road transport system.

6.2 Direct tangible impacts: road infrastructure impacts

6.2.1 Exposure assessment

The distribution of surface road length is uneven due to the significant differences in land area among GBA cities. As shown in Figure 6.1, Guangzhou has the longest expressway with a length of 3,226.39 km, the longest national highway with a length of 1,524.54 km, the longest provincial road with a length of 2,011.98 km, and the longest township-level road with a length of 4,285.69 km. The longest county-level road was discovered in Foshan, with a length of 2,284.09 km, followed by Shenzhen, with a length of 2,022.53 km. The lowest road length value is found in Macao. Indeed, the total length of all roads in Macao is 206 km, which can be attributed to its 32.9 square kilometre land area. It can be found that the total length of all roads in

Guangzhou is more than 60 times longer than that in Macao. Zhaoqing has the largest land area, but its road length (6,882.5 km) is shorter than Dongguan (7,102.1 km), Shenzhen (8,048.03 km), Huizhou (8,591.88 km), Foshan (9,060.36 km) and Guangzhou (13,030.43 km).

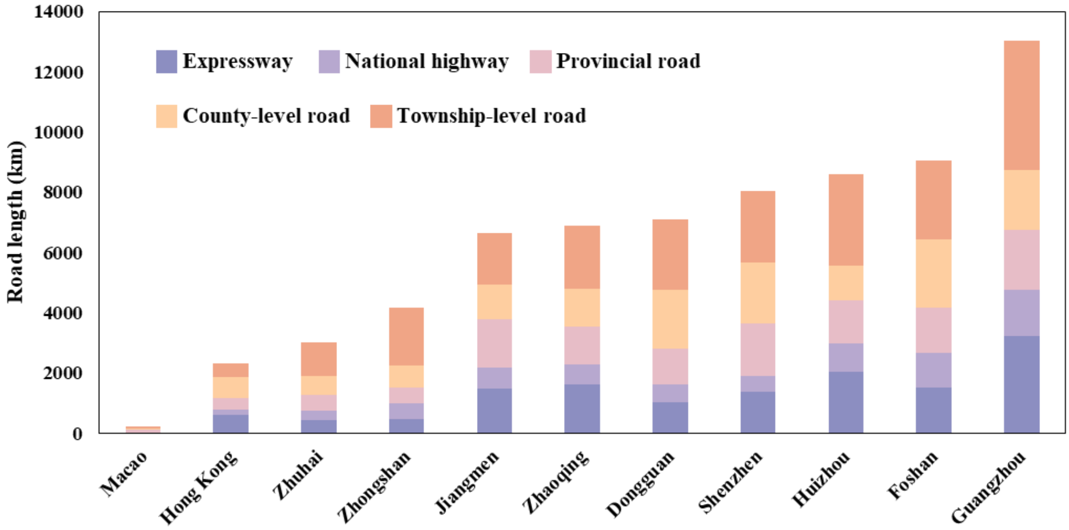

Figure 6.1 The characteristics of various road lengths in GBA cities

As presented in Figure 6.2, Guangzhou has the highest surface road value (222.72 billion RMB), followed by Huizhou (143.3 billion RMB), Foshan (134.67 billion RMB), and Shenzhen (117.11 billion RMB). The total surface value of these four cities accounts for 57% of the total surface road value in the GBA. Macao has the lowest surface road value (i.e., 2.26 billion RMB). Notably, the maximum value of surface roads is about 100 times the minimum value of surface roads. Surface road grades and lengths determine surface road value. Although the surface roads in Foshan are longer than those in Huizhou, the surface road value of Foshan is lower than that of Huizhou. It can be found that the total value of road length in Dongguan is higher than that in Zhaoqing and Jiangmen (see Figure 6.1). Nonetheless, Dongguan (95.55 billion RMB) has a lower surface road value than Zhaoqing (115.5 billion RMB) and Jiangmen (113.05 billion RMB). The length of high-grade roads (i.e., expressway and national highway) is 2,281.11 km, 2,187.39 km, and 1,635.58 km in Zhaoqing, Jiangmen, and Dongguan, respectively.

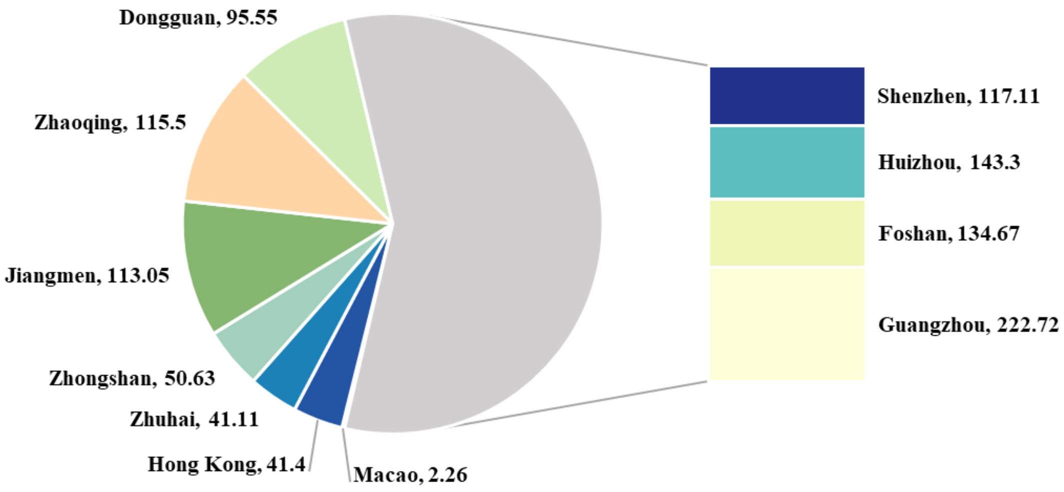

Figure 6.2 The characteristics of surface road value (billion RMB) in GBA cities

Figure 6.3a-e shows the distribution of various roads at the district scale in the GBA. Significantly, there is no administrative district in Dongguan City and Zhongshan City. This study considers Dongguan and Zhongshan as Dongguan District and Zhongshan District, respectively. Hence, Dongguan District and Zhongshan District generally have a higher surface road length than other districts. Except for the two districts, the districts with a long length of expressway include Nanhai and Shunde District of Foshan, Zengcheng, Baiyun and Conghua District of Guangzhou, Boluo and Huicheng District of Huizhou (see Figure 6.3a). Nanhai District (543.77 km) has the longest expressway length, followed by Zengcheng District (537.04 km) and Boluo District (523.86 km). There are seven districts in Macao without expressways.

As shown in Figure 6.3b, Shunde District (420.07 km) has the longest length of the national highway, followed by Nanhai District (368.72 km) and Boluo District (308.18 km). The number of districts without national highways is one, two, four, and eight in Zhaoqing, Shenzhen, Hongkong, and Macao, respectively. It can be discovered that most of the expressways and national highways are distributed in the non-central districts. As presented in Figure 6.3c, the top three districts with the longest length of provincial roads include Nanhai District (541.78 km), Huicheng District (447.63 km), and Baoan District (417.27 km) of Shenzhen. Figure 6.3d shows that Nanhai District and Shunde District have more than 700 km length of county-level roads. Indeed, Nanhai District (794.47 km) has a longer county-level road than Zhongshan (741.40 km). As for the township-level roads (see Figure 6.3e), the district with the longest length is Huidong District (1,130.16 km) of Huizhou.

According to the distribution of various roads, the surface road value in the western GBA is lower than that in the central and eastern GBA. As shown in Figure 6.3f, Dongguan (95.55 billion RMB) has the highest surface road value, followed by Zhongshan (50.63 billion RMB). The districts with more than 30 billion RMB surface road value include Nanhai District (47.40 billion RMB), Shunde District (39.11 billion RMB), Huicheng District (34.40 billion RMB), Luobo District (34.38 billion RMB), Zengcheng District (33.18 billion RMB) and Baiyun District (32.85 billion RMB). The districts with low surface road value are concentrated in Hong Kong and Macao due to their low value of surface road length. Within a city, the surface road values in the central districts are lower than those in the non-central districts. For example, the total surface road value of central districts (including Tianhe, Haizhu, Liwan, and Yuexiu District) is 32.06 billion RMB. The surface road value of Zengcheng and Baiyun District is 33.12 billion RMB and 32.85 billion RMB, respectively.

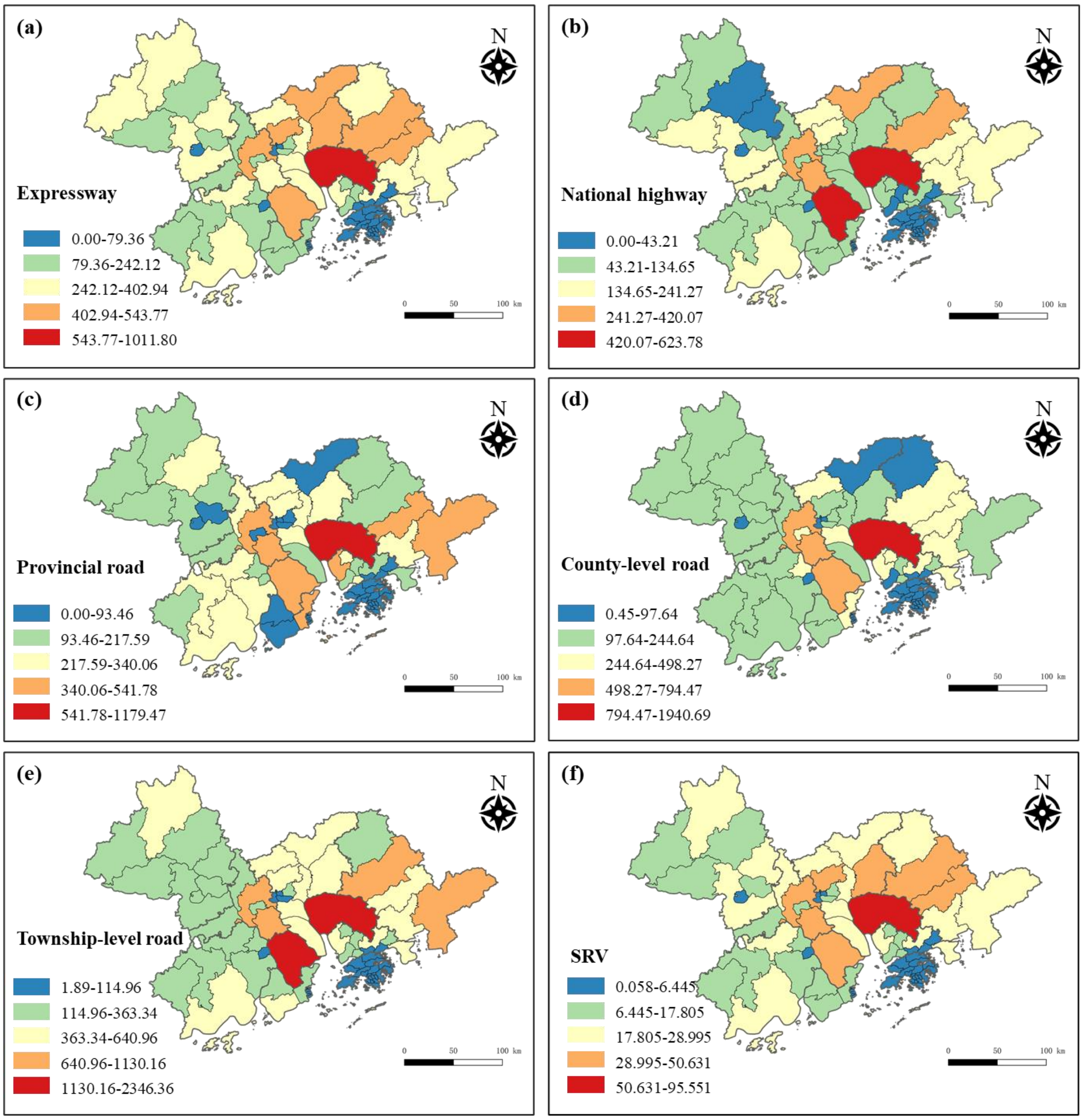

Figure 6.3 The distributions of various roads and surface road values in the GBA, (a) the length of expressway (km), (b) the length of national highway (km), (c) the length of provincial road (km), (d) the length of county-level road (km), (e) the length of township-level road (km), (f) surface road value (billion RMB)

The results of the exposure were used in the natural breaks method to categorise at five levels: very low (0.02-0.13), low (0.13-0.24), moderate (0.24-0.34), high (0.34-0.46), and very high (0.46-0.74). Under normal rainfall conditions, 38.96% of total districts have very high or high exposure to surface roads in GBA cities (see Figure 6.4a). Only 5 districts (6.49%) have very low exposure, i.e., Duanzhou District, Dinghu District, Gaoyao District in Zhaoqing, Nanshan District in Shenzhen, and Haizhu District in Guangzhou. Figure 6.4b shows the proportions of districts with various grade exposures in different GBA cities. Most high-exposure districts are concentrated in Guangzhou (7) and Hong Kong (13). Those districts with higher exposure are likely to suffer more physical losses of road infrastructures when surface water floods occur. There is no high or very high exposure district in Macao, Zhaoqing and Zhongshan.

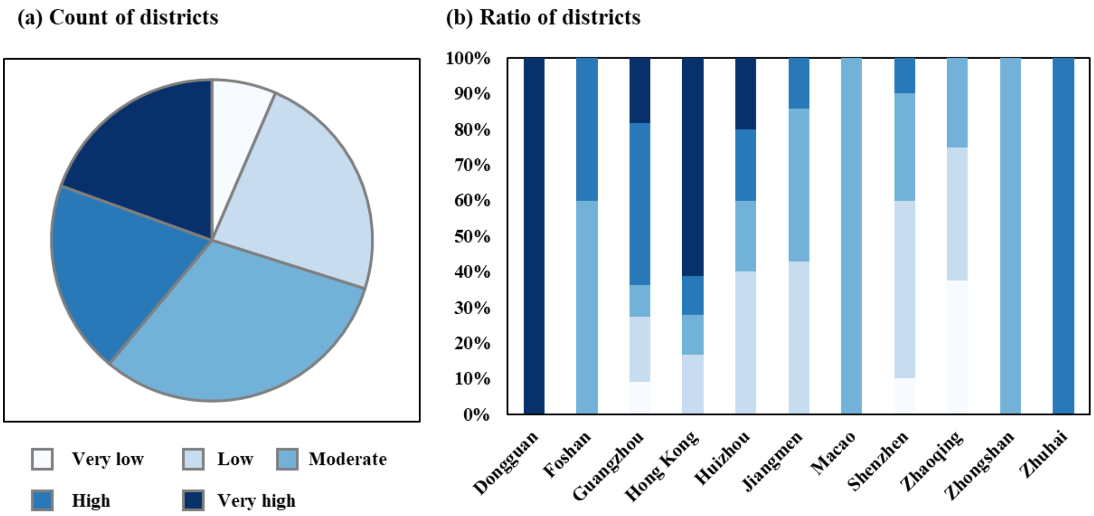

Figure 6.4 Characteristics of exposure in the GBA cities. (a) The total count of districts at various exposure index grades. (b) The ratio of districts at various exposure index grades in different GBA cities

Districts exhibiting characteristics of long road mileage, high road grades, and strong annual rainfall were more sensitive to floods. As shown in Figure 6.5, the highest exposure district was Dongguan, which can be attributed to the high value (95.5 billion RMB) of high-grade roads (i.e., expressways, national highways, and provincial roads). It is worth noting that Dongguan City does not encompass distinct administrative districts; hence, it was treated as a single district within the scope of this study. Apart from Dongguan, the district with the next highest level of exposure was Wong Tai Sin District (0.614) in Hong Kong, followed closely by Longmen County (0.600) in Huizhou and Sha Tin District (0.585) in Hong Kong. The annual rainfall in these three districts exceeded 2000 mm, surpassing the average annual rainfall levels observed in the broader context of the 77 districts.

Within a city, most Central Business Districts (CBDs) exhibited relatively lower exposure levels due to the prevalence of low-grade surface roads, namely county-level roads and township-level roads. In cities such as Foshan, Guangzhou, and Zhaoqing, the districts with the lower exposure levels were predominantly situated within CBDs, including Chancheng District (0.291), Haizhu District (0.131), Yuexiu District (0.151), and Duanzhou District (0.019). Notably, there was no significant difference in exposure in the different districts of Macao, primarily owing to the limited geographical extent of Macao as the smallest provincial city in China. In Macao, the district with the highest exposure was Jiamo Tang District (0.280), while the district with the lowest road infrastructure vulnerability was São Francisco de Xavier District (0.278). In contrast, the disparity between the districts with the highest and lowest exposure in Guangzhou was notably higher, at 0.417.

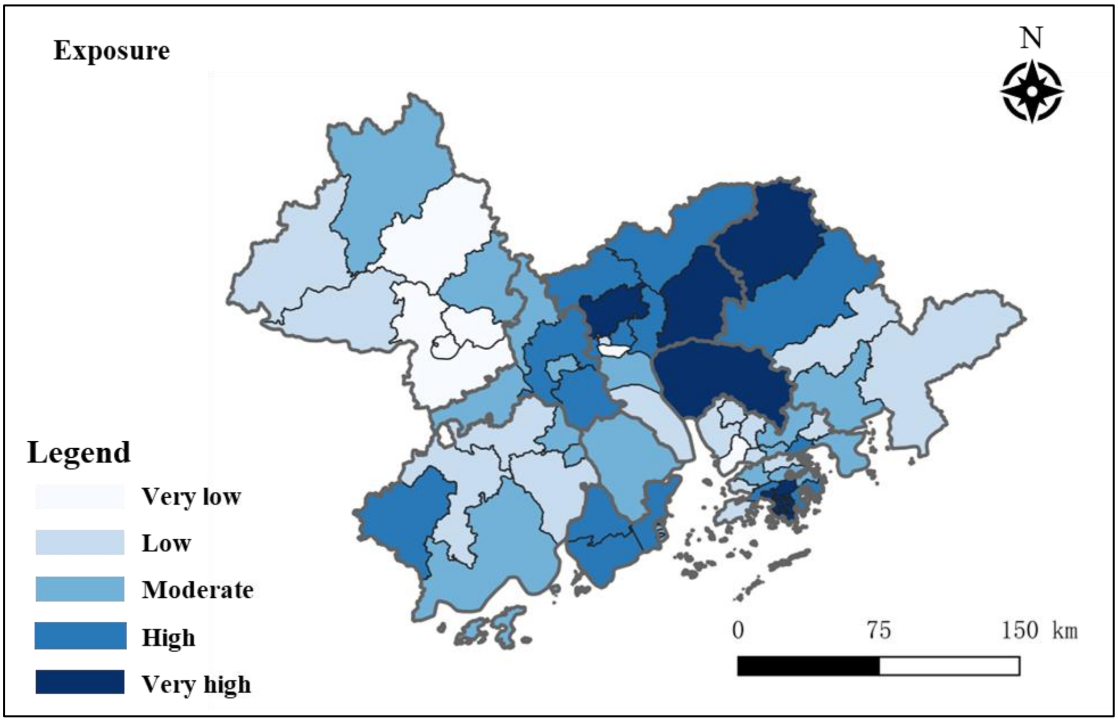

Figure 6.5 The distribution of exposure in the GBA

6.2.2 Disaster reduction capability assessment

Figure 6.6 shows the proportion of various roads in GBA cities. The proportion of low-grade roads (i.e., county-level roads and township-level roads) is higher than that of high-grade roads (i.e., expressways and national highways). The low-grade roads account for more than 50% of Zhongshan (63.5%), Dongguan (60.3%), Zhuhai (57.5%), Shenzhen (54.9%) and Foshan (54.1%). The high-grade roads account for more than

30% of Guangzhou (36.5%), Huizhou (34.6%), Zhaoqing (33.2%), Hong Kong (33.2%) and Jiangmen (32.9%). The proportion of national highways is low in most cities of the GBA. Notably, the proportion of national highways (12.8%) is higher than expressways (11.1%) and provincial roads (12.6%). The city with the most uneven proportion of various roads is Macao. In Macao, the roads with the highest and lowest proportions are provincial roads (54.5%) and national highways (0%). The proportion of various roads is even in Foshan. In Foshan, the proportion of expressways, national highways, provincial roads, county-level roads, and township-level roads is 16.7%, 12.9%, 16.3%, 25.2% and 28.9%, respectively.

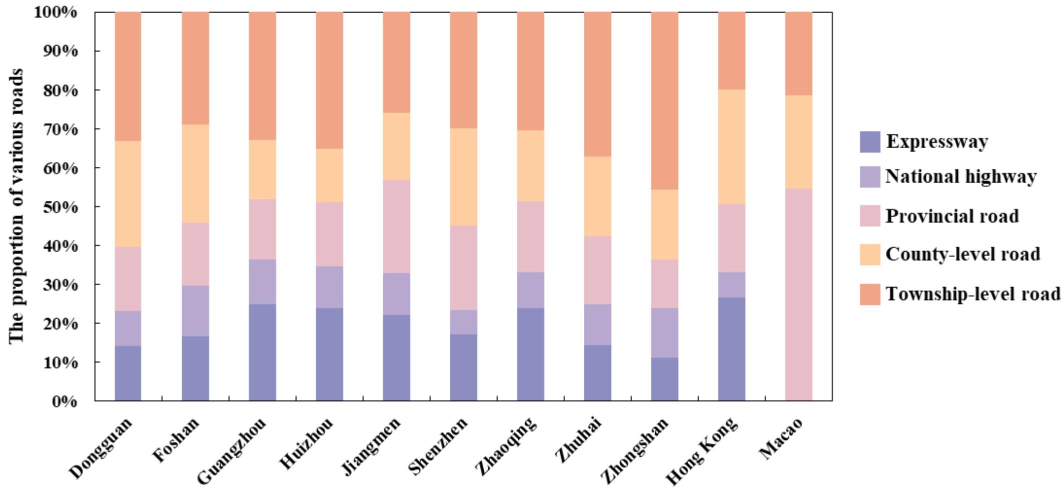

Figure 6.6 The proportion of various roads in GBA cities

As shown in Figure 6.7, the distributions of surface road density, road bridge density, and road culvert density are uneven in GBA cities. It can be found that the cities with large areas have sparse surface roads, bridges, and culverts. Figure 6.7a shows that Macao has the highest surface road density (6.262 km/km^2), followed by Shenzhen (4.029 km/km^2) and Dongguan (2.793 km/km^2). The surface roads are sparse in Zhaoqing (0.462 km/km^2), Huizhou (0.697 km/km^2), and Jiangmen (0.757 km/km^2). As for road bridge density (see Figure 6.7b), Macao has the highest road bridge density (1.585 km/km^2), followed by Hong Kong (0.579 km/km^2) and Shenzhen (0.466 km/km^2). In the three largest cities (i.e., Zhaoqing, Huizhou, and Jiangmen), the road bridge density is less than 0.1 km/km^2. Similarly, the three cities with the highest road culvert density are Macao (0.37 km/km^2), Hong Kong (0.156 km/km^2), and Shenzhen (0.097 km/km^2) (see Figure 6.7c). The three cities with the lowest road culvert density are Jiangmen (0.005 km/km^2), Huizhou (0.006 km/km^2) and Zhaoqing (0.006 km/km^2). Figure 6.7d shows that Hong Kong has the highest anti-disaster ability (4.614), which can be attributed to the high proportion of expressways (26.7%) (see Figure 6.6). The second-highest anti-disaster ability was observed in Guangzhou (4.546). Although Macao has the highest density of surface roads, bridges, and culverts, its anti-disaster ability is the lowest (2.885).

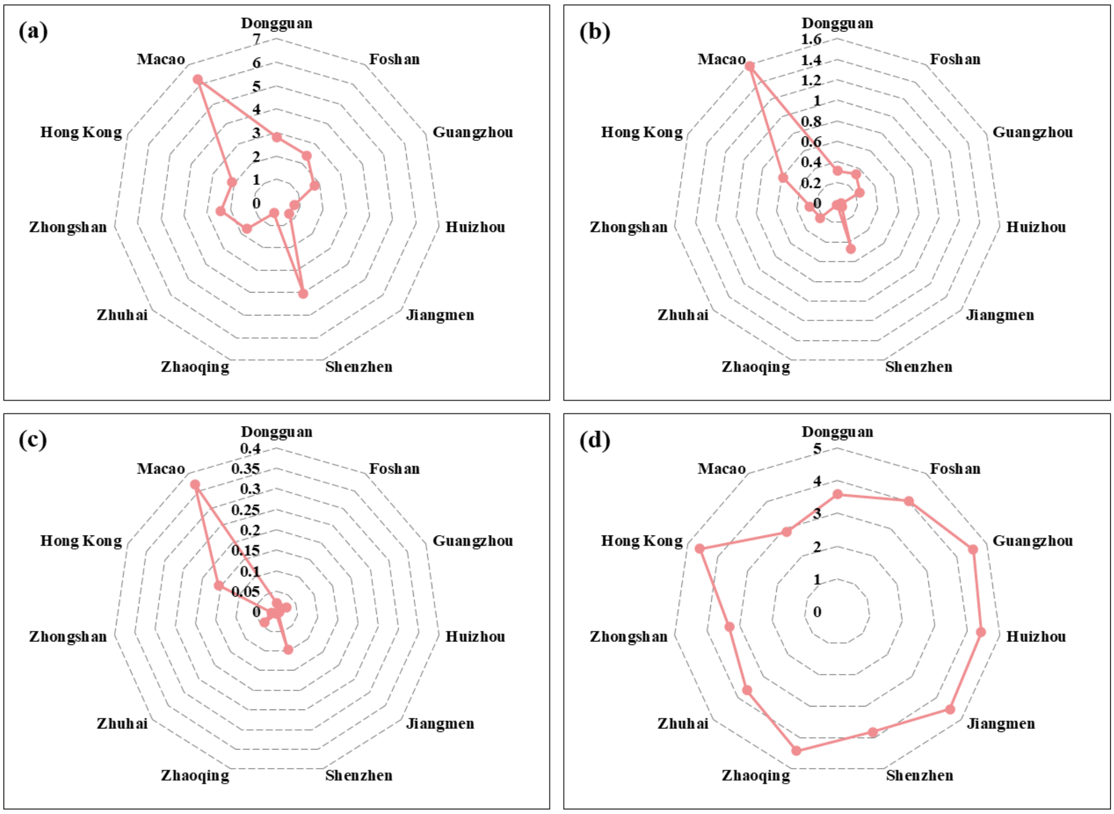

Figure 6.7 Disaster reduction capability indicators in GBA cities, (a) surface road density, (b) road bridge density, (c) road culvert density, and (d) road anti-disaster capability

Figure 6.8 presents the surface road density, road bridge density, road culvert density, and road anti-disaster ability in different districts of GBA cities. As shown in Figure 6.8a, the districts with denser surface roads are located in the central GBA, including the central and southern areas of Guangzhou, the eastern area of Foshan, the eastern area of Zhuhai, Zhongshan, Dongguan, Shenzhen, Hong Kong, and Macao. The average value of surface road density is 4.15 km/km^2 in GBA districts. Yau Tsim Mong

District of Hong Kong has the highest surface road density (20.42 km/km^2), followed by Freguesia de S．Lourenço District (17.77 km/km^2) and Freguesia de São Lazaro District (16.83 km/km^2) of Macao. The three districts with the lowest surface road density are located in Zhaoqing, including Guangning County (0.31 km/km^2), Huaiji County (0.31 km/km^2) and Fengkai County (0.32 km/km^2).

As shown in Figure 6.8b-c, road bridges and road culverts are sparse in most districts. Yau Tsim Mong District of Hong Kong has the densest road bridge (6.60 km/km^2), followed by Sé Freguesias District (6.22 km/km^2) and Freguesia de São Lazaro District (4.87 km/km^2) of Macao. The three districts with the highest road culvert density are Freguesia de S．Lourenço District (2.76 km/km^2), Yau Tsim Mong District (2.52 km/km^2), and Freguesia de São Lazaro District (1.09 km/km^2). With the exception of the three districts, the road culvert density is less than 1 km/km^2 in the GBA. Moreover, the districts with relatively high road bridge and culvert densities are located in Hong Kong and Macao.

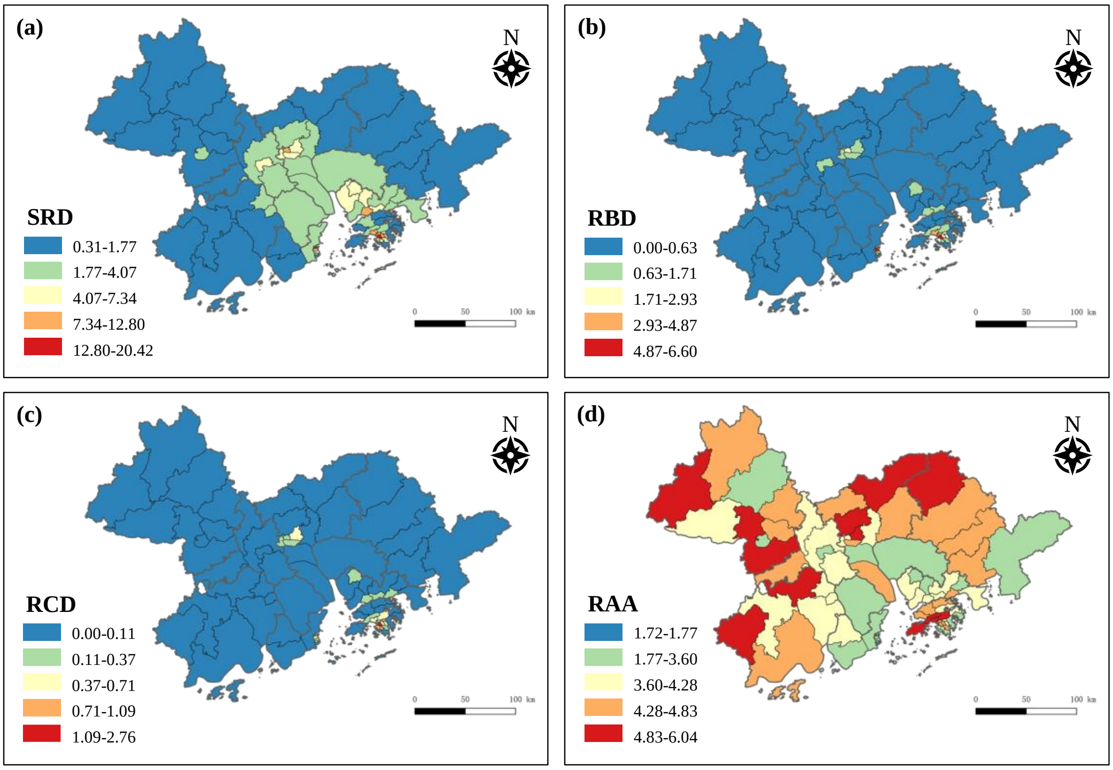

Figure 6.8 The characteristics of disaster reduction capability indicators in GBA cities, (a) surface road density, (b) road bridge density, (c) road culvert density, and (d) Road anti-disaster ability

The districts with relatively low anti-disaster ability are located in the central GBA (see Figure 6.8d), including the central area of Guangzhou, the eastern area of Foshan, Zhuhai, Zhongshan, Dongguan, Shenzhen, and Macao. The three districts with the highest anti-disaster ability are concentrated in Hong Kong, including Tsuen Wan District (6.04), Sha Tin District (5.64) and Kwai Tsing District (5.55). The lowest anti-disaster ability is found in St. Anthony Parish District (1.72), São Francisco de Xavier District (1.77) of Macao. Within a city, the anti-disaster ability of central districts is lower than that of other districts. Taking Guangzhou as an example, the highest anti-disaster ability is discovered in Conghua District (5.44). The anti-disaster ability in Yuexiu District, Liwan District, and Huadu District is 3.93, 4.17, and 4.40, respectively. That can be attributed to the high-grade roads being concentrated in the non-central districts.

The results of the disaster reduction capability were used in the natural breaks method to categorise at five levels: very low (0.014-0.184), low (0.184-0.283), moderate (0.283-0.375), high (0.375-0.534), and very high (0.534-0.824). 44.16% of total districts have low or very low disaster reduction capability of surface roads in GBA cities (see Figure 6.9a). As shown in Figure 6.9b, the districts with higher disaster reduction capabilities are located in Hong Kong and Macao. Notably, only two districts have very high disaster reduction capability, i.e., Kwai Tsing District and Yau Tsim Mong District (C Kowloon area) in Hong Kong. There is no high or very high exposure district in Dongguan, Foshan, Huizhou, Jiangmen, Shenzhen, Zhaoqing, Zhongshan and Zhuhai.

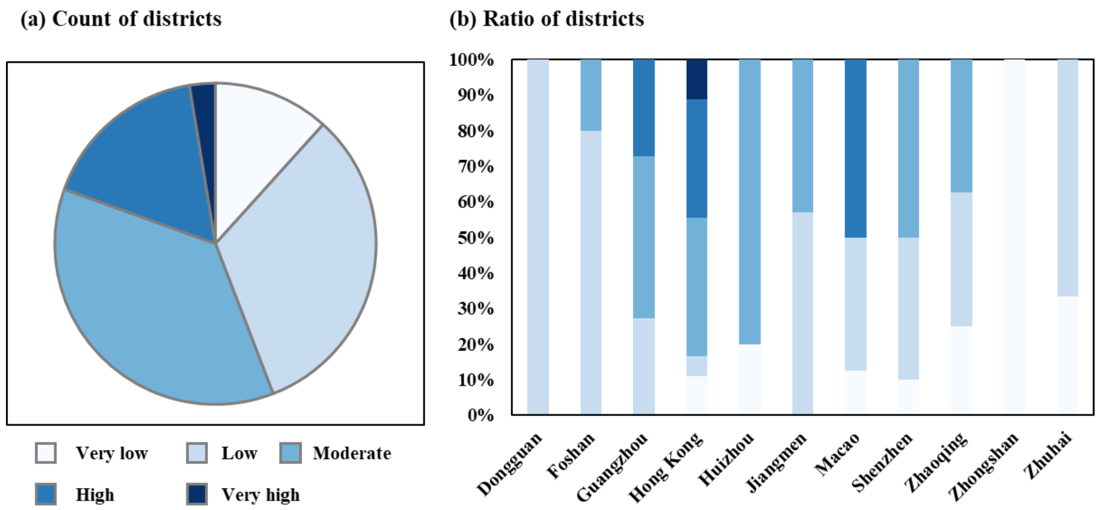

Figure 6.9 Characteristics of disaster reduction capability in the GBA cities. (a) The total count of districts at various disaster reduction capability index grades. (b) The ratio of districts at various disaster reduction capability index grades in different GBA cities

Districts characterised by a dense network of roads, bridges, and culverts typically exhibited a more excellent resistance against floods. As shown in Figure 6.10, it is evident that the disaster reduction capabilities of the districts within the nine mainland cities were notably lower when compared to those within the 2 SARs. This distinction is primarily attributed to Hong Kong and Macao considerably higher road density than the other nine cities. To delve into more detail, the district with the highest disaster reduction capability was Yau Tsim Mong District (0.824) in Hong Kong. This district boasted the most elevated levels of road density (20.4 km/km^2), bridge density (6.6 km/km^2), and culvert density (2.5 km/km^2) among all the districts in the GBA cities. Apart from Hong Kong and Macao, the disaster reduction capability in the districts of Guangzhou exceeded that of the districts in the remaining eight cities. Notably, districts with moderate or higher disaster reduction capabilities were predominantly concentrated in Guangzhou, Hong Kong, and Macao.

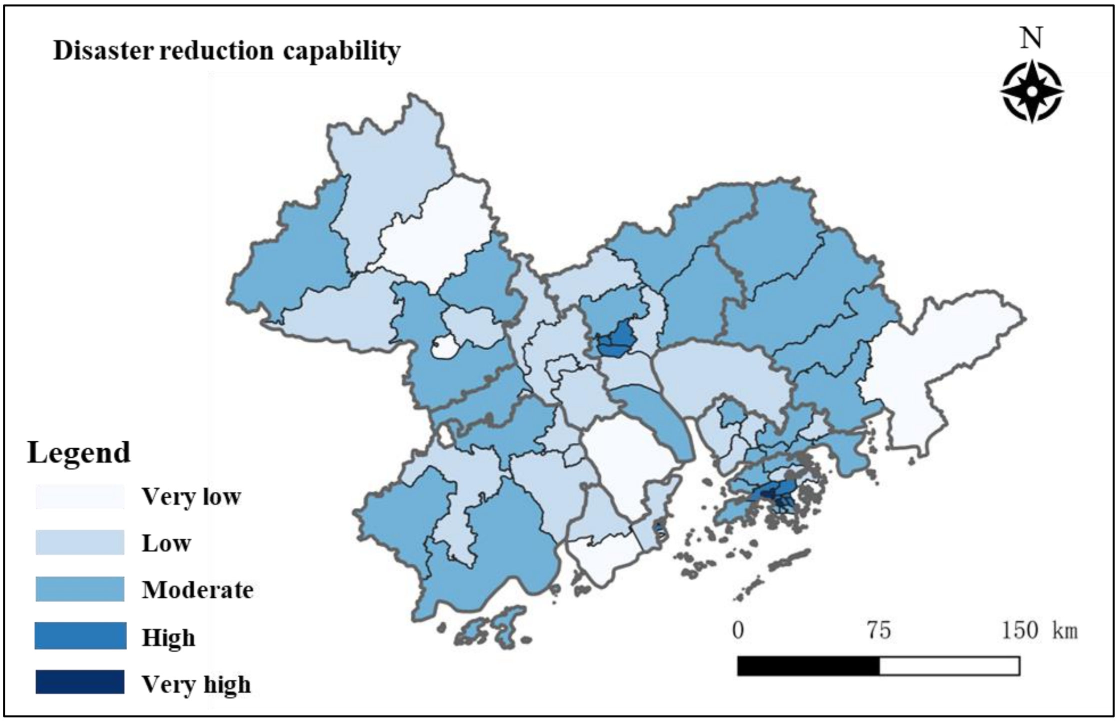

Figure 6.10 The distribution of disaster reduction capability in the GBA

6.2.3 Vulnerability assessment

The results of the road infrastructure vulnerability were used in the natural breaks method to categorise at five levels: very low (0.011-0.062), low (0.062-0.120), moderate (0.120-0.179), high (0.179-0.248), and very high (0.248-0.397). Similar to the statistical results of exposure assessment, most districts have moderate, low, or very low vulnerabilities, accounting for 71.4% of total districts (Figure 6.11a). That is due to the road infrastructure vulnerability being positively related to exposure. In relative terms, the districts with the highest road infrastructure vulnerability are Dongguan (0.40) and Southern District in Hong Kong (0.38). As shown in Figure 6.11b, no very high or high road infrastructure vulnerability districts exist in Jiangmen and Zhaoqing.

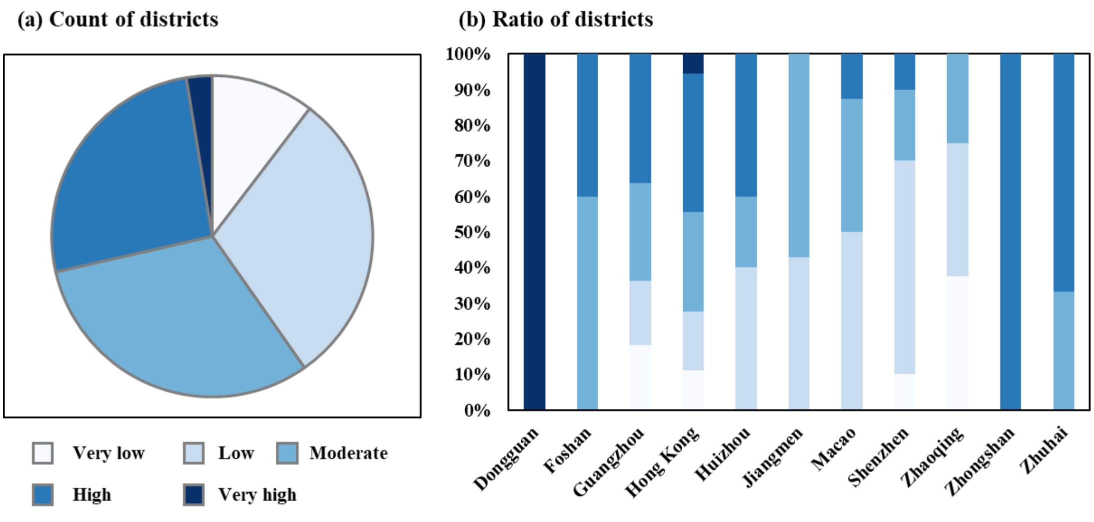

Figure 6.11 Characteristics of road infrastructure vulnerability in the GBA cities. (a) The total count of districts at various road infrastructure vulnerability index grades. (b) The ratio of districts at various road infrastructure vulnerability index grades in different GBA cities

As shown in Figure 6.12, the distribution of road infrastructure vulnerability exhibited a notable resemblance to the distribution of exposure. Districts characterised by a combination of sparse and high-grade roads were observed to be more directly and physically vulnerable to surface water floods. Except for Dongguan, which represented the district with the highest road infrastructure vulnerability, the district with the next highest road infrastructure vulnerability was Southern District (0.377) in Hong Kong, closely followed by Zengcheng District (0.248) in Guangzhou. In these districts, road densities remained below 2 km/km², while the annual rainfall consistently exceeded 1700 mm. It was discovered that the western regions of the GBA exhibited lower road vulnerabilities in contrast to the central and eastern GBA.

Within a city, districts with low and very low road infrastructure vulnerability were concentrated in the CBDs. For instance, in Guangzhou, the district with the lowest road infrastructure vulnerability was Haizhu District (0.048), closely followed by Yuexiu District (0.052) and Tianhe District (0.114), all of which represent the central districts of Guangzhou. In CBDs, emergency rescue services can swiftly respond to flood incidents, facilitating the minimisation of road damage and the restoration of accessibility. Moreover, these areas typically boasted a dense network of bridges and culverts, with fewer high-grade and costly roads. This pattern indicates that CBDs exhibited lower exposure levels and higher disaster reduction capabilities. Consequently, CBDs demonstrated more excellent resistance to floods when compared to non-central districts in GBA cities.

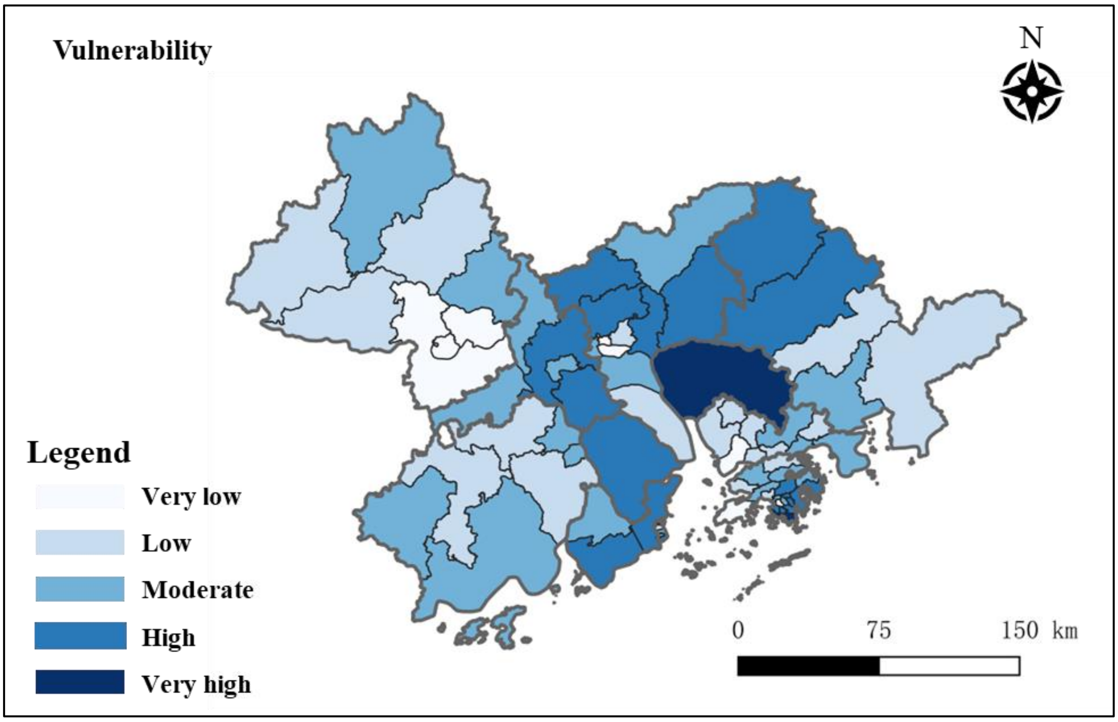

Figure 6.12 The distribution of road infrastructure vulnerability in GBA cities

The assessment results of road infrastructure vulnerability indicated that not all districts with higher exposure correspond to higher road infrastructure vulnerability. Some districts had high disaster reduction capabilities; thus, even districts with high exposures may have low road vulnerabilities. An illustrative example of this phenomenon can be found in the Yau Tsim Mong District of Hong Kong, characterised by both high exposure and an exceptionally high disaster reduction capability, resulting in very low road infrastructure vulnerability in this district. A similar pattern was also observed in Kowloon City District, Sham Shui Po District, and Kwai Tsing District of Hong Kong, where the three districts boasted high exposure levels, high to moderate disaster reduction capabilities, and notably lower road vulnerabilities. This was primarily attributable to relatively higher road anti-disaster ability and high road density in these districts.

6.2.4 Results verification and sensitive analysis

This study used previous studies and historical surface water flood information to verify the rationality of surface water flood vulnerability assessment of road infrastructure. According to this study, the distribution characteristics of the road infrastructure vulnerability are similar to the exposure distribution characteristics (Figure 6.5 and Figure 6.12). It also indicates that the higher disaster reduction capability districts are mainly concentrated in the districts with dense roads and developed traffic conditions (Figure 6.10). The districts with relatively higher road infrastructure vulnerability are near major expressways. These characteristic patterns agree with the previous studies (Huang et al., 2013; Li et al., 2015; He et al., 2021).

In the past 30 years, the number of rainstorms that caused casualties or economic losses is more than 30 in 8 districts of the GBA mainland cities (Wang and Zhai, et al., 2022). In this study, most of these districts have a moderate and above vulnerability, including Longmen County and Huicheng District of Huizhou, Shunde District of Foshan, Huaiji County of Zhaoqing, and Longgang District of Shenzhen. Moreover, Huaiji County and Longmen County are the most physically vulnerable areas in Zhaoqing and Huizhou, respectively. It can be regarded that the high-vulnerability districts of surface water floods in the GBA mainly suffer higher economic losses. Therefore, the vulnerability index developed in this study can reflect the characteristics of the vulnerability of road infrastructure to surface water floods.

Moreover, sensitivity analysis was conducted to explore the impacts of increasing the length of different roads by 10% on road infrastructure vulnerability (see Table 6.1). It can be found that variation in county-level road length has the greatest impact on road infrastructure vulnerability. With the increasing length of county-level roads by 10%, 32 districts have a decreased road infrastructure vulnerability. The variations in expressway length and national highway length have a low impact on road infrastructure vulnerability. Hence, the length of low-grade roads is the major or primary factor affecting road infrastructure vulnerability with no variation of other factors. Meanwhile, sensitivity analysis was adopted to investigate the impact of other factors and variations on road infrastructure vulnerability. An increase of 10% in annual rainfall has no significant impact on road infrastructure vulnerability.

Table 6.1 Sensitivity factor sorting

Road grades	Variation of road length	The variation in road infrastructure vulnerability	The number of districts	
			Decreased road infrastructure vulnerability	Increased road infrastructure vulnerability
Expressway	+10%	-1.01% - 1.86%	28	49
National highway	+10%	-1.30% - 2.47%	49	28
Provincial road	+10%	-1.04% - 1.69%	32	45
County-level road	+10%	-1.43% - 1.84%	50	27
Township-level road	+10%	-24.44% - 9.89%	32	45

6.3 Indirect tangible impacts: road transport impacts

6.3.1 Categories of indirect impacts

Surface water build-up is the initial event and a significant hazard of floods to road transport (Hooper 2013). As the flooding on roads increases in depth, traffic delays would ensue and worsen over time. Deficient performance of road traffic can reduce and even interrupt transport services (Lu et al., 2022a). Moreover, traffic accidents would occur due to reducing drivers' visibility and congestion. Traffic accidents during flood events can pose significant challenges to road safety and transport. Hence, indirect tangible impact was divided into four categories based on the GDELT themes, including public transport, logistics transport, road traffic, and traffic accidents. Table 6.2 shows the themes pertaining to each category of potential issues caused by surface road floods.

Public transport refers to the transport system that is available for use by the general public, typically consisting of vehicles or infrastructure. The purpose of public transport is to provide an efficient, affordable, and accessible means of moving people from one place to another within a city, region, or country. In the GBA, public transport is well-developed and offers various options for moving around the region. As shown in Table 6.2, there is no secondary classification of public transport. The frequency of public transport is 41889.

Logistics transport refers to the movement of goods, materials, and products using the road or highway network as the primary mode of transport. In the GBA, the role of highway logistics transport is to connect various cities and facilitate the movement of goods within and beyond the region. Efficient roads and integrated multimodal transport networks contribute to the seamless movement of goods and materials, enhancing the competitiveness of the GBA as a major economic hub. According to the GDELT project, there are three categories of logistics transport (see Table 6.2). CRISISLEX_C04_LOGISTICS_TRANSPORT (41728) has the highest number of media mentions among the three categories. This is because this theme was developed to explore the use of news media for crisis and disaster response (CrisisLex.org 2014).

Road traffic refers to the movement of vehicles, pedestrians, and other users on roads, streets, and highways. The GBA is known for its dynamic and busy road traffic due to its high population density, economic activity, and connectivity between major cities. Surface water floods can inundate roads, rendering them impassable. This leads to temporary road congestions, closures, detours, and disruptions to normal traffic routes, which can result in longer travel times and delays for commuters and goods transport. As shown in Table 6.2, two themes of the GDELT project are related to road traffic, i.e., WB_1810_TRAFFIC_CONTROL_AND_MONITORING (442) and TRAFFIC (22233).

Surface water floods can create hazardous conditions that increase the risk of accidents and incidents on the road. Heavy rainfall and floodwaters can significantly reduce visibility for drivers. This limited visibility makes it difficult to see other vehicles, road signs, and obstacles, increasing the likelihood of collisions. Aquaplaning occurs when a layer of water builds up between the road surface and a vehicle’s tyres, causing the tyres to lose traction. This can lead to loss of control and accidents, especially at higher speeds. According to the theme information of the GDELT project, 10 themes are related to traffic accidents, and 3 themes are related to safety.

Table 6.2 Summary of the category list and its associated themes

Category	Code	GDELT theme	Frequency
Public transport	T101	PUBLIC_TRANSPORT	41889
Logistics transport	T201	CRISISLEX_C04_LOGISTICS_TRANSPORT	41728
	T202	WB_793_TRANSPORT_AND_LOGISTICS_SERVICES	29409
	T203	WB_1173_TRANSPORT_LOGISTICS_PROVIDERS	102
Road traffic	T301	TRAFFIC	22233
	T302	WB_1810_TRAFFIC_CONTROL_AND_MONITORING	442
Traffic accident	T401	SOC_TRAFFICACCIDENT	1109
	T402	ROAD_INCIDENT	963
	T403	MANMADE_DISASTER_CAR_ACCIDENT	447
	T404	MANMADE_DISASTER_ROAD_ACCIDENT	172
	T405	MANMADE_DISASTER_CAR_CRASH	49
	T406	MANMADE_DISASTER_TRAFFIC_ACCIDENT	137
	T407	MANMADE_DISASTER_VEHICLE_CRASH	32
	T408	MANMADE_DISASTER_TRANSPORT_DISASTER	9
	T409	MANMADE_DISASTER_TRANSPORTATION_DISASTER	5
	T410	ROAD_INCIDENT_CAR_ACCIDENT	4
	T411	WB_1808_TRANSPORT_SAFETY	456
	T412	WB_1429_ROAD_SAFETY	234
	T413	WB_784_TRAFFIC_AND_ROAD_SAFETY	234

6.3.2 Characteristics of indirect tangible impacts

Judging by the classified counts of the four damage categories, logistics transport has the most damage reports (70194), accounting for 50.7% of the total news articles. The second most reported damage category is public transport (41787), accounting for 30.2% of the total news articles. Logistics transport and public transport were of the greatest concern to news media. The level of these damage categories (i.e., logistics transport and public transport) may also be more severe during surface water floods. The damage category with the lowest news media attention is the traffic accident, with 3825 news articles. It can be found that surface water floods lead to a few damages to traffic accidents and the safety of the GBA.

Logistics transport has the highest news media attention in each city of the GBA, followed by public transport (see Figure 6.13). The proportion of news articles related to public transport in Foshan (31.3%), Hong Kong (36.0%), Macao (34.6%), and Zhongshan (34.5%) is higher than the average value of all cities. More than half of news articles are related to logistics transport in the five cities, including Foshan, Huizhou, Jiangmen, Shenzhen, Zhaoqing (52.1%), and Zhuhai. In particular, more than 58% of news articles are related to logistics transport in Zhuhai. The proportion of news articles related to road traffic is 18.1%, 18.4%, 17.5%, and 19.0% in Dongguan, Guangzhou, Huizhou and Zhongshan, respectively. The four values are higher than the average value, which is 16.3%. Traffic accidents have the lowest news media attention in each city of the GBA. The variation in the traffic accident proportion range is from 1.6% in Hong Kong to 4.5% in Dongguan.

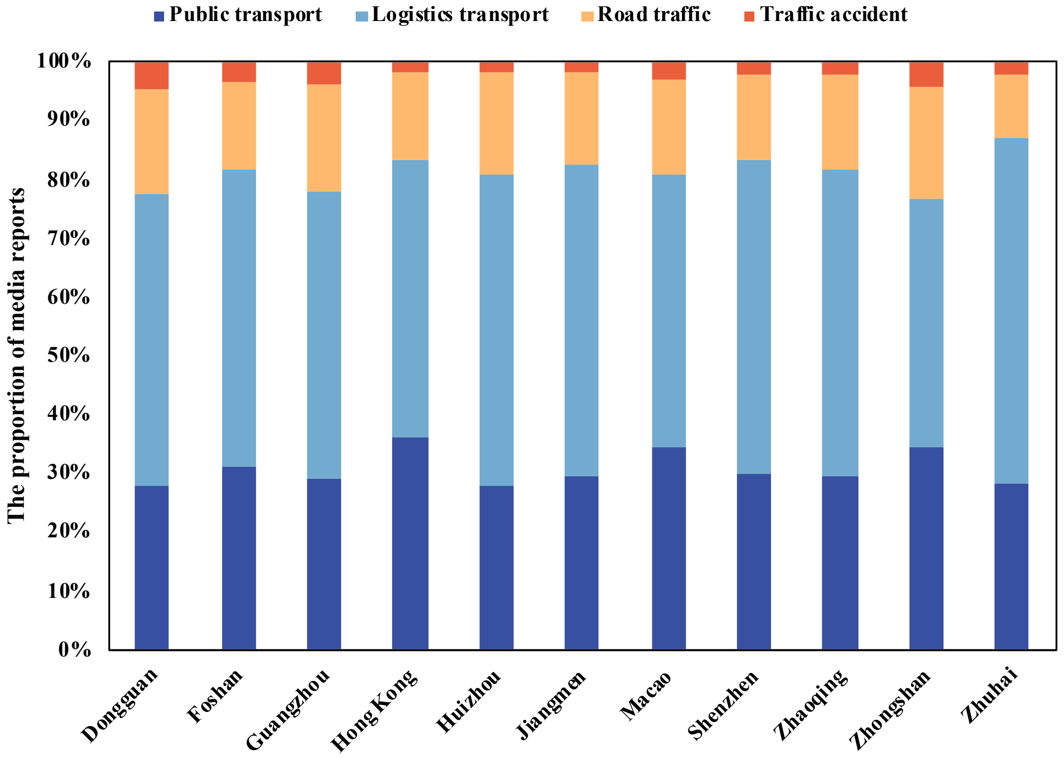

Figure 6.13 The proportion of different indirect tangible impacts in each city of the GBA

From the perspective of the impact of information on cities, news media attention on transport issues is uneven among GBA cities (see Figure 6.14). Guangzhou is the city with the most news articles counts. In Guangzhou, the number of news articles related to public transport, logistics transport, road traffic, and traffic accidents is 14922, 24689, 9374, and 1902, respectively. Shenzhen is closely followed, which has 11611, 20875, 5594, and 1902 news articles relating to public transport, logistics transport, road traffic, and traffic accidents, respectively. It can be found that news media attention is concentrated in densely populated and economically developed cities of the GBA.

These cities have great pressure on urban traffic, public transport, and logistics transport. Hence, surface water floods may impact road transport in these cities more. Moreover, residents tend to have greater access to technology and social media in more developed cities, which can increase the spread of news and information about surface water flood events.

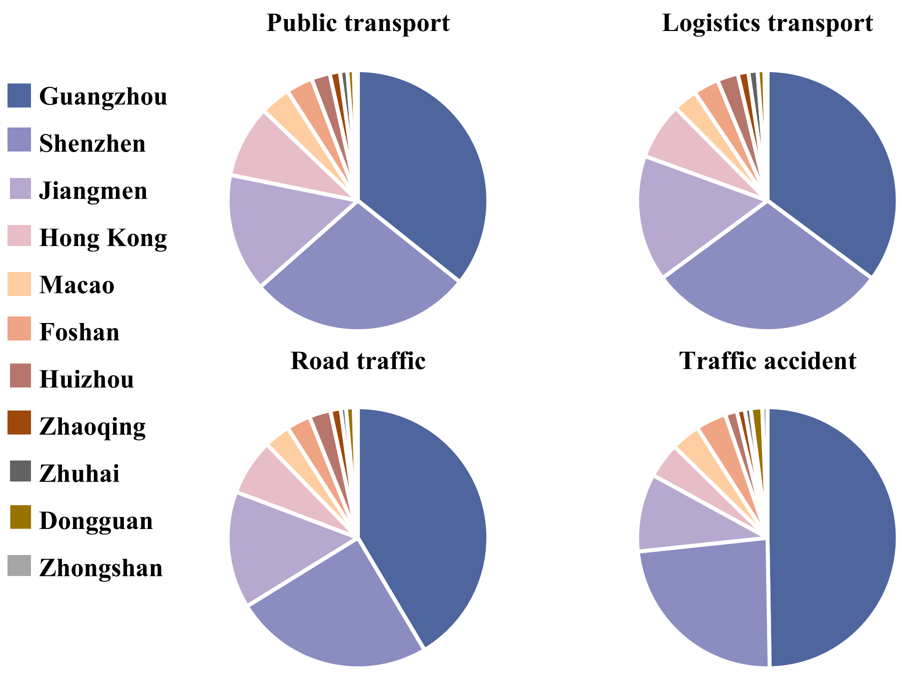

Figure 6.14 The proportion of each impact in different cities.

According to the four damage categories caused by surface water floods in Section 6.3.1, Table 6.3 shows the news sentiments to these damages. The value of news sentiment to public transport, logistics transport, road traffic, and traffic accidents is -1.18, -1.08, -1.34, and -2.16, respectively. It can be found that the indirect tangible impact of extremely serious negative emotions is traffic accidents. The indirect tangible impact with slight serious negative emotion is logistics transport. As mentioned in Section 6.3.1, logistics transport has the highest number of news articles, while traffic accidents have the lowest number of news articles. Notably, the ranking of the number of news articles on the four impacts is exactly opposite to the ranking of their news sentiment. The results indicate that surface water floods lead to few traffic accidents, but the damage is often extremely serious. Surface water floods lead to frequent logistics disruption, but the damage is often slightly serious. It can be observed that the lower the frequency of the damages, the more serious the consequences they bring.

From the perspective of the public transport damage in cities (see Table 6.3), Hong Kong is the most negative city (-4.42), followed by Macao (-2.21) and Zhaoqing (-1.15). Except for Hong Kong and Macao, the news sentiment in other cities is higher than the average value of 11 cities. The highest value of news sentiment to public transport is 0.25 in Zhuhai, followed by -0.14 in Huizhou and -0.37 in Zhongshan. As for logistics transport, Hong Kong has the lowest news sentiment value (-3.82). The top three cities with the highest value of news sentiment are Zhuhai (-0.39), Jiangmen (-0.65), and Guangzhou (-0.67). From the perspective of road traffic, cities with a value lower than the average value of 11 cities included Foshan (-1.49), Hong Kong (-4.06), Huizhou (-1.34), Macao (-2.24), Shenzhen (-1.35), Zhongshan (-1.38) and Zhuhai (-1.82). It can be found that Hong Kong has the lowest news sentiment on public transport, logistics transport, and road traffic. The lowest value of news sentiment to traffic accident exits in Zhuhai (-4.25), closely followed by Hong Kong (-4.00), Foshan (-3.68), and Huizhou (-2.80).

As shown in Table 6.3, news sentiments in road traffic damage and traffic accidents are more negative than those in public transport damage and logistics transport damage in Huizhou, Jiangmen, Shenzhen, and Zhuhai. Notably, the difference in news sentiment in public transport damage and traffic accidents is 4.5 in Zhuhai. News sentiments in logistics transport damage and traffic accidents are more negative than in public transport damage and road traffic damage in Dongguan, Foshan, and Zhaoqing. The results indicate that surface water floods lead to more severe damages on logistics transport and traffic accidents than on public transport and road traffic in the three cities. All cities should pay more attention to the traffic accidents caused by surface water floods. In addition, Huizhou, Jiangmen, Shenzhen, and Zhuhai should pay more attention to road traffic damage, and Dongguan, Foshan, and Zhaoqing should focus on logistics transport damage.

Table 6.3 The news sentiment to four damage categories in different cities

City	Public transport	Logistics transport	Road traffic	Traffic accident
Dongguan	-0.83	-1.60	-1.09	-2.42
Foshan	-0.69	-1.58	-1.49	-3.68
Guangzhou	-1.07	-0.67	-0.86	-1.93
Hong Kong	-4.42	-3.82	-4.06	-4.00
Huizhou	-0.14	-1.07	-1.34	-2.80
Jiangmen	-0.38	-0.65	-1.08	-2.58
Macao	-2.21	-2.17	-2.24	0.72
Shenzhen	-0.77	-0.99	-1.35	-2.45
Zhaoqing	-1.15	-0.75	-1.13	-1.42
Zhongshan	-0.37	-1.68	-1.38	-1.82
Zhuhai	0.25	-0.39	-1.82	-4.25

6.3.3 Flood-prone roads investigation

The roads in Shenzhen, Guangzhou, Zhuhai, Zhongshan, and Dongguan were frequently mentioned in news articles (see Figure 6.15). Table 6.4 shows the top ten roads with the most news articles in the GBA in the past seven years. There are 4 roads and 3 roads located in Guangzhou and Shenzhen, respectively. The number of news articles on the ten roads is 8217, accounting for more than 85% of the total news articles on roads. These roads are the major roads of their cities, such as Shennan Avenue of Shenzhen. These roads were of the greatest concern to news media, and the level of these damaged roads may also be more severe in the surface water flood. Except for the top ten roads, all others have been mentioned less than 100 times in the past seven years. These roads were hardly affected by surface water flood and were operating normally during the flood period.

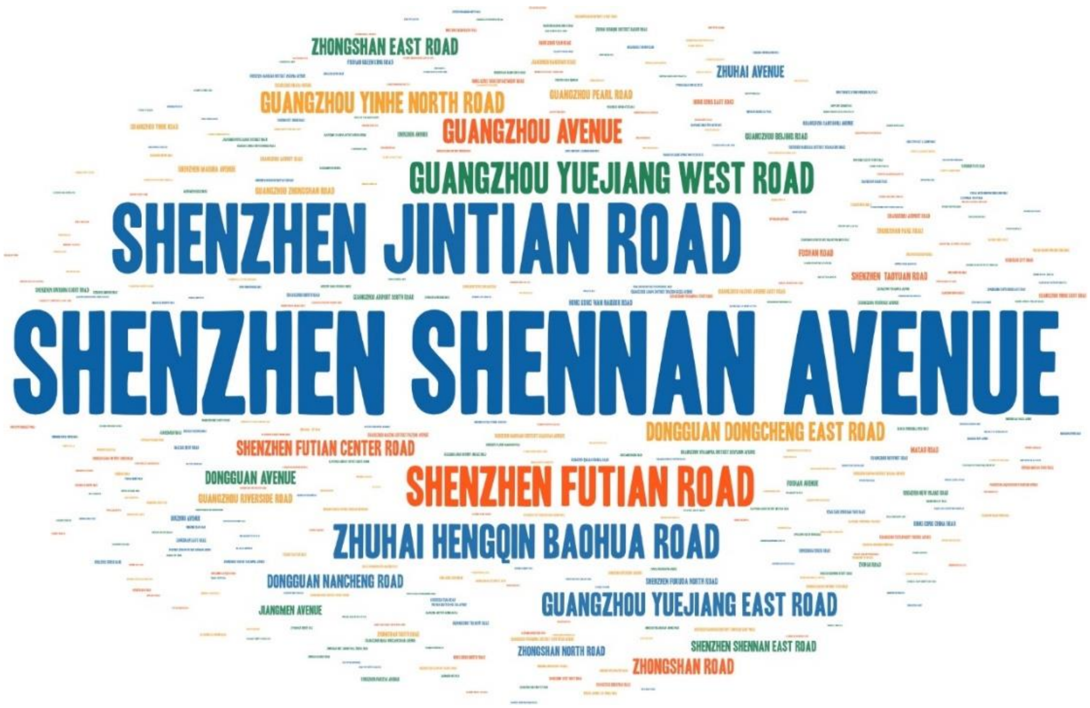

Figure 6.15 Word cloud of the mentioned road in the GBA

Shenzhen Shennan Avenue has the highest news media attention (4038), followed by Shenzhen Jintian Road (1881) and Shenzhen Futian Road (613). Shennan Avenue is a major thoroughfare and one of the most significant roads in the city of Shenzhen. Shennan Avenue runs through the heart of Shenzhen and is often referred to as the city's 'central axis.' It serves as a key transportation artery, a commercial hub, and a symbol of the city's rapid development. Shennan Avenue is well-connected to transport network in Shenzhen. It intersects with various major roads and highways, making it easily accessible for both residents and visitors. Hence, surface water floods can have significant impacts on Shennan Avenue, including disruptions in daily life, transport, and business activities. It can be found that the top three roads with the highest news media attention are located in Shenzhen. Notably, most sections of the three roads are located in Futian District. Some sections of Shennan Avenue are located in Luohu and Nanshan District.

Zhuhai Hengqin Baohua Road has been mentioned 446 times, ranking fourth. Baohua Road is a major road in the Hengqin New Area, which is a special economic zone located close to Macao. It has been developed as a hub for economic, tourism, and cultural activities. Baohua Road plays a significant role in connecting various parts of Hengqin and facilitating transportation within the area. The following 4 roads are all located in Guangzhou, i.e., Yuejiang West Road, Guangzhou Avenue, Yuejiang East Road, and Yinhe North Road. Three of these four roads are located in Haizhu District, and Yinhe North Road is located in Zengcheng District. In particular, Yuejiang West Road is a prominent road that runs along the Pearl River and is known for its scenic waterfront views and connectivity within the city.

Table 6.4 The top ten roads with the most news articles in the GBA

Rank	Road	City	District	Frequency
1	Shennan Avenue	Shenzhen	Luohu district, Nanshan district, Futian district	4038
2	Jintian Road	Shenzhen	Futian district	1881
3	Futian Road	Shenzhen	Futian district	613
4	Hengqin Baohua Road	Zhuhai	Xiangzhou district	446
5	Yuejiang West Road	Guangzhou	Haizhu district	382
6	Guangzhou Avenue	Guangzhou	Haizhu district	226
7	Yuejiang East Road	Guangzhou	Haizhu district	212
8	Yinhe North Road	Guangzhou	Zengcheng district	174
9	Dongguan Dongcheng East Road	Dongguan	Dongguan	135
10	Zhongshan East Road	Zhongshan	Zhongshan	110

The mentioned frequency of Dongguan Dongcheng East Road and Zhongshan East Road is 135 and 110, respectively. Dongcheng East Road is situated in the Dongcheng District, contributing to the accessibility and connectivity of the district. Given the focus on manufacturing and economic development in Dongguan, Dongcheng East Road might pass through or be near commercial areas, industrial zones, and business districts. Zhongshan East Road is a major road within the city of Zhongshan, which might pass through or be adjacent to commercial areas, business districts, shopping centres, and other economic hubs.

6.4 Discussion

With the increasing exposure of road infrastructure to surface water floods, national and local governments have emphasised the optimisation of the road network structure to enhance disaster reduction capabilities (The State Council 2019b; The State Council 2016). Districts with high exposure, low to moderate disaster reduction capability, and high road infrastructure vulnerability need to focus on increasing road density, such as

Dongguan, Zengcheng District of Guangzhou, and Longmen County of Huizhou. Increasing surface road density could enhance the accessibility of emergency rescue services during surface water flood events in vulnerable districts. The results of this study are consistent with current surface road planning. For example, the 14th Five-Year Plan for Guangzhou Transportation mentions that increasing surface road density is one of the critical objectives for the next five years (Guangzhou Municipal Transportation Bureau, 2021).

Districts with low exposure, low disaster reduction capability, and moderate to high road infrastructure vulnerability should focus on constructing high-grade roads and bridges. Examples include São Francisco de Xavier District of Macao, Huidong County of Huizhou, and Guangning County of Zhaoqing. Additionally, permeable pavements (known as 'Sponge Road') should be integrated with increased standards for road drainage systems in new road constructions (Guo et al., 2019; Li et al., 2021). For instance, Dengliang Road in the central urban area of Shenzhen was the first 'Sponge Road' constructed in 2017. Since its construction, road flooding has not occurred on Dengliang Road (sznews.com 2018).

For districts with low exposure, high disaster reduction capability, and low road infrastructure vulnerability, BGI is an efficient practice. These districts are primarily found in Zhaoqing, Guangzhou, Hong Kong, Macao, and Shenzhen, such as Duanzhou District of Zhaoqing, Yuexiu District and Haizhu District of Guangzhou, Freguesia de S. Lourenço District of Macao, and Nanshan District of Shenzhen. These districts are typically located in the CBDs of cities. Improving the standards of drainage systems for roads in these districts is challenging, as it would require extensive rebuilding of road sections and retrofitting practices. For example, the local government needs to consider the disruptions of existing infrastructure (e.g., water pipes, telecommunication cables, etc.) when contemplating rebuilding sewer drainage systems, as seen in Beijing (Gong et al., 2019). Additionally, there may be potential inconveniences to local communities and increased costs associated with these disruptions (Pregnolato et al., 2017). Thus, raising the standards of road drainage systems for certain existing roads would result in higher economic expenses compared to those caused by surface water floods (Koks et al., 2019; Lu et al., 2022).

City authorities are increasingly turning to BGI as a solution to the economic challenge of improving drainage system standards. BGI utilises water bodies and vegetation to reduce surface runoff in urban areas (Li et al., 2021). For example, increasing the use of green and blue-green spaces can boost urban stormwater intake by 30-40%. Additionally, these green infrastructures can help restore the urban hydrological cycle (Han et al., 2023). The construction of BGI in the GBA and other Chinese cities is a common strategy to enhance resilience against surface water floods (Chan et al., 2018). Bio-swales on roadsides are particularly crucial, as they can absorb sudden runoff from intense rainstorms, reducing the pressure on urban drainage pipe networks. Previous success stories in Nanning, Guangxi Province, have shown that implementing sponge infrastructure can reduce urban stormwater runoff by about 45% due to the swales' absorption capacity, which alleviates the pressure on urban drainage networks (Li et al., 2019).

Integrating vulnerability and news media assessments can provide insights beyond road infrastructure impacts, helping understand the effects on road transport activities. This approach not only enhances the performance of the transport system but also stimulates increased economic activity. The findings highlight an inverse relationship between impact frequency and severity, indicating that even infrequent impacts can have highly consequential outcomes. For example, while surface water floods may lead to few traffic accidents, the consequences are often severe. Therefore, prioritising the prevention of traffic accidents caused by surface water floods is crucial for all cities. Furthermore, the results suggest tailored recommendations for specific cities. Huizhou, Jiangmen, Shenzhen, and Zhuhai should focus on mitigating road traffic damage, while Dongguan, Foshan, and Zhaoqing would benefit more from addressing logistics transportation damage. Implementing these targeted strategies can significantly enhance flood preparedness capabilities in these areas.

6.5 Summary

This chapter implemented the potential impact analysis outlined in Chapter 3 (see Section 3.5). Both road infrastructure (i.e., direct tangible) and transport (i.e., indirect tangible) impacts were assessed via vulnerability assessment and word frequency analysis. In summary, the results showed that:

(a) Spatially, districts with sparse and high-grade roads are more physically vulnerable to surface water floods. It was discovered that the road infrastructure vulnerabilities in the western GBA districts are lower than in the central and eastern GBA districts. Within a city, the low and very low road infrastructure vulnerability districts are concentrated in the CBDs.

(b) The assessment results of road infrastructure vulnerability indicate that not all districts with higher exposure correspond to higher road infrastructure vulnerability. Some districts have high and very high disaster reduction capabilities, and thus, even districts with high exposures may have low road infrastructure vulnerabilities. Some districts have low and very low disaster reduction capabilities; thus, even districts with low exposures may have moderate vulnerabilities.

(c) Surface water floods lead to few traffic accidents, but the damage is often extremely serious. Surface water floods lead to frequent logistics disruption, but the damage is often slightly serious. It can be observed that the lower the frequency of the damages, the more serious the consequences they bring.

(d) From the perspective of the impact of information on cities, media attention on transport issues is uneven among GBA cities, which is consistent with the results of Chapter 4. Cities with dense populations and high economies have great pressure on urban traffic, public transport, and logistics transport. Hence, surface water floods may have more impacts on road transport in these cities.

Based on the key results of this chapter, implications for transport and flood managers were discussed. It provided invaluable insights and policy directives for advancing flood management within the road transport system. These recommendations span various domains, including road design and planning and transport operations, all of which enhance the overall resilience of the road transport system in the GBAs.

Finally, Chapter 7 draws overall conclusions from this study, outlining the main achievements and considering the potential direction of future studies.

Chapter 7: Discussion and conclusion

7.1 Introduction

Road transport networks are becoming increasingly vulnerable to adverse flood events with rapid urbanisation and climate change. The inadequate performance of road networks can cause significant disruptions to the urban system. It is crucial to prioritise the development of flexible and adaptable strategies to effectively manage dynamic and uncertain conditions. Based on a review of practical problems and existing academic literature related to surface water flood and road transport, the following research questions were defined:

How can flood management in the road transport system be enhanced via news media data analytics?

The research also addresses the following sub-questions:

RQ (1): How to adopt the news media analysis for better flood preparedness and early warning?

RQ (2): How useful is news media as a source for exploring government agency collaboration for flood response and recovery?

RQ (3): How can potential flood impacts on the road transport system be assessed by combining news media analytics and vulnerability assessment?

These questions have been explored through the integrated framework combining news media data and conventional data through the above chapters of this thesis. To answer these questions, the broader issues of surface water flood in road transport systems were investigated, and the gaps in current scientific research were identified in Chapter 2. An original integrated framework was developed to explore the adoption of news media for flood management in road transport systems, as shown in Chapter 3. The framework was applied to investigate news media activities related to surface water flood and transport networks in Chapter 4. The government agency collaboration for flood response and recovery in the transport system was explored in Chapter 5. News media analysis and vulnerability assessment were integrated to investigate the potential flood impacts on road transport systems in Chapter 6. Moreover, Chapters 4-6 discussed the recommendations for flood management in road transport systems based on analysis results. Chapter 7 provides a concise summary of the research presented in this thesis, emphasising its key accomplishments and innovative contributions. It also discusses the main limitations encountered thus far and suggests potential directions for future research.

7.2 Review of objectives and key findings

7.2.1 Current research progress and proposed framework

Objective (1): to review the current research progress on surface water flood and road transport systems and propose an integrated framework, was achieved in Chapter 2 and Chapter 3. In Chapter 2, publications on the surface water flood and road transport systems were reviewed. Four limitations of existing literature were successfully identified: (a) most of the previous studies focused on social media data analysis rather than news media data analysis, (b) Limited understanding of how news media enhances flood preparedness in the road transport system, (c) Few studies have conducted network analysis to explore government agency engagement and collaboration during flood events, and (d) Limited understanding of how to assess flood impacts on complex transport networks by combining news media and vulnerability assessment.

This thesis tackles the identified problems by developing a unified framework, as described in Chapter 3. The initial issue that guided this research was associated with the increase in frequency and intensity of heavy rainfall in the context of climate change and rapid urbanisation. Moreover, road transport networks are often damaged by heavy rainfall-induced surface water floods. The proposed framework is coupled with the major phases of flood management: ‘preparedness and early warning—response and recovery—mitigation, risk and vulnerability modelling’. The method analysed the news media activities related to the flood and transport networks and how to efficiently adopt news media for better preparedness and early warning. Then, government agency collaboration for flood management in transport systems was explored based on the network analysis, which can contribute to enhancing the performance of flood response and recovery. Finally, potential flood impacts on road infrastructure and transport were assessed, and recommendations for future road design and transport operations were discussed.

7.2.2 Temporal and spatial pattern of news media activity

Objective (2): to investigate news media activities, including media attention and news sentiment, related to surface water flood and transport networks, was achieved in Chapter 4. According to the flood management cycle, Chapter 4 focused on the phase of preparedness and early warning. An analysis of media attention and news sentiment related to flood and transport networks was undertaken from a spatial and temporal perspective. Key findings are as follows:

(a) Media attention is concentrated in densely populated and economically developed cities of the GBA. As for the news sentiment, there is no such significant phenomenon.

(b) From the perspective of temporal evolution, there was a decrease in media attention and an increase in news sentiment over the past seven years. The monthly distribution of news articles mirrors that of rainfall, with concentrations typically occurring from May to September during the wet season.

(c) Media attention on typhoon-induced floods was higher than that on non-typhoon floods, even if they did not lead to severe consequences. As a consequence, low media attention may lead to higher economic losses, especially in situations with higher rainfall.

(d) Media attention on road transport damages displayed an inverted V-shaped pattern during surface water flood events. A predominant observation is that most news articles were published during the flood periods rather than preceding them.

7.2.3 Government agency engagement and collaboration

Objective (3): to explore government agency engagement and collaboration for flood response and recovery, was achieved in Chapter 5. According to the flood management cycle, Chapter 5 focused on the phase of response and recovery. It aims to explore the government agency collaboration for flood management in the transport system. More specifically, this chapter analyses the performance of government agency networks using representative annual flood events from 2017 to 2021 as cases. Key findings are as follows:

(a) The agencies with higher centrality were also more active. These agencies were the key agencies involved in flood management in transport networks, with distinct responsibilities to ensure an efficient response and recovery process.

(b) The government agency collaboration during typhoon-induced floods was closer than during non-typhoon floods. Moreover, the more severe the flood, the closer the collaboration will be.

(c) Agencies with regular connections may collaborate more easily, while it might be difficult for unfamiliar agencies.

7.2.4 Potential flood impacts on road infrastructure and transport

Objective (4): to assess the potential impacts of surface water floods on road infrastructure and transport, was achieved in Chapter 6. According to the flood management cycle, Chapter 6 focused on the phase of mitigation, risk and vulnerability modelling. It aims to address the identified issues to mitigate flood impacts in road transport systems via integrating news media analysis and vulnerability assessment. Key findings are as follows:

(a) Spatially, districts with sparse and high-grade roads are more physically vulnerable to surface water floods. It was discovered that the road infrastructure vulnerabilities in the western GBA districts are lower than in the central and eastern GBA districts.

Within a city, the low and very low road infrastructure vulnerability districts are concentrated in the CBDs.

(b) Some districts have high and very high disaster reduction capabilities, and thus, even districts with high exposures may have low road infrastructure vulnerabilities. Some districts have low and very low disaster reduction capabilities; thus, even districts with low exposures may have moderate vulnerabilities.

(c) Surface water floods lead to few traffic accidents, but the damage is often extremely serious. Surface water floods lead to frequent logistics disruption, but the damage is often slightly severe.

(d) From the perspective of the impact of information on cities, media attention on transport issues is uneven among GBA cities, which is consistent with the results of Chapter 4.

7.3 Implications of this study

7.3.1 Theoretical contributions

This research contributes to the flood management theory in the road transport system and proposes an integrated methodology for the adoption of news media analytics for flood management. Based on the literature review in Chapter 2, previous studies have primarily focused on social media data analysis due to the limited resources of news media data collection. Since 2015, utilising advancements in digital media mining, a promising technology with transformative potential in this domain has emerged: the GKG of the GDELT project. Hence, this research expands the analysis model of news media data and contributes to different phases of flood management via news media analytics. This methodology is not only applicable to the GBA but also to other cities in China and even the world. The following paragraphs present the theoretical contributions in more detail.

Chapter 4 contributes to research related to the analysis of news media data for flood preparedness. Previous studies focused on flood damages/hazards/characteristics through news media data analysis while neglecting the role of the news media itself. News media is one of the most important channels to timely convey rainstorm information, including the intensity, scope, and possible consequences of rainstorms. Hence, the enthusiasm of news media may affect the dissemination of information and response to floods. Chapter 4 conducted the analysis of news media activities (including media attention and news sentiment) to explore the practical issues with existing news media applications and how to utilise news media for better flood preparedness and early warning. It can be found that this study sheds new light on the adoption of news media analysis for flood preparedness and early warning.

Chapter 5 makes two important contributions to the research related to news media analysis for flood response and recovery. Firstly, previous studies have largely focused on conducting media data analysis to explore public response to flood events without paying much attention to the actions of government agencies in response to floods. This study provides the perspective and method for government network analysis via news media data. Secondly, this study offers novel insights into the research on government agency collaboration during flood response and recovery. Previous studies often measure government agency networks through multiple sources of data, such as interviews and questionnaires. These methods sometimes cannot objectively reflect the real situation of agency engagement and collaboration. News media provides an additional source of data to evaluate whether flood governance networks have operated according to their designed policies and plans.

Chapter 6 contributes to the flood damage assessment by integrating news media analytics and vulnerability assessment. This study confirms the utility of the conventional method with news media data in flood damage investigations. Most applied studies of the road transport impacts of flooding rely upon social media data. The integrated method in this study can provide information that extends beyond road infrastructure damages, providing an understanding of the effects on road transport activities at a large scale. Moreover, the proposed method can solve the challenges (e.g., subjective user-generated content, specific areas) of social media data.

7.3.2 Practical contributions

The GBA authorities have already worked under the umbrella of the cooperation mechanism at the Guangdong Provincial level (that includes Hong Kong and Macao), which has liaised with the climate change mitigations and adaptations (Chan, Yang, et al., 2021). The governments of GBA cities have already focused heavily on enhancing flood management. For example, the Guangzhou government has already enacted the Guangzhou White Paper to improve flood protection (Guangzhou Water Bureau 2014). In particular, increasing flood protection standards in central districts was a positive approach. For example, areas besides the Pearl River should be equipped for a 1-in-100-year return period.

However, GBA cities have experienced intensive rainstorms and enhanced floods during the last five years, such as intensive rainstorms enhanced floods around the Dragon Boat Festival, namely the '*Dragon Boat Flood*' (Lu et al., 2022; Chan et al., 2021b). Furthermore, flood events are expected to be more frequent with climate change and impervious surface expansion (Chan et al., 2018; Wang et al., 2020). GBA cities frequently face cyclonic effects on increasing intensive rainstorms, storm surges and combined (compound flood hazards on rainfall and storm-surges and tidal effects) flood hazards (Lai et al., 2021). Improving the current flood management plans necessary to inter-connected and enact more resilient transport practices is urgent. This research contributes to the flood management practices in the road transport system by providing recommendations for city authorities.

Based on the key findings of news media activities related to flood and road transport (see Chapter 4), this research recommended that city authorities should enhance awareness of information disclosure during Dragon Boat Rain season. In other words, media attention needs to be increased during Dragon Boat Rain season. Meanwhile, city authorities should provide more information on the coming rainstorms to both the public and news organisations. More news articles should be released before the flooding rather than only during the flooding. Moreover, the consequences of previous floods, such as traffic disruption and car flooding, could be integrated with early warning signals, which may enhance public awareness of flood preparation.

Based on the key findings of government agency engagement and collaboration (see Chapter 5), this research recommended that more agencies with different functions need to participate during non-typhoon floods. Given the intricate and unpredictable nature of floods, city authorities should adopt a comprehensive approach and an inclusive stance toward cooperation. They should also emphasise occasional yet critical collaborations that significantly impact the overall flood management efforts. Institutional designers should strive to optimise the system network's structure and establish mechanisms that ensure various departments, despite their differences, collaborate effectively during extreme conditions. This proactive approach enhances the efficiency of resource allocation, facilitating better response and management strategies during flood events.

Based on the key findings of potential flood impacts on road infrastructure and transport operation (see Chapter 6), this research recommended that the districts with high exposure, low/moderate disaster reduction capability, and high physical vulnerability need to focus on increasing road density. The districts with low exposure, low disaster reduction capability, and moderate/high physical vulnerability need to focus on constructing high-grade roads and bridges. As for the districts with low exposure, high disaster reduction capability, and low physical vulnerability, BGI is an efficient practice. As for transport operations, prioritising the prevention of traffic accidents caused by surface water floods is essential for all cities. Furthermore, the results suggest tailored recommendations for specific cities (see Section 6.4).

7.4 Limitations and future studies

7.4.1 Limitations

Despite progress being made via this study, substantial limitations still require further research.

Chapter 4 investigated the temporal and spatial patterns of news media activity related to surface water flood and road transport. Moreover, the relationship between rainfall intensity and news media activity has been explored based on the information on specific flood events. However, owing to the lack of data such as real transport damage data, the action mechanism of news media activity on road and transport damage is vague and uncertain in this study. In other words, it is still unclear whether the level of news media activity has an impact on the consequences of surface water floods. For example, does more news media coverage before floods effectively reduce road transport losses? The unclear relationship between flooding intensity and duration and the slope of the V-shaped line also a significant limitation of this studies.

As for the network analysis, Chapter 5 only focused on government agency engagement and collaboration. Notably, non-government organisations (NGOs) complement the efforts of government agencies in responding to floods and helping communities recover from their impacts. NGOs also raise public awareness about the importance of flood preparedness. According to the data quality assessment, the quality of NGO information in the GDELT project is not as good as that of government agencies. It is challenging to extract NGOs from massive organisations in the GDELT project. Regrettably, NGO network analysis was not conducted in this thesis.

Additionally, Chapter 6 analysed the potential flood impacts on road infrastructure and transport via news media analytics and vulnerability assessment. However, this research concentrated on the macroscopical analysis, and the results only reflected the flood impacts on road transport systems (i.e., direct tangible impacts and indirect tangible impacts). The understanding of transport damage impacts on the entire urban system was still limited, such as how transport disruptions affect socio-economic activities. Such kind of analysis requires more data (e.g., traffic flow data) and models (e.g., hydrologic model and traffic model).

Therefore, this PhD thesis discussed only the beginning of the application of news media analytics for flood management in the road transport system. Whereas some limitations exist, this study clearly illustrates that the adoption of news media data provided insights into flood management in the road transport system.

7.4.2 Future studies

There are various potential directions for future work identified from the research detailed in this thesis. Here, this section provides a list of possible future research as follows:

Firstly, more efforts can be made to collect real damage data, such as accurate transport damage data, via data sharing with transport departments, questionnaires, and interviews. For example, transport departments can share data on road closures, infrastructure damage, and traffic disruptions caused by floods. They can also provide information on the cost of repairs and the duration of disruptions. Additionally, surveys and interviews can be conducted with transport users and stakeholders to gather information on the impact of floods on transport services and infrastructure. If such real data records are unavailable, developing image identification methods can explore the flood damage from images or videos on social media platforms or news media websites. Algorithms that can analyse images and videos can be developed to identify flooded areas, damaged roads, and stranded vehicles. These methods can help gather data on the extent and severity of flood damage when real data is lacking.

Based on the damage data, the correlation analysis between news media activity and transport damage can answer whether news media activity can affect the consequences of flood on transport and how news media activity can reduce the damage. For instance, the study can analyse news coverage before, during, and after flood events to determine if increased media attention leads to better preparedness and response measures, ultimately reducing transport damage. They can also examine how specific media campaigns or messages influence public behaviour and decision-making during floods, which can help identify effective strategies for reducing damage.

Secondly, a list of NGOs involved in flood management should be compiled to extract NGO information from news media data. For example, a database of NGOs that are active in flood management can be created as a reference for extracting NGO information from news articles. Text mining algorithms can be developed to improve the accuracy of NGO information extraction. These algorithms can be trained on a dataset of news articles and NGO information to learn patterns and keywords associated with NGOs. If there is a shortage of NGO information from news articles, social media data (e.g., Weibo, Twitter) can be used as a supplement. For instance, future studies can collect tweets or posts related to floods and extract information about NGOs mentioned in these posts. Then, network analysis can be conducted to explore the engagement and collaboration among NGOs or between government agencies and NGOs. The network analysis may reveal gaps in collaboration or areas where coordination can be improved. This information can be used to develop strategies for strengthening partnerships between NGOs and government agencies, ultimately improving the effectiveness of flood management efforts. Additionally, by understanding the network of organisations involved in flood management, local communities can better prepare for future floods and respond more effectively when they occur.

Finally, simulation models, such as the hydrodynamic model and traffic model, can be combined with news media data to investigate intangible impacts of surface water flood on road transport systems. Hydrodynamic models can be used to simulate the extent and depth of flooding on roads, considering factors such as rainfall intensity and topography. Traffic models can then be used to simulate how the flooding affects traffic flow and travel times on affected roads. Additionally, social-economic data, such as GDP per capita, can be integrated to explore socio-economic sensitivity caused by transport damage from surface water floods. Incorporating this data into simulation models can offer a more holistic insight into how surface water floods affect road transport systems and help identify strategies for reducing their socio-economic impact.

Moreover, the impacts analysis could consider different scenarios to predict future long-term flood impacts on road transport. For example, future studies could develop scenarios based on projected changes in climate and land use to assess how these factors might affect the frequency and severity of surface water floods and their impacts on road transport systems. Scenarios related to infrastructure development and maintenance could also be considered to evaluate how investments in road infrastructure could mitigate the impacts of floods. By analysing these scenarios, potential future challenges and opportunities can be identified for road transport systems in the face of surface water floods. This information can help policymakers and planners develop strategies to enhance the resilience of road transport systems and reduce their vulnerability to floods.

References

Abbasi, A., Kapucu, N., 2012. Structural Dynamics of Organizations during the Evolution of Interorganizational Networks in Disaster Response [online]. *Journal of Homeland Security and Emergency Management*, 9(1). Available at: https://www.degruyter.com/document/doi/10.1515/1547-7355.1975/html [Accessed 6 January 2024].

Abdeen, F.N. et al., 2021. Challenges in multi-agency collaboration in disaster management: A Sri Lankan perspective. *International Journal of Disaster Risk Reduction*, 62, p.102399. 10.1016/j.ijdrr.2021.102399.

Abdi, Herve, 2007. Multiple correlation coefficient. *Encyclopedia of measurement and statistics*, 648(651), p.19.

Abdi, Hervé, 2007. The Kendall rank correlation coefficient. *Encyclopedia of measurement and statistics*, 2, pp.508–510.

Abebe, Y., Kabir, G., Tesfamariam, S., 2018. Assessing urban areas vulnerability to pluvial flooding using GIS applications and Bayesian Belief Network model. *Journal of Cleaner Production*, 174, pp.1629–1641. 10.1016/j.jclepro.2017.11.066.

Adger, W.N., 2006. Vulnerability. *Global Environmental Change*, 16(3), pp.268–281. 10.1016/j.gloenvcha.2006.02.006.

Ahmad, K. et al., 2019. Automatic detection of passable roads after floods in remote sensed and social media data. *Signal Processing: Image Communication*, 74, pp.110–118. 10.1016/j.image.2019.02.002.

Ahmed, Y.A. et al., 2019. Social media for knowledge-sharing: A systematic literature review. *Telematics and Informatics*, 37, pp.72–112. 10.1016/j.tele.2018.01.015.

Alipour Sarvari, P., Nozari, M., Khadraoui, D., 2019. The Potential of Data Analytics in Disaster Management. In: Calisir, F., Cevikcan, E., Camgoz Akdag, H., eds. *Industrial Engineering in the Big Data Era*. Lecture Notes in Management and Industrial Engineering. Cham: Springer International Publishing, pp. 335–348. 10.1007/978-3-030-03317-0_28.

Almoradie, A., Cortes, V. j., Jonoski, A., 2015. Web-based stakeholder collaboration in flood risk management. *Journal of Flood Risk Management*, 8(1), pp.19–38. 10.1111/jfr3.12076.

Aluko, F. et al., 2020. Evaluating the Influence of Resident Agencies' Participation in Flood Management via Social Media, in Nigeria. *Pertanika Journal of Social Sciences and Humanities*, 28. 10.47836/pjssh.28.4.15.

Andrade, M.M.N. de, Szlafsztein, C.F., 2018. Vulnerability assessment including tangible and intangible components in the index composition: An Amazon case study of flooding and flash flooding. *Science of The Total Environment*, 630, pp.903–912. 10.1016/j.scitotenv.2018.02.271.

Andrasi, B. et al., 2021. Quantifying the road-effect zone for a critically endangered primate. *Conservation Letters*, 14(6), p.e12839. 10.1111/conl.12839.

Aroca-Jiménez, E., Bodoque, J.M., García, J.A., 2020. How to construct and validate an Integrated Socio-Economic Vulnerability Index: Implementation at regional scale in urban areas prone to flash flooding. *Science of The Total Environment*, 746, p.140905. 10.1016/j.scitotenv.2020.140905.

Arrighi, C., Pregnolato, M., Castelli, F., 2021. Indirect flood impacts and cascade risk across interdependent linear infrastructures. *Natural Hazards and Earth System Sciences*, 21(6), pp.1955–1969. 10.5194/nhess-21-1955-2021.

Asomani-Boateng, R., Fricano, R.J., Adarkwa, F., 2015. Assessing the socio-economic impacts of rural road improvements in Ghana: A case study of Transport Sector Program Support (II). *Case Studies on Transport Policy*, 3(4), pp.355–366. 10.1016/j.cstp.2015.04.006.

Aung, T.M., Lim, S., 2021. Evolution of Collaborative Governance in the 2015, 2016, and 2018 Myanmar Flood Disaster Responses: A Longitudinal Approach to a Network Analysis. *International Journal of Disaster Risk Science*, 12(2), pp.267–280. 10.1007/s13753-021-00332-y.

Avellaneda, P.M. et al., 2020. Improving Hydrological Models With the Assimilation of Crowdsourced Data. *Water Resources Research*, 56(5), p.e2019WR026325. 10.1029/2019WR026325.

Balogun, A.-L. et al., 2020. Assessing the Potentials of Digitalization as a Tool for Climate Change Adaptation and Sustainable Development in Urban Centres. *Sustainable Cities and Society*, 53, p.101888. 10.1016/j.scs.2019.101888.

Benesty, J. et al., 2009. Pearson Correlation Coefficient [eBook]. In: Cohen, I. … Benesty, J., eds. *Noise Reduction in Speech Processing*. Berlin, Heidelberg: Springer, 2009, pp. 1–4. Available at: https://doi.org/10.1007/978-3-642-00296-0_5 [Accessed 14 June 2024].

Benito, G. et al., 2004. Use of Systematic, Palaeoflood and Historical Data for the Improvement of Flood Risk Estimation. Review of Scientific Methods. *Natural Hazards*, 31(3), pp.623–643. 10.1023/B:NHAZ.0000024895.48463.eb.

Bohensky, E.L., Leitch, A.M., 2014. Framing the flood: a media analysis of themes of resilience in the 2011 Brisbane flood. *Regional Environmental Change*, 14(2), pp.475–488. 10.1007/s10113-013-0438-2.

Cao, Z. et al., 2020. Explicit Spatializing Heat-Exposure Risk and Local Associated Factors by coupling social media data and automatic meteorological station data. *Environmental Research*, 188, p.109813. 10.1016/j.envres.2020.109813.

Carr, C.T., Hayes, R.A., 2015. Social Media: Defining, Developing, and Divining. *Atlantic Journal of Communication*, 23(1), pp.46–65. 10.1080/15456870.2015.972282.

Cascini, L., 2008. Applicability of landslide susceptibility and hazard zoning at different scales. *Engineering Geology*, 102(3–4), pp.164–177. 10.1016/j.enggeo.2008.03.016.

Chan, F.K.S., Chen, W.Y., et al., 2021. Build in prevention and preparedness to improve climate resilience in coastal cities: Lessons from China's GBA. *One Earth*, 4(10), pp.1356–1360. 10.1016/j.oneear.2021.09.016.

Chan, F.K.S. et al., 2018. "Sponge City" in China—A breakthrough of planning and flood risk management in the urban context. *Land Use Policy*, 76, pp.772–778. 10.1016/j.landusepol.2018.03.005.

Chan, F.K.S., Yang, L.E., et al., 2021. Urban flood risks and emerging challenges in a Chinese delta: The case of the Pearl River Delta. *Environmental Science & Policy*, 122, pp.101–115. 10.1016/j.envsci.2021.04.009.

Chang, C.-T. et al., 2018. Shifts in stream hydrochemistry in responses to typhoon and non-typhoon precipitation. *Biogeosciences*, 15(8), pp.2379–2391. 10.5194/bg-15-2379-2018.

Chaoran, L., Yuanzhi, Z., 2021. The average time of EMS response is 18 minutes in Beijing [online]. Available at: https://www.jksb.com.cn/html/life/headlines/2021/0104/168551.html.

Chaves, H.M.L., Alipaz, S., 2007. An Integrated Indicator Based on Basin Hydrology, Environment, Life, and Policy: The Watershed Sustainability Index. *Water Resources Management*, 21(5), pp.883–895. 10.1007/s11269-006-9107-2.

Chen, C.-H. et al., 2005. Development of a dynamic strategy planning theory and system for sustainable river basin land use management. *Science of The Total Environment*, 346(1), pp.17–37. 10.1016/j.scitotenv.2004.12.057.

Chen, M. et al., 2014. The provincial pattern of the relationship between urbanization and economic development in China. *Journal of Geographical Sciences*, 24(1), pp.33–45. 10.1007/s11442-014-1071-9.

Chen, X. et al., 2019. Study on the classification of typhoon and non-typhoon related rainstorm flood. *China Flood Drought Manag*, 29(4), pp.18–21.

Chen, Z. et al., 2021. Sustainability drivers in road transportation system: Evidence from China. *Science of The Total Environment*, 798, p.149259. 10.1016/j.scitotenv.2021.149259.

Cheng, H. et al., 2024. Different responses of event-based flood to typhoon and non-typhoon rainstorms under land use change in Xixi Basin of southeastern China. *CATENA*, 234, p.107562. 10.1016/j.catena.2023.107562.

Cheong, F., Cheong, C., 2011. Social Media Data Mining: A Social Network Analysis Of Tweets During The 2010-2011 Australian Floods [online]. *PACIS 2011 Proceedings*. Available at: https://aisel.aisnet.org/pacis2011/46.

China daily, 2011. Heavy rain disrupts Beijing traffic [online]. Available at: http://www.chinadaily.com.cn/ethnic/photo/2011-06/23/content_12763843_2.htm [Accessed 4 March 2021].

China meteorological administration, 2018. *Specifications for urban waterlogging risk investigation*.

Cho, S.Y., Chang, H., 2017. Recent research approaches to urban flood vulnerability, 2006–2016. *Natural Hazards*, 88(1), pp.633–649. 10.1007/s11069-017-2869-4.

Choubin, B. et al., 2019. An ensemble prediction of flood susceptibility using multivariate discriminant analysis, classification and regression trees, and support vector machines. *Science of The Total Environment*, 651, pp.2087–2096. 10.1016/j.scitotenv.2018.10.064.

Choy, C., Wu, M., Lee, T., 2020. Assessment of the damages and direct economic loss in Hong Kong due to Super Typhoon Mangkhut in 2018. *Tropical Cyclone Research and Review*, 9(4), pp.193–205. 10.1016/j.tcrr.2020.11.001.

Chung, E.-S., Lee, K.S., 2009. Identification of Spatial Ranking of Hydrological Vulnerability Using Multi-Criteria Decision Making Techniques: Case Study of Korea. *Water Resources Management*, 23(12), pp.2395–2416. 10.1007/s11269-008-9387-9.

Cohen, A. et al., 2005. Using co-occurrence network structure to extract synonymous gene and protein names from MEDLINE abstracts. *BMC Bioinformatics*, 6, p.103. 10.1186/1471-2105-6-103.

Cojanu, V., Dobre, R., Pătru-Stupariu, I., 2012. The Accessibility Buffer – A Basic GIS Tool in Determining the Competitive Potential Index. *Procedia Environmental Sciences*, 14, pp.237–246. 10.1016/j.proenv.2012.03.023.

Coles, D. et al., 2017. Beyond ‘flood hotspots’: Modelling emergency service accessibility during flooding in York, UK. *Journal of Hydrology*, 546, pp.419–436. 10.1016/j.jhydrol.2016.12.013.

Constitutional and Mainland Affairs Bureau, 2022. Guangdong-Hong Kong-Macao Greater Bay Area - Home [online]. Available at: https://www.bayarea.gov.hk/en/home/index.html [Accessed 12 March 2023].

Cook, S. et al., 2019. WSUD "Best in Class"—Case Studies From Australia, New Zealand, United States, Europe, and Asia [eBook]. In: *Approaches to Water Sensitive Urban Design*. Elsevier, 2019, pp. 561–585. Available at: https://linkinghub.elsevier.com/retrieve/pii/B9780128128435000277 [Accessed 15 July 2021].

Copestake, A., 2018. 13: Betweenness Centrality - Machine Learning and Real-world Data (MLRD) [online]. Available at: https://www.cl.cam.ac.uk/teaching/1718/MLRD/slides/slides13.pdf.

CRED, UNISDR, 2020. Human Cost of Disasters 2000-2019 [online]. Available at: https://www.preventionweb.net/files/74124_humancostofdisasters20002019reportu.pdf.

CRED, UNISDR, 2015. The Human Cost of Weather-Related Disasters 1995-2015 [online]. Available at: https://www.undrr.org/publication/human-cost-weather-related-disasters-1995-2015.

CrisisLex.org, 2014. CrisisLex: Crisis-Related Social Media Data and Tools [online]. Available at: http://crisislex.org/ [Accessed 23 August 2023].

Dame, J. et al., 2019. Urbanisation and socio-ecological challenges in high mountain towns: Insights from Leh (Ladakh), India. *Landscape and Urban Planning*, 189, pp.189–199. 10.1016/j.landurbplan.2019.04.017.

Dandapat, K., Panda, G.K., 2017. Flood vulnerability analysis and risk assessment using analytical hierarchy process. *Modeling Earth Systems and Environment*, 3(4), pp.1627–1646. 10.1007/s40808-017-0388-7.

Dang, X. et al., 2020. Comparative study of city-level sustainability assessment standards in China and the United States. *Journal of Cleaner Production*, 251, p.119622. 10.1016/j.jclepro.2019.119622.

Darabi, H. et al., 2019. Urban flood risk mapping using the GARP and QUEST models: A comparative study of machine learning techniques. *Journal of Hydrology*, 569, pp.142–154. 10.1016/j.jhydrol.2018.12.002.

Debele, S.E. et al., 2019. Nature-based solutions for hydro-meteorological hazards: Revised concepts, classification schemes and databases. *Environmental Research*, 179, p.108799. 10.1016/j.envres.2019.108799.

deFur, P.L. et al., 2007. Vulnerability as a Function of Individual and Group Resources in Cumulative Risk Assessment. *Environmental Health Perspectives*, 115(5), pp.817–824. 10.1289/ehp.9332.

Delor, F., Hubert, M., 2000. Revisiting the concept of 'vulnerability'. *Social Science & Medicine*, 50(11), pp.1557–1570. 10.1016/S0277-9536(99)00465-7.

Deng, J.-L., Shen, S.-L., Xu, Y.-S., 2016. Investigation into pluvial flooding hazards caused by heavy rain and protection measures in Shanghai, China. *Natural Hazards*, 83(2), pp.1301–1320. 10.1007/s11069-016-2369-y.

Department of Transport of Guangdong Province, 2020. *Guangdong Province's expressway network planning (广东省高速公路规划)（2020-2035）*[online]. Available at: http://td.gd.gov.cn/zcwj_n/tzgg/content/post_3007389.html [Accessed 13 March 2023].

Derr, A., 2021. Network Centrality: Understanding Degree, Closeness & Betweenness Centrality [online]. *Visible Network Labs*. Available at: https://visiblenetworklabs.com/2021/04/16/understanding-network-centrality/ [Accessed 25 December 2023].

Di Matteo, M., Dandy, G.C., Maier, H.R., 2017. A multi-stakeholder portfolio optimization framework applied to stormwater best management practice (BMP) selection. *Environmental Modelling & Software*, 97, pp.16–31. 10.1016/j.envsoft.2017.07.012.

Diakoulaki, D., Mavrotas, G., Papayannakis, L., 1995. Determining objective weights in multiple criteria problems: The critic method. *Computers & Operations Research*, 22(7), pp.763–770. 10.1016/0305-0548(94)00059-H.

Dictionary, O.S., 2014. Definition Of News.

Dou, Y. et al., 2019. New media data-driven measurement for the development level of prefabricated construction in China. *Journal of Cleaner Production*, 241, p.118353. 10.1016/j.jclepro.2019.118353.

Duan, T. et al., 2021. Systematic evaluation of management measure effects on the water environment based on the DPSIR-Tapio decoupling model: A case study in the Chaohu Lake watershed, China. *Science of The Total Environment*, 801, p.149528. 10.1016/j.scitotenv.2021.149528.

Duan, Y. et al., 2022. Flood vulnerability assessment using the triangular fuzzy number-based analytic hierarchy process and support vector machine model for the Belt and Road region. *Natural Hazards*, 110(1), pp.269–294. 10.1007/s11069-021-04946-9.

Dung, N.B. et al., 2022. The Role of Factors Affecting Flood Hazard Zoning Using Analytical Hierarchy Process: A Review. *Earth Systems and Environment*, 6(3), pp.697–713. 10.1007/s41748-021-00235-4.

EEA, 2015. Dpsir — Environmental Terminology Discovery Service — EEA [online]. Available at:

https://web.archive.org/web/20150719082338/http://glossary.eea.europa.eu/terminology/concept_html?term=dpsir [Accessed 20 April 2022].

EM-DAT, 2023. Public EM-DAT platform [online]. Available at: https://public.emdat.be/data [Accessed 1 March 2024].

ESCAP/WMO Typhoon Committee, 2017. *Member Report China*.

Fan, B., Li, Z., Desouza, K.C., 2022. Interagency collaboration within the city emergency management network: a case study of Super Ministry Reform in China. *Disasters*, 46(2), pp.371–400. 10.1111/disa.12495.

Fang, J. et al., 2019. Assessing disaster impacts and response using social media data in China: A case study of 2016 Wuhan rainstorm. *International Journal of Disaster Risk Reduction*, 34, pp.275–282. 10.1016/j.ijdrr.2018.11.027.

Fauzi, M.A., 2023. Social media in disaster management: review of the literature and future trends through bibliometric analysis. *Natural Hazards*, 118(2), pp.953–975. 10.1007/s11069-023-06079-7.

Feldman, T., 1996. *An Introduction to Digital Media*. London: Routledge. 10.4324/9780203398401.

Feng, D., Shi, X., Renaud, F.G., 2023. Risk assessment for hurricane-induced pluvial flooding in urban areas using a GIS-based multi-criteria approach: A case study of Hurricane Harvey in Houston, USA. *Science of The Total Environment*, 904, p.166891. 10.1016/j.scitotenv.2023.166891.

Fistung, F.D. et al., 2014. Transport in Support of the Process of Socio-economic Development of Romania, After 1990. *Procedia Economics and Finance*, 8, pp.313–319. 10.1016/S2212-5671(14)00096-3.

Fliervoet, J.M. et al., 2016. Analyzing Collaborative Governance Through Social Network Analysis: A Case Study of River Management Along the Waal River in The Netherlands. *Environmental Management*, 57(2), pp.355–367. 10.1007/s00267-015-0606-x.

Fohringer, J. et al., 2015. Social media as an information source for rapid flood inundation mapping. *Natural Hazards and Earth System Sciences*, 15(12), pp.2725–2738. 10.5194/nhess-15-2725-2015.

Formetta, G., Feyen, L., 2019. Empirical evidence of declining global vulnerability to climate-related hazards. *Global Environmental Change*, 57, p.101920. 10.1016/j.gloenvcha.2019.05.004.

Freilich, S. et al., 2010. The large-scale organization of the bacterial network of ecological co-occurrence interactions. *Nucleic Acids Research*, 38(12), pp.3857–3868. 10.1093/nar/gkq118.

Gandini, A. et al., 2020. A holistic and multi-stakeholder methodology for vulnerability assessment of cities to flooding and extreme precipitation events. *Sustainable Cities and Society*, 63, p.102437. 10.1016/j.scs.2020.102437.

Ganesan, K., 2019. What is Term Frequency? [online blog]. *Opinosis Analytics*. Available at: https://www.opinosis-analytics.com/knowledge-base/term-frequency-explained/ [Accessed 25 December 2023].

Gao, Y. et al., 2023. Tracking Chinese newspaper coverage of elephant ivory through topic modeling. *Conservation Biology*, 37(5), p.e14072. 10.1111/cobi.14072.

Gedik, A., 2020. A review on the evaluation of the potential utilization of construction and demolition waste in hot mix asphalt pavements. *Resources, Conservation and Recycling*, 161, p.104956. 10.1016/j.resconrec.2020.104956.

Gentry-Shields, J., Bartram, J., 2014. Human health and the water environment: Using the DPSEEA framework to identify the driving forces of disease. *Science of The Total Environment*, 468–469, pp.306–314. 10.1016/j.scitotenv.2013.08.052.

George C. S. et al., 2007. *China's Urban Space: Development Under Market Socialism*.

Gimenez-Maranges, M., Breuste, J., Hof, A., 2020. Sustainable Drainage Systems for transitioning to sustainable urban flood management in the European Union: A review. *Journal of Cleaner Production*, 255, p.120191. 10.1016/j.jclepro.2020.120191.

Golbeck, J., 2013. Chapter 3 - Network Structure and Measures [eBook]. In: Golbeck, J., ed. *Analyzing the Social Web*. Boston: Morgan Kaufmann, 2013, pp. 25–44. Available at: https://www.sciencedirect.com/science/article/pii/B9780124055315000031 [Accessed 25 December 2023].

Golbeck, J., 2015. Chapter 21 - Analyzing networks [eBook]. In: Golbeck, J., ed. *Introduction to Social Media Investigation*. Boston: Syngress, 2015, pp. 221–235. Available at: https://www.sciencedirect.com/science/article/pii/B9780128016565000214 [Accessed 25 December 2023].

Gong, Y. et al., 2019. Effectiveness Analysis of Systematic Combined Sewer Overflow Control Schemes in the Sponge City Pilot Area of Beijing. *International Journal of Environmental Research and Public Health*, 16(9), p.1503. 10.3390/ijerph16091503.

Google Cloud, 2020. BigQuery Enterprise Data Warehouse [online]. *Google Cloud*. Available at: https://cloud.google.com/bigquery [Accessed 25 August 2023].

Government of Macau Special Administrative Region Statistics and Census Service, 2018. "8.23"Typhoon Caused Macao an Estimated Economic Loss of

MOP12.55 Billion [online]. *Macao SAR Government Portal*. Available at: https://www.gov.mo/en/news/92355/ [Accessed 5 December 2023].

Green, D. et al., 2017. City-scale accessibility of emergency responders operating during flood events. *Natural Hazards and Earth System Sciences*, 17(1), pp.1–16. 10.5194/nhess-17-1-2017.

Griessner, M.C., 2012. News agencies and Social Media.

Guangdong Meteorological Service, Hong Kong Observatory, Macao Meteorological and Geophysical Bureau, 2018. *Guangdong-Hong Kong-Macao Greater Bay Area Climate Bulletin 2018*.

Guangdong Meteorological Service, Hong Kong Observatory, Macao Meteorological and Geophysical Bureau, 2019. *Guangdong-Hong Kong-Macao Greater Bay Area Climate Bulletin 2019*.

Guangdong Meteorological Service, Hong Kong Observatory, Macao Meteorological and Geophysical Bureau, 2020. *Guangdong-Hong Kong-Macao Greater Bay Area Climate Bulletin 2020*.

Guangdong Meteorological Service, Hong Kong Observatory, Macao Meteorological and Geophysical Bureau, 2021. *Guangdong-Hong Kong-Macao Greater Bay Area Climate Bulletin 2021*.

Guangdong Provincial Committee of the Chinese People's Political Consultative Conference, 2021. 关于提高粤港澳大湾区城镇化高质量转型发展的提案 [online]. Available at: https://www.gdszx.gov.cn/zxhy/qthy/2021/wyta2021/content/post_21765.html [Accessed 9 March 2023].

Guangzhou Municipal Transportation Bureau, 2021. *The 14th Five-Year Plan for Guangzhou Transportation* [online]. Available at: https://www.gz.gov.cn/zt/jjsswgh/kxbz/content/post_7825207.html [Accessed 15 November 2022].

Guangzhou Water Bureau, 2014. *Guangzhou Water White Paper 2013 (in Chinese)*.

Gundersen, T. et al., 2022. A New Dark Age? Truth, Trust, and Environmental Science. *Annual Review of Environment and Resources*, 47(1), pp.5–29. 10.1146/annurev-environ-120920-015909.

Guo, X. et al., 2019. Sponge roads: the permeable asphalt pavement structures based on rainfall characteristics in central plains urban agglomeration of China. *Water Science and Technology*, 80(9), pp.1740–1750. 10.2166/wst.2019.426.

Guo, X., Kapucu, N., 2015. Examining collaborative disaster response in China: network perspectives. *Natural Hazards*, 79(3), pp.1773–1789. 10.1007/s11069-015-1925-1.

Habel, S. et al., 2017. Development of a model to simulate groundwater inundation induced by sea-level rise and high tides in Honolulu, Hawaii. *Water Research*, 114, pp.122–134. 10.1016/j.watres.2017.02.035.

Hajar Nasiri, Mohd Johari Mohd Yusof, Thamer Ahmad Mohammad Ali, 2016. An overview to flood vulnerability assessment methods. *Sustainable Water Resources Management*, 2(3), pp.331–336. 10.1007/s40899-016-0051-x.

Han, J. et al., 2023. China's sponge cities alleviate urban flooding and water shortage: a review [online]. *Environmental Chemistry Letters*. Available at: https://doi.org/10.1007/s10311-022-01559-x [Accessed 20 February 2023].

Harcup, T., O'Neill, D., 2017. What is News?: News values revisited (again). *Journalism Studies*, 18(12), pp.1470–1488. 10.1080/1461670X.2016.1150193.

He, H. et al., 2023. Current overview of impact analysis and risk assessment of urban pluvial flood on road traffic. *Sustainable Cities and Society*, 99, p.104993. 10.1016/j.scs.2023.104993.

He, Y. et al., 2021. Flash flood vulnerability assessment of roads in China based on support vector machine. *Geocarto International*, pp.1–24. 10.1080/10106049.2021.1926560.

Hélène, B. et al., 2022. Vulnerability and spatial competition: The case of fisheries and offshore wind projects. *Ecological Economics*, 197, p.107454. 10.1016/j.ecolecon.2022.107454.

Hénonin, J. et al., 2015. Citywide multi-grid urban flood modelling: the July 2012 flood in Beijing. *Urban Water Journal*, 12(1), pp.52–66. 10.1080/1573062X.2013.851710.

Henrique, K.P., Tschakert, P., 2019. Taming São Paulo's floods: Dominant discourses, exclusionary practices, and the complicity of the media. *Global Environmental Change*, 58, p.101940. 10.1016/j.gloenvcha.2019.101940.

Hernandez-Fajardo, I., Dueñas-Osorio, L., 2013. Probabilistic study of cascading failures in complex interdependent lifeline systems. *Reliability Engineering & System Safety*, 111, pp.260–272. 10.1016/j.ress.2012.10.012.

Hipple, J.D., Drazkowski, B., Thorsell, P.M., 2005. Development in the Upper Mississippi Basin: 10 years after the Great Flood of 1993. *Landscape and Urban Planning*, 72(4), pp.313–323. 10.1016/j.landurbplan.2004.03.012.

Hong Kong Observatory, 2017. Super Typhoon Hato(1713) [online]. Available at: https://www.hko.gov.hk/en/informtc/hato17/report.htm [Accessed 21 April 2023].

Hong Kong Observatory, 2018. Super Typhoon Mangkhut(1822) [online]. Available at: https://www.hko.gov.hk/en/informtc/mangkhut18/report.htm [Accessed 21 April 2023].

Hongyu Zhang, Jacek Malczewski, 2018. Accuracy Evaluation of the Canadian OpenStreetMap Road Networks.

Hooper, 2013. *Future resilient transport networks: current and future impacts of precipitation on a UK motorway corridor*. DOCTOR OF PHILOSOPHY. University of Birmingham.

Horita, F.E.A. et al., 2015. Development of a spatial decision support system for flood risk management in Brazil that combines volunteered geographic information with wireless sensor networks. *Computers & Geosciences*, 80, pp.84–94. 10.1016/j.cageo.2015.04.001.

Hosseini, F.S. et al., 2021. Towards a flood vulnerability assessment of watershed using integration of decision-making trial and evaluation laboratory, analytical network process, and fuzzy theories. *Environmental Science and Pollution Research*, 28(44), pp.62487–62498. 10.1007/s11356-021-14534-w.

Hou, J., Du, Y., 2020. Spatial simulation of rainstorm waterlogging based on a water accumulation diffusion algorithm. *Geomatics, Natural Hazards and Risk*, 11(1), pp.71–87. 10.1080/19475705.2019.1707719.

Howard, P.N., Hussain, M.M., 2011. The role of digital media. *J. Democracy*, 22, p.35.

Hu, X. et al., 2016. The spatial exposure of the Chinese infrastructure system to flooding and drought hazards. *Natural Hazards*, 80(2), pp.1083–1118. 10.1007/s11069-015-2012-3.

Huang, D. et al., 2012. An assessment of multidimensional flood vulnerability at the provincial scale in China based on the DEA method. *Natural Hazards*, 64(2), pp.1575–1586. 10.1007/s11069-012-0323-1.

Huang, H. et al., 2018. The changing pattern of urban flooding in Guangzhou, China. *Science of The Total Environment*, 622–623, pp.394–401. 10.1016/j.scitotenv.2017.11.358.

Huang, J. et al., 2013. Methodology for the assessment and classification of regional vulnerability to natural hazards in China: the application of a DEA model. *Natural Hazards*, 65(1), pp.115–134. 10.1007/s11069-012-0348-5.

Hui, E.C.M. et al., 2020. Deciphering the spatial structure of China’s megacity region: A new bay area—The Guangdong-Hong Kong-Macao Greater Bay Area in the making. *Cities*, 105, p.102168. 10.1016/j.cities.2018.10.011.

International Energy Agency, 2009. Transport Energy Efficiency.

James, C., 2022. Equal Weight Investing: Performance and Examples [online]. *Investopedia*. Available at: https://www.investopedia.com/terms/e/equalweight.asp [Accessed 13 March 2023].

Jiahong, L. et al., 2023. Waterlogging Cause and Disaster Prevention and Control of" 7· 20" Torrential Rain in Zhengzhou. *Journal of Zhengzhou University: Engineering Science*, 44(2).

Jiang, W. et al., 2012. Quantifying driving forces of urban wetlands change in Beijing City. *Journal of Geographical Sciences*, 22(2), pp.301–314. 10.1007/s11442-012-0928-z.

Jiang, Y., 2018. Urban pluvial flooding and stormwater management_ A contemporary review of China's challenges and "sponge cities" strategy. , p.12.

Jiang, Y. et al., 2020. WITHDRAWN: Potentially contaminated sites in China: Spatiotemporal distribution and current risk assessment. *Journal of Cleaner Production*, p.122480. 10.1016/j.jclepro.2020.122480.

Jiang, Z. et al., 2022. Advancing UN Comtrade for Physical Trade Flow Analysis: Addressing the Issue of Outliers. *Resources, Conservation and Recycling*, 186, p.106524. 10.1016/j.resconrec.2022.106524.

Jiexi Su, 2020. How does global warming affect precipitation? [online]. Available at: http://www.cma.gov.cn/2011xzt/2020zt/20200323/2020032301/202003/t20200323_549531.html.

Johannessen, Å., Hahn, T., 2013. Social learning towards a more adaptive paradigm? Reducing flood risk in Kristianstad municipality, Sweden. *Global Environmental Change*, 23(1), pp.372–381. 10.1016/j.gloenvcha.2012.07.009.

Jongman, B. et al., 2015. Declining vulnerability to river floods and the global benefits of adaptation [online]. *Proceedings of the National Academy of Sciences*, 112(18). Available at: https://pnas.org/doi/full/10.1073/pnas.1414439112 [Accessed 25 February 2023].

Kabisch, N. et al.eds., 2017. *Nature-Based Solutions to Climate Change Adaptation in Urban Areas: Linkages between Science, Policy and Practice* [eBook]. Cham: Springer International Publishing. Available at: http://link.springer.com/10.1007/978-3-319-56091-5 [Accessed 23 April 2021].

Kandilioti, G., Makropoulos, C., 2012. Preliminary flood risk assessment: the case of Athens. *Natural Hazards*, 61(2), pp.441–468. 10.1007/s11069-011-9930-5.

Kankanamge, N. et al., 2020. Determining disaster severity through social media analysis: Testing the methodology with South East Queensland Flood tweets. *International Journal of Disaster Risk Reduction*, 42, p.101360. 10.1016/j.ijdrr.2019.101360.

Kapetas, L. et al., 2019. Water allocation and governance in multi-stakeholder environments: Insight from Axios Delta, Greece. *Science of The Total Environment*, 695, p.133831. 10.1016/j.scitotenv.2019.133831.

Kaplan, A.M., Haenlein, M., 2010. Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, 53(1), pp.59–68. 10.1016/j.bushor.2009.09.003.

Kaźmierczak, A., Cavan, G., 2011. Surface water flooding risk to urban communities: Analysis of vulnerability, hazard and exposure. *Landscape and Urban Planning*, 103(2), pp.185–197. 10.1016/j.landurbplan.2011.07.008.

Kendon, E.J. et al., 2012. Realism of Rainfall in a Very High-Resolution Regional Climate Model. *Journal of Climate*, 25(17), pp.5791–5806. 10.1175/JCLI-D-11-00562.1.

Kim, J., Hastak, M., 2018. Social network analysis: Characteristics of online social networks after a disaster. *International Journal of Information Management*, 38(1), pp.86–96. 10.1016/j.ijinfomgt.2017.08.003.

Koetse, M.J., Rietveld, P., 2009. The impact of climate change and weather on transport: An overview of empirical findings. *Transportation Research Part D: Transport and Environment*, 14(3), pp.205–221. 10.1016/j.trd.2008.12.004.

Koks, E.E. et al., 2019. A global multi-hazard risk analysis of road and railway infrastructure assets. *Nature Communications*, 10(1), p.2677. 10.1038/s41467-019-10442-3.

Kreibich, H. et al., 2022. The challenge of unprecedented floods and droughts in risk management. *Nature*, 608(7921), pp.80–86. 10.1038/s41586-022-04917-5.

Kumar, R. et al., 2021. Revealing the benefits of entropy weights method for multi-objective optimization in machining operations: A critical review. *Journal of Materials Research and Technology*, 10, pp.1471–1492. 10.1016/j.jmrt.2020.12.114.

Lai, Y. et al., 2021. Global compound floods from precipitation and storm surge: Hazards and the roles of cyclones. *Journal of Climate*, pp.1–55. 10.1175/JCLI-D-21-0050.1.

Lallemant, D. et al., 2021. Nature-based solutions for flood risk reduction: A probabilistic modeling framework. *One Earth*, 4(9), pp.1310–1321. 10.1016/j.oneear.2021.08.010.

Langlois, B.K. et al., 2023. Usability of existing global and national data for flood related vulnerability assessment in Indonesia. *Science of The Total Environment*, 873, p.162315. 10.1016/j.scitotenv.2023.162315.

Latapy, M., 2008. Main-memory triangle computations for very large (sparse (power-law)) graphs. *Theoretical computer science*, 407(1–3), pp.458–473.

Leitch, A.M., Bohensky, E.L., 2014. Return to 'a new normal': Discourses of resilience to natural disasters in Australian newspapers 2006–2010. *Global Environmental Change*, 26, pp.14–26. 10.1016/j.gloenvcha.2014.03.006.

Leong Glastris, M., 2013. GDP and City Population in the Development Performance of City Structures [online]. Available at: https://opus.lib.uts.edu.au/handle/10453/27332 [Accessed 14 June 2024].

Li, G. et al., 2023. Flood risk assessment by using an interpretative structural modeling based Bayesian network approach (ISM-BN): An urban-level analysis of Shenzhen, China. *Journal of Environmental Management*, 329, p.117040. 10.1016/j.jenvman.2022.117040.

Li, J.-C. et al., 2015. Vulnerability Assessment of Natural Disasters of Chinese Highway. *JOURNAL OF BEIJING UNIVERSITY OF TECHNOLOGY*, 41(7).

Li, L. et al., 2021. Review of advances in urban climate study in the Guangdong-Hong Kong-Macau Greater Bay Area, China. *Atmospheric Research*, 261, p.105759. 10.1016/j.atmosres.2021.105759.

Li, L., Uyttenhove, P., Van Eetvelde, V., 2020. Planning green infrastructure to mitigate urban surface water flooding risk – A methodology to identify priority areas applied in the city of Ghent. *Landscape and Urban Planning*, 194, p.103703. 10.1016/j.landurbplan.2019.103703.

Li, M., Huang, Q., et al., 2018. Modeling the traffic disruption caused by pluvial flash flood on intra-urban road network. *Transactions in GIS*, 22(1), pp.311–322. 10.1111/tgis.12311.

Li, M., Kwan, M.-P., et al., 2018. The potential effect of a 100-year pluvial flood event on metro accessibility and ridership: A case study of central Shanghai, China. *Applied Geography*, 100, pp.21–29. 10.1016/j.apgeog.2018.09.001.

Li, Q. et al., 2019. Comprehensive performance evaluation of LID practices for the sponge city construction: A case study in Guangxi, China. *Journal of Environmental Management*, 231, pp.10–20. 10.1016/j.jenvman.2018.10.024.

Li, W. et al., 2023. A System Dynamics Model of Urban Rainstorm and Flood Resilience to Achieve the Sustainable Development Goals. *Sustainable Cities and Society*, 96, p.104631. 10.1016/j.scs.2023.104631.

Li, Y. et al., 2010. An early warning method of landscape ecological security in rapid urbanizing coastal areas and its application in Xiamen, China. *Ecological Modelling*, 221(19), pp.2251–2260. 10.1016/j.ecolmodel.2010.04.016.

Li, Y. et al., 2021. Vulnerability evaluation of rainstorm disaster based on ESA conceptual framework: A case study of Liaoning province, China. *Sustainable Cities and Society*, 64, p.102540. 10.1016/j.scs.2020.102540.

Li, Z. et al., 2021. Urban rainfall characteristics and permeable pavement structure optimization for sponge road in North China. *Water Science and Technology*, 83(8), pp.1932–1945. 10.2166/wst.2021.091.

Liao, K.-H., 2019. The socio-ecological practice of building blue-green infrastructure in high-density cities: what does the ABC Waters Program in Singapore tell us? *Socio-Ecological Practice Research*, 1(1), pp.67–81. 10.1007/s42532-019-00009-3.

Lim, H.S., Lu, X.X., 2016. Sustainable urban stormwater management in the tropics: An evaluation of Singapore's ABC Waters Program. *Journal of Hydrology*, 538, pp.842–862. 10.1016/j.jhydrol.2016.04.063.

Lin, W. et al., 2020. Scenario-based flood risk assessment for urbanizing deltas using future land-use simulation (FLUS): Guangzhou Metropolitan Area as a case study. *Science of The Total Environment*, 739, p.139899. 10.1016/j.scitotenv.2020.139899.

Lin, Z. et al., 2017. Spatial and temporal Variations of Storm-floods in Xixi Watershed of Southeast Coastal Region. *Mt. Res*, 35(4), pp.488–495.

Ling Tan, David M. Schultz, 2021. Damage classification and recovery analysis of the Chongqing, China, floods of August 2020 based on social-media data. *Journal of Cleaner Production*, 313, p.127882. 10.1016/j.jclepro.2021.127882.

Liu, D. et al., 2021. Measurement and analysis of regional flood disaster resilience based on a support vector regression model refined by the selfish herd optimizer with elite opposition-based learning. *Journal of Environmental Management*, 300, p.113764. 10.1016/j.jenvman.2021.113764.

Liu, D. et al., 2020. Random forest regression evaluation model of regional flood disaster resilience based on the whale optimization algorithm. *Journal of Cleaner Production*, 250, p.119468. 10.1016/j.jclepro.2019.119468.

Liu, K. et al., 2018. A Comprehensive Risk Analysis of Transportation Networks Affected by Rainfall-Induced Multihazards: A Comprehensive Risk Analysis of Transportation Networks. *Risk Analysis*, 38(8), pp.1618–1633. 10.1111/risa.12968.

Liu, M. et al., 2021. Social media never shake the role of trust building in relieving public risk perception. *Journal of Cleaner Production*, 282, p.124442. 10.1016/j.jclepro.2020.124442.

Liu, X. et al., 2018. Analyzing Spatial-Temporal Distribution of Natural Hazards in China by Mining News Sources. *Natural Hazards Review*, 19(3). 10.1061/(ASCE)NH.1527-6996.0000291.

Liu, Y., Huang, X., Yang, H., 2022. An integrated approach to investigate the coupling coordination between urbanization and flood disasters in China. *Journal of Cleaner Production*, 375, p.134191. 10.1016/j.jclepro.2022.134191.

Lu, X. et al., 2022. An overview of flood-induced transport disruptions on urban streets and roads in Chinese megacities: Lessons and future agendas. *Journal of Environmental Management*, 321, p.115991. 10.1016/j.jenvman.2022.115991.

Lyu, H.-M. et al., 2019. Inundation analysis of metro systems with the storm water management model incorporated into a geographical information system: a case study in Shanghai. *Hydrology and Earth System Sciences*, 23(10), pp.4293–4307. 10.5194/hess-23-4293-2019.

M. Jibhakate, S., V. Timbadiya, P., L. Patel, P., 2023. Multiparameter flood hazard, socioeconomic vulnerability and flood risk assessment for densely populated coastal city. *Journal of Environmental Management*, 344, p.118405. 10.1016/j.jenvman.2023.118405.

Macau SMG, 2017. *Typhoon Hato (1713)* [online]. Available at: https://cms.smg.gov.mo/uploads/sync/pdf/tc/2017/e_1713.pdf.

Magazzino, C., Mele, M., 2021. On the relationship between transportation infrastructure and economic development in China. *Research in Transportation Economics*, 88, p.100947. 10.1016/j.retrec.2020.100947.

Mahmoud, S.H., Gan, T.Y., 2018. Multi-criteria approach to develop flood susceptibility maps in arid regions of Middle East. *Journal of Cleaner Production*, 196, pp.216–229. 10.1016/j.jclepro.2018.06.047.

Maria Pregnolato et al., 2017. Impact of Climate Change on Disruption to Urban Transport Networks from Pluvial Flooding. *Journal of Infrastructure Systems*, 23(4), p.04017015. 10.1061/(ASCE)IS.1943-555X.0000372.

Markolf, S.A. et al., 2019. Transportation resilience to climate change and extreme weather events – Beyond risk and robustness. *Transport Policy*, 74, pp.174–186. 10.1016/j.tranpol.2018.11.003.

Matos, C. et al., 2019. An approach to the implementation of Low Impact Development measures towards an EcoCampus classification. *Journal of Environmental Management*, 232, pp.654–659. 10.1016/j.jenvman.2018.11.085.

Metcalf, L., Casey, W., 2016. Chapter 5 - Graph theory [eBook]. In: Metcalf, L., Casey, W., eds. *Cybersecurity and Applied Mathematics*. Boston: Syngress, 2016, pp. 67–94. Available at:

https://www.sciencedirect.com/science/article/pii/B9780128044520000051 [Accessed 25 December 2023].

Meteorological Bureau of Shenzhen Municipality, 2020. *Shenzhen Climate Bulletin 2019* [online]. Meteorological Bureau of Shenzhen Municipality. Available at: http://weather.sz.gov.cn/qixiangfuwu/qihoufuwu/qihouguanceyupinggu/nianduqihougongbao/202002/W020200213461489383427.pdf.

Miles, B., Morse, S., 2007. The role of news media in natural disaster risk and recovery. *Ecological Economics*, 63(2), pp.365–373. 10.1016/j.ecolecon.2006.08.007.

Milgram, S., 1967. The small world problem. *Psychology today*, 2(1), pp.60–67.

Minaei, M., 2020. Evolution, density and completeness of OpenStreetMap road networks in developing countries: The case of Iran. *Applied Geography*, 119, p.102246. 10.1016/j.apgeog.2020.102246.

Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2016a. *Code for the design of urban green space(GB 50420—2007)*.

Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2016b. Code for Urban Planning on Flood Control (GB 51079-2016) [online]. Available at: https://www.mohurd.gov.cn/gongkai/fdzdgknr/tzgg/201607/20160725_228281.html [Accessed 21 April 2023].

Ministry of Transport of the People's Republic of China, 2015. *Technical Standards of Highway Engineering* [online]. Available at: https://xxgk.mot.gov.cn/2020/jigou/glj/202006/t20200623_3312242.html [Accessed 8 March 2023].

Monica, L., 2020. *Guangzhou Metro Line 13 suspended due to rainstorms* [online]. Newsgd.com. Available at: http://www.newsgd.com/news/exclusive/content/2020-05/22/content_190938685.htm [Accessed 8 January 2021].

Moore, S., Eng, E., Daniel, M., 2003. International NGOs and the Role of Network Centrality in Humanitarian Aid Operations: A Case Study of Coordination During the 2000 Mozambique Floods. *Disasters*, 27(4), pp.305–318. 10.1111/j.0361-3666.2003.00235.x.

Mruksirisuk, P. et al., 2023. Flood vulnerability assessment of Thailand's flood-prone Pathum Thani province and vulnerability mitigation strategies. *Journal of Environmental Management*, 347, p.119276. 10.1016/j.jenvman.2023.119276.

Munoz, S.E. et al., 2018. Climatic control of Mississippi River flood hazard amplified by river engineering. *Nature*, 556(7699), pp.95–98. 10.1038/nature26145.

Narayan, S. et al., 2012. A holistic model for coastal flooding using system diagrams and the Source-Pathway-Receptor (SPR) concept. *Natural Hazards and Earth System Sciences*, 12(5), pp.1431–1439. 10.5194/nhess-12-1431-2012.

Nasiri, H. et al., 2019. District flood vulnerability index: urban decision-making tool. *International Journal of Environmental Science and Technology*, 16(5), pp.2249–2258. 10.1007/s13762-018-1797-5.

Nasiri, H., Mohd Yusof, M.J., Mohammad Ali, T.A., 2016. An overview to flood vulnerability assessment methods. *Sustainable Water Resources Management*, 2(3), pp.331–336. 10.1007/s40899-016-0051-x.

National Development and Reform Commission, 2016. The thirteenth Five-Year Plan [online]. Available at: http://www.gov.cn/xinwen/2016-03/17/content_5054992.htm [Accessed 12 March 2023].

National Development and Reform Commission, 2022. 【织密“交通走廊” 打通“产业连廊” 粤港澳大湾区打造百公里“黄金内湾”】-国家发展和改革委员会 [online]. Available at: https://www.ndrc.gov.cn/xwdt/ztzl/ygadwqjs1/202209/t20220906_1335242.html?state=123&state=123&state=123 [Accessed 13 March 2023].

OECD, 1993. OECD Core Set of Indicators for Environmental Performance Reviews: A Synthesis Report by the Group on the State of the Environment. *OECD Environment Monographs*, 93(179), p.39.

Okechukwu, E., Madonsela, N., Adetunla, A., 2021. *The Effect of Transportation Infrastructure on Economic Development*.

Onodugo, V.A. et al., 2019. Future Planning of Global South Cities with Inclusive Informal Economic Growth in Perspective [eBook]. In: *Sustainability in Urban Planning and Design*. IntechOpen, 2019. Available at: https://www.intechopen.com/chapters/69045 [Accessed 3 January 2024].

Ouyang, M. et al., 2022. Employment of hydraulic model and social media data for flood hazard assessment in an urban city. *Journal of Hydrology: Regional Studies*, 44, p.101261. 10.1016/j.ejrh.2022.101261.

Pall, P. et al., 2011. Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. *Nature*, 470(7334), pp.382–385. 10.1038/nature09762.

Panteras, G. et al., 2015. Triangulating Social Multimedia Content for Event Localization using Flickr and Twitter. *Transactions in GIS*, 19(5), pp.694–715. 10.1111/tgis.12122.

Pathan, A.I. et al., 2022. AHP and TOPSIS based flood risk assessment- a case study of the Navsari City, Gujarat, India. *Environmental Monitoring and Assessment*, 194(7), p.509. 10.1007/s10661-022-10111-x.

Peng, J., Zhang, J., 2022. Urban flooding risk assessment based on GIS- game theory combination weight: A case study of Zhengzhou City. *International Journal of Disaster Risk Reduction*, 77, p.103080. 10.1016/j.ijdrr.2022.103080.

People Government of Guangzhou Province, 2011. 广州市社会急救医疗管理条例. Available at: http://www.gd.gov.cn/zwgk/wjk/zcfgk/content/post_2935987.html.

Phan Nhut Duy, 2019. *EVELOPING FLOOD RESILIENT TRANSPORT SYSTEMS IN COASTAL CITIES: A CASE STUDY OF HO CHI MINH CITY, VIETNAM*. the University of Birmingham.

Plantin, J.-C. et al., 2018. Infrastructure studies meet platform studies in the age of Google and Facebook. *New Media & Society*, 20(1), pp.293–310. 10.1177/1461444816661553.

Plate, E.J., 2002. Flood risk and flood management. *Journal of Hydrology*, 267(1–2), pp.2–11. 10.1016/S0022-1694(02)00135-X.

Prasoon Singh et al., 2018. Vulnerability assessment of urban road network from urban flood. *International Journal of Disaster Risk Reduction*, 28, pp.237–250. 10.1016/j.ijdrr.2018.03.017.

Pregnolato, M. et al., 2016. Assessing urban strategies for reducing the impacts of extreme weather on infrastructure networks. *Royal Society Open Science*, 3(5), p.160023. 10.1098/rsos.160023.

Pregnolato, M. et al., 2017. Impact of Climate Change on Disruption to Urban Transport Networks from Pluvial Flooding. *Journal of Infrastructure Systems*, 23(4), p.04017015. 10.1061/(ASCE)IS.1943-555X.0000372.

Pregnolato, M., 2017. *Risk analysis of the disruption to urban transport networks from pluvial flooding*.

Pricope, N.G. et al., 2022. Shifting landscapes of risk: Quantifying pluvial flood vulnerability beyond the regulated floodplain. *Journal of Environmental Management*, 304, p.114221. 10.1016/j.jenvman.2021.114221.

Priest, S.J. et al., 2011. Assessing options for the development of surface water flood warning in England and Wales. *Journal of Environmental Management*, 92(12), pp.3038–3048. 10.1016/j.jenvman.2011.06.041.

Pyatkova, K. et al., 2019. Flood Impacts on Road Transportation Using Microscopic Traffic Modelling Techniques [eBook]. In: Behrisch, M., Weber, M., eds. *Simulating Urban Traffic Scenarios*. Lecture Notes in Mobility. Cham: Springer International Publishing, 2019, pp. 115–126. Available at: http://link.springer.com/10.1007/978-3-319-33616-9_8 [Accessed 30 June 2023].

Qadir, R.I., Bukhari, S.I., 2016. Singh's index accuracy with dexa scan for evaluation of osteoporosis. *Journal of Medical Sciences (Peshawar)*, 24(1), pp.12–15.

Qiang, Y., Zhang, L., Xiao, T., 2020. Spatial-temporal rain field generation for the Guangdong-Hong Kong-Macau Greater Bay Area considering climate change. *Journal of Hydrology*, 583, p.124584. 10.1016/j.jhydrol.2020.124584.

Qin, X., Hu, X., Xia, W., 2023. Investigating the dynamic decoupling relationship between regional social economy and lake water environment: The application of DPSIR-Extended Tapio decoupling model. *Journal of Environmental Management*, 345, p.118926. 10.1016/j.jenvman.2023.118926.

Ragini, J.R., Anand, P.M.R., Bhaskar, V., 2018. Big data analytics for disaster response and recovery through sentiment analysis. *International Journal of Information Management*, 42, pp.13–24. 10.1016/j.ijinfomgt.2018.05.004.

Rebally, A. et al., 2021. Flood Impact Assessments on Transportation Networks: A Review of Methods and Associated Temporal and Spatial Scales. *Frontiers in Sustainable Cities*, 3, p.732181. 10.3389/frsc.2021.732181.

Rehman, S. et al., 2019. A systematic review on approaches and methods used for flood vulnerability assessment: framework for future research. *Natural Hazards*, 96(2), pp.975–998. 10.1007/s11069-018-03567-z.

Rezende, O.M. et al., 2020. Mapping the flood risk to Socioeconomic Recovery Capacity through a multicriteria index. *Journal of Cleaner Production*, 255, p.120251. 10.1016/j.jclepro.2020.120251.

Ritchie, H., Roser, M., 2023. Urbanization [online]. *Our World in Data*. Available at: https://ourworldindata.org/urbanization [Accessed 3 January 2024].

Rodrigue, J.-P., Notteboom, T., 2013. Transportation and economic development. *The Journal of Geography of Transportation*, pp.1–29.

Roeseler, W.G., von Dosky, D., 1991. Joint development in urban transportation: a practical approach to modern growth management. *Landscape and Urban Planning*, 20(4), pp.325–346. 10.1016/0169-2046(91)90006-8.

Rozenberg, J., Marianne, F., 2019. *Beyond the gap: How countries can afford the infrastructure they need while protecting the planet*. The World Bank.

Sahoo, M. et al., 2016. Effectiveness evaluation of objective and subjective weighting methods for aquifer vulnerability assessment in urban context. *Journal of Hydrology*, 541, pp.1303–1315. 10.1016/j.jhydrol.2016.08.035.

Sarkar, D., Saha, S., Mondal, P., 2022. GIS-based frequency ratio and Shannon's entropy techniques for flood vulnerability assessment in Patna district, Central Bihar, India. *International Journal of Environmental Science and Technology*, 19(9), pp.8911–8932. 10.1007/s13762-021-03627-1.

Scotti, V., Giannini, M., Cioffi, F., 2020. Enhanced flood mapping using synthetic aperture radar (SAR) images, hydraulic modelling, and social media: A case study of Hurricane Harvey (Houston, TX). *Journal of Flood Risk Management*, 13(4), p.e12647. 10.1111/jfr3.12647.

Senent-Aparicio, J. et al., 2015. Evaluating Groundwater Management Sustainability under Limited Data Availability in Semiarid Zones. *Water*, 7(8), pp.4305–4322. 10.3390/w7084305.

Seo, J.P., Cho, W., Cheong, T.S., 2015. Development of priority setting process for the small stream restoration projects using multi criteria decision analysis. *Journal of Hydroinformatics*, 17(2), pp.211–225. 10.2166/hydro.2014.058.

Sergio, L., 2019. *EXPLORATION OF PUBLIC SENTIMENT AS AN INDICATOR OF PUBLIC RESPONSE TO NATURAL DISASTERS: AN ANALYSIS OF HURRICANE SCENARIOS*.

Setyani, R.E., Saputra, R., 2016. Flood-prone Areas Mapping at Semarang City by Using Simple Additive Weighting Method. *Procedia - Social and Behavioral Sciences*, 227, pp.378–386. 10.1016/j.sbspro.2016.06.089.

Shanghai Municipal Peoples Government, 2016. 关于深化本市院前急救体系改革与发展的指导意见. Available at: http://wsjkw.sh.gov.cn/zcwjjzqk/20200422/7581752643f04276b500dd0ed85bc174.html.

Shenzhen Municipal Health Commission, 2018. 深圳经济特区医疗急救条例. Available at: http://wjw.sz.gov.cn/xxgk/zcfggfxwj/mybh_5/content/post_3163756.html.

Shenzhen Municipal Transportation Bureau, 2022. *The 14th Five-Year Plan for Shenzhen Transportation* [online]. Available at: http://drc.sz.gov.cn/gkmlpt/content/10/10157/mpost_10157684.html#1854 [Accessed 21 November 2022].

Shoyama, K. et al., 2021. Emergency flood detection using multiple information sources: Integrated analysis of natural hazard monitoring and social media data. *Science of The Total Environment*, 767, p.144371. 10.1016/j.scitotenv.2020.144371.

Singla, A., Agrawal, R., 2022. Social media and disaster management: investigating challenges and enablers. *Global Knowledge, Memory and Communication*, 73(1/2), pp.100–122. 10.1108/GKMC-12-2021-0206.

Smith, L. et al., 2017. Assessing the utility of social media as a data source for flood risk management using a real-time modelling framework. *Journal of Flood Risk Management*, 10(3), pp.370–380. 10.1111/jfr3.12154.

Song, C. et al., 2022. Establishing coordinated development index of urbanization based on multi-source data: A case study of Guangdong-Hong Kong-Macao Greater Bay Area, China. *Ecological Indicators*, 140, p.109030. 10.1016/j.ecolind.2022.109030.

Soomro, S. et al., 2024. How effective is twitter (X) social media data for urban flood management? *Journal of Hydrology,* 634, p.131129. 10.1016/j.jhydrol.2024.131129.

Sorichetta, A. et al., 2011. Reliability of groundwater vulnerability maps obtained through statistical methods. *Journal of Environmental Management*, 92(4), pp.1215–1224. 10.1016/j.jenvman.2010.12.009.

Špitalar, M. et al., 2014. Analysis of flash flood parameters and human impacts in the US from 2006 to 2012. *Journal of Hydrology*, 519, pp.863–870. 10.1016/j.jhydrol.2014.07.004.

Statista, 2021. China: road density 2021 [online]. *Statista*. Available at: https://www.statista.com/statistics/258345/road-density-in-china/ [Accessed 3 January 2024].

Statistia, 2022. China: population in the Greater Bay Area 2021 [online]. *Statista*. Available at: https://www.statista.com/statistics/1172165/china-population-in-the-greater-bay-area-cities/ [Accessed 9 March 2023].

Su, B., 2016. Integrated simulation method for waterlogging and traffic congestion under urban rainstorms. *Nat Hazards*, p.18.

Sun, F. et al., 2020. Initial allocation of flood drainage rights based on a PSR model and entropy-based matter-element theory in the Sunan Canal, China Zhou, G., ed. *PLOS ONE*, 15(6), p.e0233570. 10.1371/journal.pone.0233570.

Sun, L. et al., 2020. Dramatic uneven urbanization of large cities throughout the world in recent decades. *Nature Communications*, 11(1), p.5366. 10.1038/s41467-020-19158-1.

swj.sz.gov.cn, 2021. Sponge transformation and landscape upgrading project of Shenzhen Tianjianhuayuan (深圳天健花园海绵化改造景观提升工程) [online]. Available at: http://swj.sz.gov.cn/ztzl/bmzdgz/hmcsjs/shcy/content/post_9040854.html.

sznews.com, 2018. Dengliang Road in Nanshan of Shenzhen [online]. Available at: http://www.sznews.com/mb/content/2018-08/24/content_19949290.htm [Accessed 22 November 2022].

Taghavi, N. et al., 2022. Groundwater vulnerability assessment: A review including new statistical and hybrid methods. *Science of The Total Environment*, 822, p.153486. 10.1016/j.scitotenv.2022.153486.

Takagi, H., Xiong, Y., Furukawa, F., 2018. Track analysis and storm surge investigation of 2017 Typhoon Hato: were the warning signals issued in Macau and Hong Kong timed appropriately? *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, 12(4), pp.297–307. 10.1080/17499518.2018.1465573.

Tan, L., Schultz, D.M., 2021. Damage classification and recovery analysis of the Chongqing, China, floods of August 2020 based on social-media data. *Journal of Cleaner Production*, 313, p.127882. 10.1016/j.jclepro.2021.127882.

The China Meteorological Administration, 2020. Meteorological Development Plan for the Guangdong-Hong Kong-Macao Greater Bay Area (2020-2035) [online]. Available at: https://www.cma.gov.cn/2011xwzx/2011xqxxw/2011xqxyw/202004/t20200429_552407.html [Accessed 30 November 2023].

The Education University of Hong Kong, 2022. *Learning and Teaching Resources on Guangdong-Hong Kong-Macao Greater Bay Area (Greater Bay Area)* [online]. Available at: https://www.edb.gov.hk/attachment/en/curriculum-development/kla/pshe/references-and-resources/geography/Transportation_E.pdf [Accessed 13 March 2023].

The Ministry of Housing and Urban-Rural Development of the People's Republic of China, 2017. *Technical code for urban flooding prevention and control*.

The people's Government of Beijing City, 2020. 关于加强本市院前医疗急救体系建设的实施方案. Available at: http://www.beijing.gov.cn/zhengce/zfwj/zfwj2016/bgtwj/202006/t20200630_1935612.html.

The State Council, 2019a. Guangdong-Hong Kong-Macao Greater Bay Area Development Plan [online]. Available at: http://www.gov.cn/gongbao/content/2019/content_5370836.htm [Accessed 12 March 2023].

The State Council, 2023. 一图看懂：新一届国务院机构设置_图解图表_中国政府网 [online]. Available at: https://www.gov.cn/xinwen/2023-03/20/content_5747537.htm?fromModule=lemma_middle-info [Accessed 6 December 2023].

The State Council, 2019b. 交通强国建设纲要. Available at: http://www.gov.cn/zhengce/2019-09/19/content_5431432.htm [Accessed 15 November 2022].

The State Council, 2016. 关于进一步 加强城市规划建设管理工作的若干意见. Available at: http://www.gov.cn/gongbao/content/2016/content_5051277.htm [Accessed 15 November 2022].

Tjallingii, S.P., 2000. Ecology on the edge:: Landscape and ecology between town and country. *Landscape and Urban Planning*, 48(3), pp.103–119. 10.1016/S0169-2046(00)00035-9.

Transport and Logistics Bureau, 2022. Hong Kong–Zhuhai–Macao Bridge(HZMB) Project Highlights [online]. Available at: https://www.hzmb.gov.hk/en/project.html [Accessed 13 March 2023].

Truong, M.-X.A., Clayton, S., 2020. Technologically transformed experiences of nature: A challenge for environmental conservation? *Biological Conservation*, 244, p.108532. 10.1016/j.biocon.2020.108532.

Tschakert, P. et al., 2016. Micropolitics in collective learning spaces for adaptive decision making. *Global Environmental Change*, 40, pp.182–194. 10.1016/j.gloenvcha.2016.07.004.

United Nations, 2019. *World Urbanization Prospects The 2018 Revision*. UN DESA.

Vaddiraju, S.C., Talari, R., 2022. Urban flood susceptibility analysis of Saroor Nagar Watershed of India using Geomatics-based multi-criteria analysis framework. *Environmental Science and Pollution Research*, 30(49), pp.107021–107040. 10.1007/s11356-022-24672-4.

Vamvakeridou-Lyroudia, L.S. et al., 2020. Assessing and visualising hazard impacts to enhance the resilience of Critical Infrastructures to urban flooding. *Science of The Total Environment*, 707, p.136078. 10.1016/j.scitotenv.2019.136078.

Vardoulakis, S. et al., 2015. Impact of climate change on the domestic indoor environment and associated health risks in the UK. *Environment International*, 85, pp.299–313. 10.1016/j.envint.2015.09.010.

Waheed, B. et al., 2011. Uncertainty-based quantitative assessment of sustainability for higher education institutions. *Journal of Cleaner Production*, 19(6), pp.720–732. 10.1016/j.jclepro.2010.12.013.

Wang, B. et al., 2020. Urban resilience from the lens of social media data: Responses to urban flooding in Nanjing, China. *Cities*, 106, p.102884. 10.1016/j.cities.2020.102884.

Wang, M. et al., 2023. Assessing urban flooding risk in response to climate change and urbanization based on shared socio-economic pathways. *Science of The Total Environment*, 880, p.163470. 10.1016/j.scitotenv.2023.163470.

Wang, Q. et al., 2019. Forecast and Service Performance on Rapidly Intensification Process of Typhoons Rammasun (2014) and Hato (2017). *Tropical Cyclone Research and Review*, 8(1), pp.18–26. 10.1016/j.tcrr.2019.07.002.

Wang, Q. et al., 2018. Investigating vulnerability of ecological industrial symbiosis network based on automatic control theory. *Environmental Science and Pollution Research*, 25(27), pp.27321–27333. 10.1007/s11356-018-2753-0.

Wang, T., 2020. Climate change research on transportation systems_ Climate risks, adaptation and planning. , p.17.

Wang, Y. et al., 2023. Exploring the relationship between urban flood risk and resilience at a high-resolution grid cell scale. *Science of The Total Environment*, 893, p.164852. 10.1016/j.scitotenv.2023.164852.

Wang, Y. et al., 2020. Rapid estimation of an earthquake impact area using a spatial logistic growth model based on social media data. In: *Social Sensing and Big Data Computing for Disaster Management*. Routledge, 2020.

Wang, Y., Zhai, J., et al., 2022. Risk assessment of rainstorm disasters in the Guangdong–Hong Kong–Macao greater Bay area of China during 1990–2018. *Geomatics, Natural Hazards and Risk*, 13(1), pp.267–288. 10.1080/19475705.2021.2023224.

Wang, Y., Yin, Y., Song, L., 2022. Risk Assessment of Typhoon Disaster Chains in the Guangdong–Hong Kong–Macau Greater Bay Area, China. *Frontiers in Earth Science*, 10, p.839733. 10.3389/feart.2022.839733.

Wasserman, S., Faust, K., 1994. Social network analysis: Methods and applications.

Water Authority of Shenzhen Municipality, 2016a. 各区内涝点整治任务表--深圳市水务局 [online]. Available at: http://swj.sz.gov.cn/ztzl/ndmsss/yldzl/gqnldzl/ [Accessed 20 April 2023].

Water Authority of Shenzhen Municipality, 2016b. 海绵城市建设--深圳市水务局 [online]. Available at: http://swj.sz.gov.cn/ztzl/bmzdgz/hmcsjs/ [Accessed 20 April 2023].

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of ‘small-world’networks. *nature*, 393(6684), pp.440–442.

Wehn, U. et al., 2015. Participation in flood risk management and the potential of citizen observatories: A governance analysis. *Environmental Science & Policy*, 48, pp.225–236. 10.1016/j.envsci.2014.12.017.

White, K., 1993. Signs of an Olive Branch: Confronting the Environmental Health Consequences of the Midwestern Floods. *Environmental Health Perspectives*, 101(7), pp.584–588. 10.2307/3431642.

WHO, 1999. ENVIRONMENTAL HEALTH INDICATORS: FRAMEWORK AND METHODOLOGIES.

Williamson, F., 2016. The “great flood” of 1926: environmental change and post-disaster management in british malaya. *Ecosystem Health and Sustainability*, 2(11), p.e01248. 10.1002/ehs2.1248.

Wiśniewski, S. et al., 2020. Vulnerability of the accessibility to grocery shopping in the event of flooding. *Transportation Research Part D: Transport and Environment*, 87, p.102510. 10.1016/j.trd.2020.102510.

Wu, C. et al., 2021. Vertical profiling of black carbon and ozone using a multicopter unmanned aerial vehicle (UAV) in urban Shenzhen of South China. *Science of The Total Environment*, 801, p.149689. 10.1016/j.scitotenv.2021.149689.

Wu, J. et al., 2019. Planned sheltering as an adaptation strategy to climate change: Lessons learned from the severe flooding in Anhui Province of China in 2016. *Science of The Total Environment*, 694, p.133586. 10.1016/j.scitotenv.2019.133586.

Wu, J., Chen, X., Lu, J., 2022. Assessment of long and short-term flood risk using the multi-criteria analysis model with the AHP-Entropy method in Poyang Lake basin. *International Journal of Disaster Risk Reduction*, 75, p.102968. 10.1016/j.ijdrr.2022.102968.

Xia, J. et al., 2017. Opportunities and challenges of the Sponge City construction related to urban water issues in China. *Science China Earth Sciences*, 60(4), pp.652–658. 10.1007/s11430-016-0111-8.

Xiao, Y., Huang, Q., Wu, K., 2015. Understanding social media data for disaster management. *Natural Hazards*, 79(3), pp.1663–1679. 10.1007/s11069-015-1918-0.

Xie, X. et al., 2021. A simple Monte Carlo method for estimating the chance of a cyclone impact. *Natural Hazards*, 107(3), pp.2573–2582. 10.1007/s11069-021-04505-2.

Xinhua News Agency, 2022. 河南郑州“7·20”特大暴雨灾害调查报告公布_滚动新闻_中国政府网 [online]. Available at: https://www.gov.cn/xinwen/2022-01/21/content_5669723.htm [Accessed 1 March 2024].

Xu, K. et al., 2019. Projection and uncertainty of precipitation extremes in the CMIP5 multimodel ensembles over nine major basins in China. *Atmospheric Research*, 226, pp.122–137. 10.1016/j.atmosres.2019.04.018.

Xu, Y.-S. et al., 2018. Design of sponge city: Lessons learnt from an ancient drainage system in Ganzhou, China. *Journal of Hydrology*, 563, pp.900–908. 10.1016/j.jhydrol.2018.06.075.

Yan, B. et al., 2016. Socio-economic vulnerability of the megacity of Shanghai (China) to sea-level rise and associated storm surges. *Regional Environmental Change*, 16(5), pp.1443–1456. 10.1007/s10113-015-0878-y.

Yang, C. et al., 2020. Rapid urbanization and policy variation greatly drive ecological quality evolution in Guangdong-Hong Kong-Macau Greater Bay Area of China: A remote sensing perspective. *Ecological Indicators*, 115, p.106373. 10.1016/j.ecolind.2020.106373.

Yang, C. et al., 2014. The Potential of Dental Stem Cells Differentiating into Neurogenic Cell Lineage after Cultivation in Different Modes In Vitro. *Cellular Reprogramming*, 16(5), pp.379–391. 10.1089/cell.2014.0026.

Yang, Y. et al., 2019. A physics-based framework for analyzing the resilience of interdependent civil infrastructure systems: A climatic extreme event case in Hong Kong. *Sustainable Cities and Society*, 47, p.101485. 10.1016/j.scs.2019.101485.

Yao, Y. et al., 2023. Evaluating the response and adaptation of urban stormwater systems to changed rainfall with the CMIP6 projections. *Journal of Environmental Management*, 347, p.119135. 10.1016/j.jenvman.2023.119135.

Yeo, J., Knox, C.C., Hu, Q., 2022. Disaster Recovery Communication in the Digital Era: Social Media and the 2016 Southern Louisiana Flood. *Risk Analysis*, 42(8), pp.1670–1685. 10.1111/risa.13652.

Yin, J. et al., 2015. Modelling the anthropogenic impacts on fluvial flood risks in a coastal mega-city: A scenario-based case study in Shanghai, China. *Landscape and Urban Planning*, 136, pp.144–155. 10.1016/j.landurbplan.2014.12.009.

Young, A., 1990. Appeals to valuelessness: Objectivity, authenticity and the news discourse. *Textual Practice*, 4(1), pp.38–53. 10.1080/09502369008582075.

Yu, H., Hu, X., Gao, J., 2023. Can haze warning policy reduce traffic accidents: evidence from China. *Environmental Science and Pollution Research*, 30(2), pp.2703–2720. 10.1007/s11356-022-22322-3.

Yue, S. et al., 2021. The super typhoon Lekima (2019) resulted in massive losses in large seagrass (Zostera japonica) meadows, soil organic carbon and nitrogen pools in the intertidal Yellow River Delta, China. *Science of The Total Environment*, 793, p.148398. 10.1016/j.scitotenv.2021.148398.

Yujie Wang et al., 2022. Risk assessment of rainstorm disasters in the Guangdong–Hong Kong–Macao greater Bay area of China during 1990–2018. *Geomatics, Natural Hazards and Risk*, 13(1), pp.267–288. 10.1080/19475705.2021.2023224.

Zander, K.K. et al., 2022. How do Australians use social media during natural hazards? A survey. *International Journal of Disaster Risk Reduction*, 81, p.103207. 10.1016/j.ijdrr.2022.103207.

Zar, J.H., 2005. Spearman Rank Correlation [eBook]. In: *Encyclopedia of Biostatistics*. John Wiley & Sons, Ltd, 2005. Available at:

https://onlinelibrary.wiley.com/doi/abs/10.1002/0470011815.b2a15150 [Accessed 14 June 2024].

Zare, M. et al., 2022. Progressive improvement of DRASTICA and SI models for groundwater vulnerability assessment based on evolutionary algorithms. *Environmental Science and Pollution Research*, 29(37), pp.55845–55865. 10.1007/s11356-022-19620-1.

Zaw, T.N., Lim, S., 2017. The military's role in disaster management and response during the 2015 Myanmar floods: A social network approach. *International Journal of Disaster Risk Reduction*, 25, pp.1–21. 10.1016/j.ijdrr.2017.06.023.

Zhang, H., Malczewski, J., 2018. Accuracy Evaluation of the Canadian OpenStreetMap Road Networks.

Zhang, S., Guo, Y., Wang, Z., 2015. Correlation between flood frequency and geomorphologic complexity of rivers network – A case study of Hangzhou China. *Journal of Hydrology*, 527, pp.113–118. 10.1016/j.jhydrol.2015.04.060.

Zhang, W. et al., 2019. Impact Analysis of Rainfall on Traffic Flow Characteristics in Beijing. *International Journal of Intelligent Transportation Systems Research*, 17(2), pp.150–160. 10.1007/s13177-018-0162-x.

Zhang, Y., Zhang, R., Zhang, C., 2022. Insight into the driving force of environmental performance improvement: Environmental regulation or media coverage. *Journal of Cleaner Production*, 358, p.132024. 10.1016/j.jclepro.2022.132024.

Zhang, Y.-L., You, W.-J., 2014. Social vulnerability to floods: a case study of Huaihe River Basin. *Natural Hazards*, 71(3), pp.2113–2125. 10.1007/s11069-013-0996-0.

Zhao, P. et al., 2015. Statistical analysis on the evolution of OpenStreetMap road networks in Beijing. *Physica A: Statistical Mechanics and its Applications*, 420, pp.59–72. 10.1016/j.physa.2014.10.076.

Zhao, X., Li, H., Qi, Y., 2022. Are Chinese Cities Prepared to Manage the Risks of Extreme Weather Events? Evidence from the 2021.07.20 Zhengzhou Flood in Henan Province [online]. *SSRN Electronic Journal*. Available at: https://www.ssrn.com/abstract=4043303 [Accessed 14 June 2024].

Zhou, Q. et al., 2012. Framework for economic pluvial flood risk assessment considering climate change effects and adaptation benefits. *Journal of Hydrology*, 414–415, pp.539–549. 10.1016/j.jhydrol.2011.11.031.

Zhou, Z., Qu, L., Zou, T., 2015. Quantitative Analysis of Urban Pluvial Flood Alleviation by Open Surface Water Systems in New Towns: Comparing Almere and Tianjin Eco-City. *Sustainability*, 7(10), pp.13378–13398. 10.3390/su71013378.

Zhu, Z. et al., 2016. Approach for evaluating inundation risks in urban drainage systems. *Science of The Total Environment*, 553, pp.1–12. 10.1016/j.scitotenv.2016.02.025.

Abbreviations

ABC: Active Beautiful and Clean

AHP: Analytic Hierarchy Process

AR: Rainfall amount

BGI: Blue-green infrastructures

BMPs: Best Management Practices

CBDs: Central Business District

CI: Critical Infrastructure

CRITIC: Criteria Importance Though Intercrieria Correlation

DPSEEA: Driving Force-Pressure-State-Exposure-Effect-Action

DPSIR: Driving Force-Pressure-State-Impact-Response

DSR: Driving Force-State-Response

EWM: Entropy Weighting Method

GBA: Guangdong-Hong Kong-Macao Greater Bay Area

GDELT: Global Database of Events, Language and Tone

GDP: Gross Domestic Product

GKG: Global Knowledge Graph

LID: Low Impact Development

MEM: Ministry of Emergency Management

MHURD: Ministry of Housing and Urban-Rural Development

MOF: Ministry of Finance

MOT: Ministry of Transport

MWR: Ministry of Water Resources

NBS: Nature-Based Solutions

NGO: Non-government Organisation

OECD: Organisation for Economic Cooperation and Development

OSM: OpenStreetMap

PRD: Pearl River Delta

PSR: Pressure-State-Response

RAA: Road anti-disaster ability

RBD: Road bridge density

RCD: Road culvert density

SARs: Special Administrative Regions

SAW: Simple additive weighting

SCP: Sponge City Program

SNA: Social Network Analysis

SPRC: Source-Pathway-Receptor-Consequence

SRD: Surface road density

SRV: Surface road value

SuDs: Sustainable Drainage Systems

TF: Term Frequency

TOPSIS: Technique for Order Preference by Similarity to Ideal Solution

WSUD: Water Sensitive Urban Design

Appendices

Appendix 1 Sample data of news media data from the GDELT project

Here is a data record of the GDELT database:

1,2015/2/22,245,-2.49500998,深圳市,’TAX_DISEASE_TINNITUS,7184;TAX_FNCACT_PROFESSOR,5293;TAX_FNCACT_PROFESSOR,8124;TAX_FNCACT_PROFESSOR,9053;TAX_FNCACT_DIRECTOR,4449;TAX_FNCACT_DIRECTOR,6905;RETIREMENT,8501;MEDIA_MSM,4484;MEDIA_MSM,4852;TAX_FNCACT_REPORTER,4484;TAX_FNCACT_REPORTER,4852;TAX_FNCACT_CHILD,7805;TAX_FNCACT_CHILD,7836;TAX_DISEASE_HEPATITIS,6183;HEALTH_SEXTRANSDISEASE,6183;SOC_POINTSOFINTEREST_HOSPITAL,4807;SOC_POINTSOFINTEREST_HOSPITAL,5099;SOC_POINTSOFINTEREST_HOSPITAL,6875;SOC_POINTSOFINTEREST_HOSPITAL,11739;TAX_DISEASE_CANCER,7255;TAX_DISEASE_CANCER,7342;TAX_DISEASE_CANCER,7354;NEGOTIATIONS,9126;TAX_DISEASE_POISONING,4627;TAX_DISEASE_POISONING,6047;TAX_WORLDMAMMALS_LION,5542;TAX_FNCACT_CITIZEN,8516;TAX_DISEASE_AMBLYOPIA,6980;ECON_DEVELOPMENTORGS_WORLD_HEALTH_ORGANISATION,1244;ECON_DEVELOPMENTORGS_WORLD_HEALTH_ORGANISATION,10917;ECON_DEVELOPMENTORGS_WORLD_HEALTH_ORGANISATION,11017;TAX_AIDGROUPS,1244;TAX_AIDGROUPS,10917;TAX_AIDGROUPS,11017;GENERAL_HEALTH,1198;GENERAL_HEALTH,1231;GENERAL_HEALTH,1289;GENERAL_HEALTH,1602;GENERAL_HEALTH,4408;GENERAL_HEALTH,5214;GENERAL_HEALTH,5399;GENERAL_HEALTH,7427;GENERAL_HEALTH,7979;GENERAL_HEALTH,8012;GENERAL_HEALTH,10815;GENERAL_HEALTH,10874;GENERAL_HEALTH,10904;GENERAL_HEALTH,11004;MEDICAL,1198;MEDICAL,1231;MEDICAL,1289;MEDICAL,1602;MEDICAL,4408;MEDICAL,5214;MEDICAL,5399;MEDICAL,7427;MEDICAL,7979;MEDICAL,8012;MEDICAL,10815;MEDICAL,10874;MEDICAL,10904;MEDICAL,11004;NATURAL_DISASTER_FLOODED,

10423;TAX_FNCACT_HERO,8708;GEN_HOLIDAY,787;GEN_HOLIDAY,3048;TAX_FNCACT_PHYSICIAN,4838;TAX_FNCACT_CHAIRMAN,5277;EDUCATION,4794;EDUCATION,6518;EDUCATION,9019;SOC_POINTSOFINTEREST_UNIVERSITY,4794;SOC_POINTSOFINTEREST_UNIVERSITY,6518;SOC_POINTSOFINTEREST_UNIVERSITY,9019;TAX_FOODSTAPLES_BREAD,11410;NATURAL_DISASTER_FLOOD,5283;NATURAL_DISASTER_FLOOD,5680;NATURAL_DISASTER_FLOOD,5825;NATURAL_DISASTER_FLOOD,7290;NATURAL_DISASTER_FLOOD,9169;NATURAL_DISASTER_FLOOD,10448;NATURAL_DISASTER_FLOOD,10514;NATURAL_DISASTER_EROSION,6393;TAX_DISEASE_ULCERS,6385;MANMADE_DISASTER_IMPLIED,4556;MANMADE_DISASTER_IMPLIED,4693;PUBLIC_TRANSPORT,4556;PUBLIC_TRANSPORT,4693;TAX_ETHNICITY_CHINESE,708;TAX_ETHNICITY_CHINESE,770;TAX_ETHNICITY_CHINESE,2794;TAX_ETHNICITY_CHINESE,2967;TAX_ETHNICITY_CHINESE,3031;TAX_ETHNICITY_CHINESE,3955;TAX_ETHNICITY_CHINESE,4494;TAX_ETHNICITY_CHINESE,4869;TAX_WORLDLANGUAGES_CHINESE,708;TAX_WORLDLANGUAGES_CHINESE,770;TAX_WORLDLANGUAGES_CHINESE,2794;TAX_WORLDLANGUAGES_CHINESE,2967;TAX_WORLDLANGUAGES_CHINESE,3031;TAX_WORLDLANGUAGES_CHINESE,3955;TAX_WORLDLANGUAGES_CHINESE,4494;TAX_WORLDLANGUAGES_CHINESE,4869;TAX_FNCACT_GENTLEMAN,5363;’,’5#Inner Mongolia, Nei Mongol, China#EG#CH20#13198#44#112#-1920094#9586;4#Shenzhen, Guangdong, China#EG#CH30#13036#22.2#111.117#-1925267#4056;4#Shenzhen, Guangdong, CH30#13046#23.872#116.409#10074125#8213;1#Germany#EG#GM##51#9#GM#6502;4#Hubei, Guangdong, China#EG#CH30#13047#23.2656#116.054#10073728#482;4#Hubei, Guangdong, China#EG#CH30#13047#23.2656#116.054#10073728#2219;1#United States#EG#US##38#-97#US#5865;1#Chinese#EG#CH##35#105#CH#708;1#Chinese#EG#CH##35#105#CH#770;1#Chinese#EG#CH##35#105#CH#2794;1#Chinese#EG#CH##35#105#CH

#2967;1#Chinese#EG#CH##35#105#CH#3031;1#Chinese#EG#CH##35#105#CH#3955;1#Chinese#EG#CH##35#105#CH#4494;1#Chinese#EG#CH##35#105#CH#4869;1#Vietnam#EG#VM##16#106#VM#10986;4#Peking, Beijing, China#EG#CH22#13001#39.9289#116.388#-1898541#4776;1#China#EG#CH##35#105#CH#278;1#China#EG#CH##35#105#CH#489;1#China#EG#CH##35#105#CH#603;1#China#EG#CH##35#105#CH#1068;1#China#EG#CH##35#105#CH#2035;1#China#EG#CH##35#105#CH#2226;1#China#EG#CH##35#105#CH#3668;1#China#EG#CH##35#105#CH#4063;1#China#EG#CH##35#105#CH#4147;1#China#EG#CH##35#105#CH#4662;1#China#EG#CH##35#105#CH#4783;1#China#EG#CH##35#105#CH#5195;1#China#EG#CH##35#105#CH#8086;1#China#EG#CH##35#105#CH#8144;1#China#EG#CH##35#105#CH#8220;1#China#EG#CH##35#105#CH#8882;1#China#EG#CH##35#105#CH#9593;1#China#EG#CH##35#105#CH#9785;1#China#EG#CH##35#105#CH#10673','Department Of Commerce,3810;Center Center,4440;Shanghai Fudan University Department Of Sociology Professor,9053;World Health Organisation,1244;World Health Organisation,10917;World Health Organisation,11017;Germany Hyde University Medicine,6527;United States,5865','Shandong Habitat,42;Shandong Channel Phoenix,101;Shandong Habitat,147; New Year,3974;Chinese New Year,4107;Center Center,4579;Chinese New Year,4644;Chinese New Year,5009;New Year,5075;United States,6008;Germany Hyde University Medicine,6676;Beijing Military General Hospital,7032;Zhou Rong Bin,7076;South China Normal Psychology Associate Professor,8292;Shanghai Fudan University Department,9196;Sociology Professor,9219;Features North,9700;Inner Mongolia,9757;West Country,9910;Zhao Light,10692;World Health Organisation,11195'

Appendix 2 Government-related word list

Government-related word list I: the words related to government organisation include Department, Ministry, Administration, Agency, Bureau, Army, Committee, Authority, Commission, Office, Police, Hospital.

Government-related word list II: the word related to government agency category include Agriculture, Farm, Fisheries, Animal Husbandry, Audit, Home Affairs, Civil Affairs, Trade, Commerce, Business, Culture, Cultural, Tourism, Customs, Armed Forces Department, China Military Commission, Defense, People's Liberation Army, Development, Reform, Education, Disaster Reduction, Emergency, Sanitation, Environmental Protection, Environment, Finance, Economy, Economic, Revenue, Tax, Foreign, Health, Hospital, International Committee A Red Cross, Drug, Housing, Buildings, Construction, Urban Management, City management, City Administration, Human, Labour, Personnel, Family Planning, Industry, Industrial, Information, Justice, Regulations, Legislative, Meteorology, Weather, Meteorological, Planning, Land Resources, Land, Ocean, Oceanic, Sea, Forest, Forestry, Power Supply, Public Security, Police, Fire, Science, Statistics, Transportation, Traffic, Transport, Port, Water, Irrigation, Hydrological, Drainage, River, Lake.

Appendix 3 Results of government agency frequency

Appendix Table 1 Government agency frequency in the 2017 flood

Agency	Frequency
Information	213
Public Security	153
Meteorology	152
Transportation	122
People’s Liberation Army	120
Finance	81
Natural Resources and Planning	69
Agriculture and Rural Affairs	62
Commerce	54
Urban Management	45
Police	36
Education	35
Regulation	34
Health	33
Ocean	33
Defense	27
Justice	26
Animal Husbandry	25
Water Resources	22
Economy	21
Ecology and Environment	20
Hospital	20
Construction	19
Audit	18
Development and Reform	17
Housing	16
River and Lake	16
Civil Affair	14
Forestry	14
Port	14
Culture and Tourism	12
Emergency Management	9
Foreign Affairs	9
Power Supply	9
Fire Brigade	8
Customs	6
Human Resources	6
Armed Forces Department	5
Industry	5
International Committee A Red Cross	4
Legislative	3
Medical Products	3
Revenue	3
Buildings Department	2
China Military Commission	2
Disaster Reduction	2
Science and Technology	2
Family Planning	1
Statistics	1

Appendix Table 2 Government agency frequency in the 2018 flood

Agency	Frequency
Police	646
Meteorology	567
Public Security	206
People's Liberation Army	140
Transportation	121
Commerce	107
Defense	107
Power Supply	58
Education	49
Health	47
Culture and Tourism	41
Natural Resources and Planning	38
Ecology and Environment	33
Agriculture and Rural Affairs	32
Ocean	30
Finance	28
Civil Affair	24
Construction	23
Hospital	23
Revenue	23
Water Resources	17
Fire Brigade	14
Economy	13
Urban management	13
Justice	12
River and Lake	12
Armed Forces Department	11
Foreign Affairs	10
Forestry	8
Industry	8
Customs	5
Housing	5
Human Resources	5
Medical Products	5
Legislative	4
Port	4
Emergency Management	3
Statistics	3
Disaster Reduction	2
Audit	1
Buildings Department	1
Development and Reform	1
International Committee A Red Cross	1
Regulation	1
Trade	1

Appendix Table 3 Government agency frequency in the 2019 flood

Agency	Frequency
Commerce	65
Public Security	59
Culture and Tourism	49
Transportation	28
Natural Resources and Planning	22
Finance	21
Construction	19

Agency	Frequency
Forestry	19
Ecology and Environment	18
Education	16
Audit	15
Health	14
Meteorology	11
Finance	8
Defense	6
Justice	6
Revenue	5
Agriculture and Rural Affairs	5
Industry	4
Customs	4
Power Supply	4
Human resources	4
Hospital	3
Housing	3
Urban management	3
Fire Brigade	3
River and Lake	3
Ocean	2
Armed Forces Department	2
People's Liberation Army	1
Development and Reform	1
Public Security	1
China Military Commission	1

Appendix Table 4 Government agency frequency in the 2020 flood

Agency	Frequency
Meteorology	63
Public Security	47
Transportation	33
Finance	27
Ecology and Environment	26
Construction	24
Education	24
Customs	21
Audit	20
Commerce	18
Natural Resources and Planning	15
Health	12
People's Liberation Army	10
Housing	9
Fire Brigade	8
Regulation	7
Forestry	6
Development and Reform	5
Finance	5
Defense	4
River and Lake	4
Justice	4
Agriculture and Rural Affairs	4
Industry	4
Water Resources	4
Human Resources	4
Foreign Affairs	4
Port	3

Agency	Frequency
Culture and Tourism	3
Public Security	3
Statistics	2
Revenue	2
Urban management	2
Armed Forces Department	2
Power Supply	2
Civil Affairs	1

Appendix Table 5 Government agency frequency in the 2021 flood

Agency	Frequency
Finance	143
Commerce	62
Public Security	54
Defense	39
Transportation	30
Meteorology	21
Natural Resources and Planning	18
Education	18
Finance	13
Construction	13
Industry	12
Development and Reform	11
Justice	11
Human Resources	10
Culture and Tourism	8
Audit	8
Health	8
Agriculture and Rural Affairs	7
Housing	6
Ecology and Environment	6
Customs	4
Regulation	4
People’s Liberation Army	4
Hospital	3
River and Lake	3
Foreign Affairs	2
Power Supply	2
Ocean	1
Forestry	1
Armed Forces Department	1
Fire Brigade	1

Appendix 4 Results of network centrality

Appendix Table 6 The top ten agencies in terms of degree centrality, betweenness centrality, and closeness centrality during the five floods

Year	Agency	Degree centrality	Agency	Betweenness centrality	Agency	Closeness centrality
2017	Finance	36	Finance	133.84	Finance	0.79
	Public Security	36	Public Security	91.96	Public Security	0.79
	Commerce	33	Meteorology	76.97	Commerce	0.75
	Natural Resources and Planning	33	Hospital	68.37	Natural Resources and Planning	0.75
	Transportation	32	Agriculture and Rural Affairs	66.67	Transportation	0.74
	Agriculture and Rural Affairs	29	Commerce	61.26	Agriculture and Rural Affairs	0.71
	Construction	29	Natural Resources and Planning	56.44	Construction	0.71
	Meteorology	29	Transportation	53.61	Meteorology	0.71
	Housing	27	Health	39.88	Housing	0.68
	Ecology and Environment	25	Housing	26.51	Ecology and Environment	0.67
2018	Public Security	25	Public Security	150.96	Public Security	0.70
	Education	21	Meteorology	102.74	Education	0.64
	Health	21	Health	85.69	Health	0.64
	Natural Resources and Planning	20	Finance	76.44	Meteorology	0.64
	Meteorology	19	Transportation	75.79	Natural Resources and Planning	0.63
	Transportation	18	Education	68.74	Transportation	0.62
	Commerce	17	Commerce	46.27	Commerce	0.61
	Finance	17	Disaster Reduction	38.00	Finance	0.61
	Construction	16	Natural Resources and Planning	35.11	Construction	0.60
	Ocean	16	Culture and Tourism	32.84	Ocean	0.59
2019	Public Security	14	Public Security	62.42	Industry	1
	Commerce	12	Ecology and Environment	35.22	People’s Liberation Army	1
	Ecology and Environment	10	Commerce	29.08	Public Security	0.70
	Finance	9	Defense	21.83	Commerce	0.66
	Natural Resources and Planning	9	Education	19.47	Ecology and Environment	0.63
	Education	8	Transportation	18.00	Finance	0.59
	Forestry	8	Finance	15.33	Natural Resources and Planning	0.56

	Transportation	6	Natural Resources and Planning	6.20	Education	0.56
	Construction	5	Audit	1.28	Forestry	0.54
	Customs	5	Forestry	1.17	Customs	0.53
2020	Finance	21	Finance	97.96	Finance	0.81
	Transportation	17	Meteorology	49.25	Education	0.69
	Education	16	Construction	33.38	Transportation	0.68
	Natural Resources and Planning	15	Natural Resources and Planning	32.38	Construction	0.66
	Public Security	14	Education	27.83	Natural Resources and Planning	0.64
	Construction	14	Transportation	21.57	Public Security	0.63
	Forestry	13	Public Security	18.23	Health	0.63
	Health	12	Housing	8.38	Housing	0.63
	Housing	12	Health	6.73	Forestry	0.61
	Justice	11	Customs	5.10	Justice	0.61
2021	Finance	19	Finance	63.44	Finance	0.70
	Public Security	15	Justice	60.13	Public Security	0.67
	Justice	13	Transportation	51.15	Justice	0.63
	Commerce	13	Public Security	49.93	Commerce	0.60
	Meteorology	11	Commerce	38.21	Meteorology	0.60
	Education	11	Education	29.26	Education	0.58
	Defense	10	Meteorology	25.52	Construction	0.58
	Construction	9	Construction	19.46	Foreign Affairs	0.57
	Natural Resources and Planning	9	Natural Resources and Planning	13.40	Natural Resources and Planning	0.55
	Foreign Affairs	8	Defense	12.42	Defense	0.54

Appendix 5 Quantitative results of vulnerability

Appendix Table 7 The results of exposure, disaster reduction capability, and vulnerability

District	Exposure	Disaster reduction capability	Vulnerability
Dongguan District	0.744295	0.217412	0.397249
Southern District	0.569184	0.114144	0.376884
Zengcheng District	0.548067	0.300237	0.24776
Saint Francis parish	0.277865	0.014077	0.244898
Longmen District	0.600179	0.358104	0.241021
Central and Western District	0.571981	0.357057	0.230198
Sai Kung District	0.354957	0.126581	0.228669
Huangpu District	0.460214	0.257563	0.226652
Wan Chai District	0.558722	0.356445	0.225148
Eastern District	0.571411	0.375001	0.221494
Wong Tai Sin District	0.614381	0.421037	0.215725
Xiangzhou District	0.383842	0.1989	0.212655
Baiyun District	0.534437	0.364407	0.211818
Nanhai District	0.417099	0.258831	0.204898
Boluo District	0.441844	0.287953	0.204745
Jinwan District	0.356783	0.182796	0.204241
Shunde District	0.408143	0.259326	0.2003
Zhongshan District	0.341982	0.184174	0.195219
Dapeng District	0.331915	0.170261	0.194957
Huadu District	0.403787	0.282712	0.189091
Shatian District	0.58508	0.462373	0.187237
Guantang District	0.572722	0.458891	0.184752
Conghua District	0.452962	0.366308	0.178814
Enping District	0.431955	0.355502	0.174406
Doumen District	0.353608	0.264559	0.171729
Sanshui District	0.336951	0.252255	0.167717
Tai Po District	0.336303	0.254288	0.166716
Panyu District	0.297951	0.20112	0.164331
Huaiji District	0.322152	0.25751	0.158675
Kowloon City District	0.517994	0.481714	0.158477
Yantian District	0.369091	0.334203	0.155719
Sihui District	0.336335	0.291384	0.154782
Taishan District	0.331569	0.288874	0.153361
Cotai District	0.279276	0.214176	0.150029
Freguesia de Santo António	0.277975	0.216739	0.148563
Pengjiang District	0.292788	0.244945	0.147882
Longgang District	0.321663	0.29459	0.147077
Chancheng District	0.29135	0.252365	0.144987
Sham Shui Po District	0.524744	0.527912	0.143478
Liwan District	0.349335	0.354958	0.141207
Our Lady Of Carmel’s Parish	0.279748	0.253822	0.138809
Tsuen Wan District	0.43965	0.482413	0.134287
Huiyang District	0.29066	0.307139	0.129576
Jianghai District	0.26491	0.27815	0.125197
Yuen Long District	0.27596	0.300269	0.124743
Gaoming District	0.27676	0.3103	0.122592
Kwai Tsing District	0.58329	0.631759	0.119672
Tianhe District	0.360568	0.467285	0.11409
Deqing District	0.221622	0.240202	0.113004
Longhua District	0.220195	0.240754	0.112152
Luohu District	0.248235	0.316786	0.108519
Northern District	0.235402	0.29647	0.107228
Huidong District	0.182021	0.171758	0.106585
Pingshan District	0.193537	0.21232	0.104358

District	Exposure	Disaster reduction capability	Vulnerability
Futian District	0.233531	0.316297	0.102193
Baoan District	0.206569	0.267592	0.099712
Our Lady Fatima Parish	0.279537	0.419618	0.098459
Huicheng District	0.216593	0.298972	0.098164
Nansha District	0.222976	0.323011	0.09625
Kaiping District	0.180712	0.246851	0.090927
Sé Freguesias	0.279307	0.475874	0.086631
Heshan District	0.198921	0.33423	0.083919
Fengkai District	0.196436	0.335691	0.082623
Xinhui District	0.157872	0.241822	0.080238
Guangning District	0.130961	0.158889	0.078759
St. Lazarus Parish	0.278146	0.521021	0.077375
Tuen Mun District	0.176106	0.325609	0.075616
Freguesia de S．Lourenço	0.278424	0.533753	0.075012
Guangming District	0.165761	0.301188	0.07479
Island District	0.151726	0.345857	0.062497
Nanshan District	0.120062	0.250135	0.060015
Yuexiu District	0.150624	0.429045	0.051963
Haizhu District	0.130766	0.403613	0.04769
Yau Tsim Mong District	0.507003	0.824012	0.046771
Gaoyao District	0.08955	0.336158	0.03763
Dinghu District	0.038932	0.262776	0.018975
Duanzhou District	0.019239	0.166574	0.011387

Appendix 6 Python programme examples

Appendix Table 8 Examples for data collection

Data collection

```
#!/usr/bin/env python
# coding: utf-8

# In[1]:

import csv
import gzip
import os

# Define the file path, csv and output file
file_dir= r'C:/Users/gkg_record/'
csvtitle='data-1677052626680'

# Define the folder containing the zip files
folder = file_dir + 'gkg_csv'
csv1_filename = file_dir + csvtitle + '.csv'
folder_filename = file_dir + folder + '.csv.gz'
output_filename = file_dir + 'test.csv'

# Set the field size limit manually to 2^31-1
csv.field_size_limit(2147483647)

# Read in the data from csv1
csv1_data = {}
with open(csv1_filename, 'r', encoding='GB2312') as csv1_file:
    csv1_reader = csv.reader(csv1_file)
    next(csv1_reader) # skip header row
    for row in csv1_reader:
        csv1_data[row[0]] = row[1:]

# Write the matching data to output csv file
with open(output_filename, 'w', encoding='utf-8', newline='') as output_file:
    output_writer = csv.writer(output_file)
    output_writer.writerow(['date', 'time', 'tone', 'lat', 'log', 'city', 'DocumentIdentifier', 'V2Counts',
'V2Tone', 'V2Themes', 'V2Locations', 'V2Persons', 'V2Organisations','AllNames'])
    for filename in os.listdir(folder):
        if filename.endswith('.csv.gz'):
            zip_file_path = os.path.join(folder, filename)
            with gzip.open(zip_file_path, 'rt', encoding='utf-8') as csv2_file:
                csv2_reader = csv.reader(csv2_file)
                next(csv2_reader) # skip header row
                for row in csv2_reader:
                    if row[0] in csv1_data:
                        output_writer.writerow(csv1_data[row[0]] + row[1:])

# In[ ]:
```

Appendix Table 9 Examples for word frequency analysis

Data processing 1

```
import numpy as np
import pandas as pd
```

```
import warnings
warnings.filterwarnings('ignore')


# In[2]:

# Load the dataset into a pandas DataFrame
df = pd.read_csv(r'C:\Users\关键词及主题分析/allname_zhuhai.csv')

# Convert the date column to datetime format

df.head()

# In[27]:

# Split the V2Themes column into separate rows
df3 =
df.assign(AllNames=df.AllNames.str.split(';')).explode('AllNames').reset_index(drop=True)

# Extract the name and offset values into separate columns
df3[['allnames', 'Offset']] = df3.AllNames.str.split(',', expand=True)

# Drop the original AllNames column
df3 = df3.drop(columns='AllNames')
df3 = df3.drop(columns='Offset')

# Drop rows with NaN values in Themes column
df3.dropna(subset=['allnames'], inplace=True)
df3 = df3[df3['allnames'] != '']

df3.head(35)
df3.to_csv(r'C:\Users\关键词及主题分析/keywords_zhuhai.csv')
```

Data processing 2

```
import pandas as pd

data = pd.read_csv(r'C:\Users\关键词及主题分析\theme/theme_s2.csv')

# 使用 del, 一次只能删除一列，不能一次删除多列

# del data[':']
first_column = data.columns[0]

data = data.drop([first_column], axis=1)

data.to_csv(r'C:\Users\关键词及主题分析\theme/theme_s3.csv',encoding='utf-8',index=0)
```

Word frequency counting

```
# encoding:utf-8
__author__ = 'admin'
__date__ = '2023/4/6'

def get_word(filePath):
    '''
    读取 csv 文件获取主题信息并存储到列表中
    :param filePath: csv 文件路径
```

```
    :return word_list: 一个包含所有主题的列表
    ‘‘‘
    # 设置编码为 utf-8-sig 防止首部\ufeff 的出现,它是 windows 系统自带的 BOM,用于区分大端和小端 UTF-16 编码
    with open(filePath, ‘r’, encoding=‘utf-8-sig’) as f:
        text = f.read()
        word_list = text.split(‘\n’)  # 分割数据中的换行符’\n’两边的数据
        word_list.remove(‘‘)         # 删除列表结尾的空字符
        return word_list

def str2csv(filePath, s):
    ‘‘‘
    将字符串写入到本地 csv 文件中
    :param filePath: csv 文件路径
    :param s: 待写入字符串(逗号分隔格式)
    ‘‘‘
    with open(filePath, ‘w’, encoding=‘utf-8’) as f:
        f.write(s)
    print(‘写入文件成功,请在’+filePath+’中查看’)

def sortDictValue(dict, is_reverse):
    ‘‘‘
    将字典按照 value 排序
    :param dict: 待排序的字典
    :param is_reverse: 是否按照倒序排序
    :return s: 符合 csv 逗号分隔格式的字符串
    ‘‘‘
    # 对字典的值进行倒序排序,items()将字典的每个键值对转化为一个元组,key 输入的是函数,item[1]表示元组的第二个元素,reverse 为真表示倒序
    tups = sorted(dict.items(), key=lambda item: item[1], reverse=is_reverse)
    s = ‘‘
    for tup in tups:  # 合并成 csv 需要的逗号分隔格式
        s = s + tup[0] + ‘,’ + str(tup[1]) + ‘\n’
    return s

def build_matrix(word_list, is_reverse):
    ‘‘‘
    :param word_list: 关键词列表
    :param is_reverse: 排序是否倒序
    :return node_str: 三元组形式的节点字符串(且符合 csv 逗号分隔格式)
    ‘‘‘
    node_dict = {}  # 节点字典,包含节点名+节点权值(频数)
    # 第 1 层循环,遍历整表的每行主题信息
    for row_word in word_list:
        row_word_list = row_word.split(‘,’) # 依据’,’分割每行所有关键词,存储到列表中
        # 第 2 层循环,遍历当前行所有作者中每个作者信息
        for index, pre_au in enumerate(row_word_list): # 使用 enumerate()以获取遍历次数 index
            # 统计单个关键词出现的频次
            if pre_au not in node_dict:
                node_dict[pre_au] = 1
            else:
                node_dict[pre_au] += 1
    # 对得到的字典按照 value 进行排序
```

```
    node_str = sortDictValue(node_dict, is_reverse)  # 节点
    return node_str

if __name__ == ‘__main__’:
    readfilePath = r’C:\Users\关键词及主题分析\theme\按年\已处理\2015.csv’
    writefilePath1 = r’C:\Users\关键词及主题分析\theme\按年\已处理\2015n.csv’
    # 读取 csv 文件获取关键词信息并存储到列表中
    word_list = get_word(readfilePath)
    # 根据共同关键词列表, 构建共现矩阵(存储到字典中), 并将该字典按照权值排序
    node_str = build_matrix(word_list, is_reverse=True)
    # 将字符串写入到本地 csv 文件中
    str2csv(writefilePath1, node_str)
```

Appendix Table 10 Examples of co-occurrence analysis

Data processing 1

```
#!/usr/bin/env python
# coding: utf-8

# In[1]:

import re
import pandas as pd

# Load the whole dataset into a pandas DataFrame(把完整的数据导入成 dataframe)
df = pd.read_csv(r’C:\Users\组织分析\1025 数据处理\2017-org.csv’)

# define a function to process each row
def process_themes(row):
    # split the V2Themes string by semicolon
    themes_str = row[‘theme’]
    themes_list = themes_str.split(‘;’)

    # create a set to keep track of unique themes
    unique_themes = set()

    # iterate through each theme and extract the theme name
    cleaned_themes = []
    for theme_str in themes_list:
        theme_name = theme_str.split(‘,’)[0]
        if theme_name not in unique_themes:
            unique_themes.add(theme_name)
            cleaned_themes.append(theme_name)

    # join the cleaned themes with semicolons and return as a string
    return ‘;’.join(cleaned_themes)

# apply the process_row function to each row in the dataframe
df[‘theme’] = df.apply(process_themes, axis=1)

# In[3]:

# In[4]:

df.to_csv(r’C:\Users\组织分析\1025 数据处理\s1.csv’)
```

In[ ]:

Data processing 2

```
import numpy as np
import pandas as pd

import warnings
warnings.filterwarnings('ignore')

# In[2]:

# Load the dataset into a pandas DataFrame
df = pd.read_csv(r'C:\Users\组织分析\1025 数据处理\s1.csv')

df.head()

# In[27]:

# Split the V2Themes column into separate rows

df3 = df['theme'].str.split(';', expand=True)

df3.head()
df.drop(['theme'], axis=1, inplace=True)
df3.head()

df3.to_csv(r'C:\Users\组织分析\1025 数据处理\s2.csv')
```

Data processing 3

```
# 数据清洗：Python 将一列数据拆分成多列

import pandas as pd

test_data = pd.read_csv(r' C:\Users\组织分析\1025 数据处理\s2.csv')
columns = test_data.columns.to_list()
test_data.head()

def col_split(data):

    '''统计需要进行拆分的字段：如果某一列所有非空取值均包含';',则需要拆分
    '''

    split_col = []
    for i in columns:
        num = 0
        temp = data[i].dropna()
        if len(temp)>0 : # 对于有取值的字段，判断是否需要拆分
            for j in temp:
                if ';' in str(j) :
                    num+=1
            if num == len(temp):
                split_col.append(i)

    '''拆分数据并进行保存
    '''
    cleaned_data = pd.DataFrame()
    for i in columns:
        if i in split_col:
```

```
            temp = data[i].str.split(';',expand=True)
            cleaned_data[i] = temp[1] # 保留右侧一列

        else:
            cleaned_data[i] = data[i]
    cleaned_data.to_csv(r' C:\Users\组织分析\1025 数据处理\s2.csv',encoding='utf-8',index=0)


    return cleaned_data

col_split(test_data)
```

Co-occurrence matrix

```
# encoding:utf-8
__author__ = 'admin'
__date__ = '2023/4/6'

def get_Co_theme(filePath):
    '''
    读取 csv 文件获取组织信息并存储到列表中
    :param filePath: csv 文件路径
    :return co_theme_list: 一个包含所有组织的列表
    '''
    # 设置编码为 utf-8-sig 防止首部\ufeff 的出现,它是 windows 系统自带的 BOM,用于区分大端
和小端 UTF-16 编码
    with open(filePath, 'r', encoding='utf-8-sig') as f:
        text = f.read()
        co_theme_list = text.split('\n')  # 分割数据中的换行符'\n'两边的数据
        co_theme_list.remove('')          # 删除列表结尾的空字符
        return co_theme_list

def str2csv(filePath, s):
    '''
    将字符串写入到本地 csv 文件中
    :param filePath: csv 文件路径
    :param s: 待写入字符串(逗号分隔格式)
    '''
    with open(filePath, 'w', encoding='utf-8') as f:
        f.write(s)
    print('写入文件成功,请在'+filePath+'中查看')

def sortDictValue(dict, is_reverse):
    '''
    将字典按照 value 排序
    :param dict: 待排序的字典
    :param is_reverse: 是否按照倒序排序
    :return s: 符合 csv 逗号分隔格式的字符串
    '''
    # 对字典的值进行倒序排序,items()将字典的每个键值对转化为一个元组,key 输入的是函
数,item[1]表示元组的第二个元素,reverse 为真表示倒序
    tups = sorted(dict.items(), key=lambda item: item[1], reverse=is_reverse)
    s = ''
    for tup in tups:  # 合并成 csv 需要的逗号分隔格式
        s = s + tup[0] + ',' + str(tup[1]) + '\n'
    return s
```

```
def build_matrix(co_theme_list, is_reverse):
    '''
    根据共同组织列表,构建共现矩阵(存储到字典中),并将该字典按照权值排序
    :param co_theme_list: 共同组织列表
    :param is_reverse: 排序是否倒序
    :return node_str: 三元组形式的节点字符串(且符合 csv 逗号分隔格式)
    :return edge_str: 三元组形式的边字符串(且符合 csv 逗号分隔格式)
    '''
    # node_dict = {}  # 节点字典,包含节点名+节点权值(频数)
    edge_dict = {}  # 边字典,包含起点+目标点+边权值(频数)
    # 第 1 层循环,遍历整表的每行组织信息
    for row_theme in co_theme_list:
        row_theme_list = row_theme.split(';') # 依据';'分割每行所有组织,存储到列表中
        # 第 2 层循环,遍历当前行所有作者中每个作者信息
        for index, pre_au in enumerate(row_theme_list): # 使用 enumerate()以获取遍历次数 index
            # 统计单个组织出现的频次
            # if pre_au not in node_dict:
            #     node_dict[pre_au] = 1
            # else:
            #     node_dict[pre_au] += 1
            # # 若遍历到倒数第一个元素,则无需记录关系,结束循环即可
            # if pre_au == row_theme_list[-1]:
            #     break
            connect_list = row_theme_list[index+1:]
            # 第 3 层循环,遍历当前行该组织后面所有的共现,以统计两两组织出现的频次
            for next_au in connect_list:
                A, B = pre_au, next_au
                # 固定两两组织的顺序
                if A > B:
                    A, B = B, A
                key = A+','+B  # 格式化为逗号分隔 A,B 形式,作为字典的键
                # 若该关系不在字典中,则初始化为 1,表示组织间的共现次数
                if key not in edge_dict:
                    edge_dict[key] = 1
                else:
                    edge_dict[key] += 1
    # 对得到的字典按照 value 进行排序
    # node_str = sortDictValue(node_dict, is_reverse)  # 节点
    edge_str = sortDictValue(edge_dict, is_reverse)   # 边
    # return node_str, edge_str
    return edge_str

if __name__ == '__main__':
    readfilePath = r'C:\Users\组织分析\1025 数据处理\s2.csv''
    writefilePath2 = r'C:\Users\组织分析\1025 数据处理\s2.csv''
    co_theme_list = get_Co_theme(readfilePath)
    edge_str = build_matrix(co_theme_list, is_reverse=True)
    # 将字符串写入到本地 csv 文件中
    # str2csv(writefilePath1, node_str)
    str2csv(writefilePath2, edge_str)
```

Appendix Table 11 Examples of Structured Query Language

Create table in PostgreSQL database
create table osm_road(

```
osm_id varchar(50),
code varchar(50),
fclass varchar(50),
name varchar(100),
ref varchar(50),
oneway varchar(10),
maxspeed varchar(10),
layer varchar(10),
bridge varchar(10),
tunnel varchar (10),
adcode varchar(50),
name_2 varchar(100),
center varchar(50),
centroid varchar(50),
childrenNu varchar(50),
level varchar(50),
parent varchar(100),
subFeature varchar(100),
acroutes varchar(100),
length double precision);

create table GDELT_Flood(
record varchar(50),
date date,
time varchar(10),
tone double precision,
log double precision,
lat double precision,
city varchar(50) );
```

Data queries

```
select to_char(date::DATE, 'YYYY-MM') as month, avg(tone),count(*), city from gdelt_flood group by month, city order by month

select date, avg(rainfall), sum(tone_sum), sum(tone_count) from rainfall_GBA  where city='东莞市' or city='广州市' or city='深圳市' or city='惠州市' or city='江门市' or city='中山市' or city='珠海市' or city='佛山市' or city='肇庆' group by date

select * from organisation where org like '%Government%' or org like '%Agency%' or org like '%Ministry%' or org like '%Department%'  or org like '%Bureau%' or org like '%Commission%' or org like '%Administration%' or org like '%Office%' or org like '%Institute%' or org like '%Authority%' or org like '%Council%' or org like '%Committee%' or org like '%Government%' or org like '%Secretariat%' or org like '%Army%' or org like '%Party%' or org like '%Commission%' or org like '%Police%'

select theme, sum(frequency) from gdelt_flood where
theme='CRISISLEX_C04_LOGISTICS_TRANSPORT'
or theme='WB_793_TRANSPORT_AND_LOGISTICS_SERVICES'
or theme='WB_1173_TRANSPORT_LOGISTICS_PROVIDERS'  or
theme='WB_551_GAS_TRANSPORTATION_STORAGE_AND_DISTRIBUTION' group by
theme
```