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Framing Disaster Resilience: A Media Discourse Analysis of British Newspapers

GEO 511 Master's Thesis

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Abstract

Climate disasters already pose a significant threat to people worldwide, and this threat is projected to intensify in the future in the context of ongoing climate change. Despite the establishment of defensive structures and early warning systems to mitigate the consequences of disasters, there is an increasing acknowledgement that traditional measures cannot entirely prevent them, leading to the necessity of building disaster resilience to improve coping mechanisms. This thesis examined disaster resilience discourse in five British broadsheet newspaper outlets from 2000 to 2023. Drawing on the Disaster Resilience Integrated Framework for Transformation (DRIFT), the study analysed key community strategies and coping mechanisms across five capacities – preventive, anticipative, absorptive, adaptive and transformative – assessing how they vary spatially and change over time. Due to the systematic under-representation of disaster resilience in the Global South and of slow-onset disasters, the discourse is assessed in terms of the delineation between the Global North and the Global South, as well as between sudden- and slow-onset disasters. Supervised classification was applied to identify and extract clauses relevant to each resilience capacity, enabling a systematic analysis of the discourse. Overall, absorptive capacity received the most emphasis, whereas adaptive and transformative capacities – two important capacities for establishing resilience against changing conditions – were given the least. The results revealed a strong focus on the economic aspects of disaster resilience in the British media, with an increasing shift from reactive funding toward proactive investments. Media coverage of disaster resilience showed regional imbalances, with absorptive capacity dominating but framed differently across the Global North and South. For slow-onset disasters, media coverage highlighted more long-term planning but fewer preventive measures, partly due to political disincentives to invest in benefits beyond immediate political cycles. Overall, this thesis sheds light on the British media's discourse on disaster resilience, unveiling significant neglect of two crucial capacities: adaptive and transformative.

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Contents

List of Figures

List of Tables

List of Abbreviations

BoW Bag of Words
DRIFT Disaster Resilience Integrated Framework for Transformation
DRM Disaster Risk Management
G-77 Group of 77
IPCC Intergovernmental Panel on Climate Change
KDE Kernel Density Estimation
NER Named Entity Recognition
NLP Natural Language Processing
TF-IDF Term Frequency-Inverse Document Frequency
UNDRR United Nations Office for Disaster Risk Reduction
UNISDR United Nations International Strategy for Disaster Reduction

1 Introduction

Every year on average 40,000 to 50,000 people die due to disasters, including floods, droughts, earthquakes or wildfires (Ritchie et al., 2022). The number of deaths can vary widely especially in years with sudden shocking events, which can push annual disaster related deaths to over 200,000 (Abbass et al., 2022). Fatalities are country specific, with some countries being significantly more vulnerable than others (United Nations International Strategy for Disaster Reduction [UNISDR], 2008). Even though disaster-related fatalities have decreased in the last century, the number of affected people and the economic effects have increased (Centre for Research on the Epidemiology of Disasters & United Nations Office for Disaster Risk Reduction [UNDRR], 2020; Djalante et al., 2013). Developments, such as population growth (Wiranata et al., 2021), urbanisation (Manuel-Navarrete et al., 2007), lack of planning strategies (McEntire, 2001) and migration (Aldrich & Meyer, 2015) result in more infrastructure being placed in hazard-prone areas, more people settling there, and increased exposure (Banholzer et al., 2014), while land-use change (Martine & Guzmán, 2002) and environmental degradation such as deforestation, riverbank alteration and inappropriate hillside agriculture (Manuel-Navarrete et al., 2007) lead to greater vulnerability. The dependency of society on critical infrastructure may further escalate the effects and impacts of disasters. Simultaneously, climate change results in elevated temperatures (Wiranata et al., 2021), increased atmospheric water vapour (UNISDR, 2008), sea level rise (Aldrich & Meyer, 2015), and changes in sea surface temperature (UNISDR, 2008) which can change the frequency, intensity, extent and timing of hazardous events (Intergovernmental Panel on Climate Change [IPCC], 2022; Organisation for Economic Co-operation and Development, 2016). Outcomes of disasters can be alleviated through the implementation of preparedness and mitigation strategies (Cannon, 1994) such as forecasting and early warning systems (Popescu et al., 2010), the construction of robust infrastructure and defence structures or the formulation of suitable response plans (Abbass et al., 2022). However, there is growing recognition that disasters cannot be prevented entirely with traditional measures and immediate help is sometimes not available (Lu & Stead, 2013; Patel et al., 2017; Sharifi, 2016). This underscores the necessity for communities to build disaster resilience and for research to support them (Shukla et al., 2025; Turoff et al., 2016).

While some adverse effects cannot be entirely eliminated, resilience offers a possibility to reduce vulnerabilities. In recent decades, the concept of resilience has gained traction in scientific, political and media discourse (Leitch & Bohensky, 2014; Sharifi, 2016). Despite its prominence, the definition remains very vague and uncertain due to its varying uses in different scientific backgrounds (Berkes & Ross, 2013; Eitel, 2023; Kirmayer et al., 2009). Mentges et al. (2023) define resilience as the ability of communities or systems to cope with sudden impacts. It includes the capacity of groups or societies to prepare, cope, adapt, withstand and recover from adverse effects (Eitel, 2023; Koliou et al., 2020; Rana, 2020). Examples of resilience include the preparation for evacuation, the ability to secure infrastructure support, the planning of temporary housing, or the securing of resources for rebuilding (Thulin & Zimmerman, 2021).

The assessment of the climate disaster resilience discourse in the media can help identify and define factors that are relevant in contributing to or promoting resilience (Kirmayer et al., 2009). As daily information drivers, the media, particularly newspapers, play a prominent role in shaping public understanding and perception of discourses (Rashid, 2011; Sadman et al., 2021). In the context of disasters and disaster resilience, they cover various aspects, including coping and adaptation strategies, as well as responses by institutions (Choudhury & Haque, 2018). The assessment of resilience in the media discourse is important, as the media can influence public opinion and draw attention to certain issues and accordingly shape public agendas (Andrews & Caren, 2010) and facilitate public understanding of an issue (Schoenfeld et al., 1979). Additionally, emphasised media attention can result in political agenda setting (Walgrave & Van Aelst, 2006) and informs decision-making processes for relevant stakeholders (Sharifi, 2016).

Newspaper articles present a source of large amounts of unstructured text data (Ghasiya & Okamura, 2021). Computational approaches are required to extract and retrieve information from these texts (Sadman et al., 2021). Natural Language Processing (NLP) is a method that has been developed for the analysis of large-scale and complex unstructured data (Stede & Patz, 2021), thus facilitating the procurement of insights into the prevailing subjects discussed within newspaper articles (Sodoge et al., 2023).

Despite the publication of a number of studies that have analysed disaster resilience in a media context, no assessment has examined the discourse on a global scale. Most scientific research has addressed the discourse in the Global North (see Choudhury and Haque, 2018; Leitch and Bohensky, 2014; Torres and Alsharif, 2016), while only a few publications have evaluated disaster resilience in the context of the Global South (see Dhakal, 2018). Furthermore, the literature has largely concentrated on sudden-onset disasters, with slow-onset disasters receiving comparatively little attention (Staupe-Delgado & Rubin, 2022). Previous studies have typically adopted either a purely qualitative or quantitative approach to text analysis and information retrieval, with few attempts to combine the two.

The following work is structured around three fundamental objectives. The main objective of this thesis is (1) to analyse British broadsheet newspapers to determine key strategies and coping mechanisms discussed in the discourse of climate disaster resilience, examining temporal and spatial variations and thematic topics using a computational classification approach. Furthermore, (2) a comparison of the reporting in the Global North and Global South is conducted. Finally, (3) the differences in the reporting on slow-onset and sudden-onset disasters are evaluated.

The remainder of this thesis is organised as follows. Chapter 2 proceeds with a background section focusing on placing the disaster resilience discourse in the broader context of Disaster Risk Management (DRM). It further introduces the concept of NLP and its application for text classification and analysis of resilience discourse. An overview is provided of previous studies in this interdisciplinary research field. Chapter 3 presents the chosen data and the research methodology of the thesis. Chapter 4 describes the model performance as well as the main findings of the analysis. The implications of the results are discussed in Chapter 5. Chapter 6 emphasises the most crucial findings and outlines future research directions.

2 | Literature Review

2.1 Disaster Risk Management

Extreme events, natural hazards and disasters are interrelated yet genuinely distinct concepts. While the terms extreme events and natural hazards are often used interchangeably (Banholzer et al., 2014), disasters do not inherently stem from natural hazards. An extreme event becomes a disaster only when it has a significant impact on a community and when the community lacks the capacity to cope with the resulting impacts (Govind & Verchick, 2015). It is the influence on society that transforms a natural hazard into a disaster (Cannon, 1994; Staupe-Delgado, 2019b). Hence, the UNDRR – formerly UNISDR – defines a disaster as "a serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources" (UNISDR, 2009, p. 9). The severity of a disaster is determined by the prevailing conditions such as exposure, vulnerability or lack of preparedness of a community (Banholzer et al., 2014; UNISDR, 2008).

Due to the difficulties of delineating natural hazards and disasters in newspapers and the likelihood that natural hazards reported in newspapers already have a certain significance and severity for society, no distinction is made between the two terms in the following thesis.

Traditional DRM encompasses processes aimed at enhancing the comprehension of disaster risk, in addition to promoting disaster mitigation, preparedness, response, and recovery, with the overarching objective of increasing human security and well-being (IPCC, 2022). The DRM framework consists of three elements: hazard, exposure, and vulnerability (Simonovic, 2016). Hazard refers to the potential occurrence of an event that can cause losses or damage (Pörtner et al., 2022). Exposure is defined as the presence of people or resources that could potentially be affected by the hazard (Simonovic, 2016). Vulnerability refers to "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard" (Wisner et al., 2004, p. 11). Disaster risk is the product of the interaction between hazard, exposure of elements, and vulnerability conditions (Amirzadeh & Barakpour, 2021). To manage and reduce disaster-related risks, it is necessary to reduce both vulnerability and exposure to the hazard (Simonovic, 2016).

In recent decades, the concept of resilience has gained increasing prevalence in the field of DRM (MacAskill & Guthrie, 2014), which is largely attributable to the United Nations' *Hyogo Framework for Action 2005-2015: Building Resilience of Nations and Communities to Disasters* (Aldunce et al., 2015; Meriläinen et al., 2022). DRM aims to reduce pre-hazard vulnerabilities and exposure to decrease existing disaster risks, prevent new risks and manage residual risk to contribute to the strengthening of disaster resilience. Disaster resilience further focuses on enabling communities or societies to adapt to and cope with the impacts of hazards and to ensure the system's performance during disasters (Keating & Hanger-Kopp, 2020; Simonovic, 2016). It includes pre-disaster activities to adjust to new disaster events, as well as post-disaster strategies to cope with disasters (Matarrita-Cascante & Trejos, 2013; Tierney & Bruneau, 2007).

Besides resilience, vulnerability is also a crucial concept in DRM, focusing on pre-event characteristics that could make a community potentially susceptible to harm (Cutter et al., 2008). Resilience and vulnerability need to be looked at as interrelated concepts (Matarrita-Cascante et al., 2017). Turesson et al. (2024) emphasised the importance of understanding the vulnerabilities of communities to enhance their resilience, whereas Manyena and Gordon (2015) focused on the relevance of accepting the underlying vulnerability to effectively build resilient strategies. Improving disaster resilience, on the other hand, can also help to reduce the vulnerability of a community (Burton, 2015).

2.2 Resilience

The concept of resilience has been extensively studied across a range of academic disciplines, leading to a proliferation of definitions and understandings within the scientific literature, policies and practices (Patel et al., 2017). Nonetheless, the interdisciplinary application of resilience has resulted in a diversity of definitions and interpretations, making the term challenging to operationalize. One reason for these differences in interpretation is the diverse historical background of the concept (Mentges et al., 2023). It has been applied in several fields including engineering, psychology, development studies, behavioural science, international relations, economics, and climate policy (Eitel, 2023; Kirmayer et al., 2009; Koliou et al., 2020). The origins of the concept can be traced back to the 1800s in material science, where it was used as an indicator of toughness and to describe a material's ability to return to equilibrium after displacement (Kirmayer et al., 2009; Norris et al., 2008). The first applications of resilience within social sciences also emerged during the mid-1800s, when the term was used to describe resistance (Sousa & Moss, 2022). Over a century later, in the 1970s, Holling (1973) was among the first researchers to use resilience in the context of ecology, indicating the resilience of ecosystems (Asadzadeh, Khavarian-Garmsir, et al., 2022; Berkes & Ross, 2013). Resilience was understood as the capacity of ecosystems to absorb change and persist in a state of adversity, assuming adaptation as a part of resilience (Eitel, 2023; Koliou et al., 2020). Concurrently, resilience gained prominence in psychology to study factors that enable individuals to endure hardship and perform better under adversity (Sousa & Moss, 2022). The psychological as well as the social-ecological perspective have had a significant influence on the discourse in disaster literature (Ross & Berkes, 2014). Timmermann's (1981) conceptualisation of disaster resilience was among the earliest and drew heavily on the concept of Holling (1973), placing particular emphasis on the ability to recover after disasters (Koliou et al., 2020). The 1990s marked a turning point, as climate policy discussions brought resilience beyond academia, integrating it into policy decision making (Eitel, 2023). By the 2000s, resilience literature expanded its focus to incorporate social and human dimensions, reflecting its growing relevance across disciplines (Koliou et al., 2020).

Another reason for the diverse definitions of resilience is the multitude of applications of the concept (Mentges et al., 2023). The context in which resilience is used dictates the most suitable approach and the objectives pursued (Matarrita-Cascante et al., 2017), and thus exerts an influence on the preferred interpretation. Furthermore, there are differing opinions on how specific the resilience concept needs to be for a suitable application. Some authors argue that the concept does not require narrowing down (Baggio et al., 2015; Tamberg et al., 2022) while others advocate for more clearly defined concepts, as assessments otherwise become inefficient and meaningless (Klein et al., 2003; Patel et al., 2017).

Despite the interdisciplinary application of the concept, there are certain core factors that appear consistently across various definitions, forming a basis for its application. These core factors are: (1) resilience as a process, (2) community's active role in pursuing resilience, (3) resilience as a multi-scalar concept, and (4) resilience as a capacity. These similarities are discussed in detail below.

Resilience has long been viewed as a positive outcome in the wake of adversity. However, during the 2000s, a shift in thinking resulted in a growing recognition that resilience should be regarded as a process rather than an outcome (Fraser et al., 2004; Pfefferbaum et al., 2007). This rethinking emerged from the growing acceptance of the inevitability of future uncertainties that cannot be accurately anticipated and require a dynamic response (Sharifi, 2016). The presence of unknown future climatic impacts resulting from climate change underscores the necessity for a dynamic approach to disaster resilience (Berkes & Ross, 2013). Furthermore, resilience varies depending on the social context in which it is applied, being influenced by value systems and culture (Kirmayer et al., 2009). Resilience can be understood as "a result of social learning from previous crises that may become integral to patterns of cultural knowledge" (Eitel, 2023, p. 9).

Many definitions emphasise the community's ability to assume an active role in fostering resilience, contributing to the residents' well-being, and actively working towards a desired state (Berkes & Ross, 2013; Magis, 2010; Norris et al., 2008). The prevailing consensus in the literature is that resilience constitutes active engagement, rather than merely the potential to act (Magis, 2010). This includes recovering from adversity (Kanno et al., 2019), which supports the predominant concept that resilience is about adaptability instead of stability (Waller, 2001). For communities to demonstrate their resilience, they must adapt to changing circumstances to mitigate their vulnerability, whereas stability could indicate a lack of adjustment to disasters and a lack of resilience (Klein et al., 2003; Norris et al., 2008). To adapt to adversity, communities need to actively build and engage economic, social, cultural, and political resources (Magis, 2010), whereby people should not be framed as passive victims, but as capable agents (Amirzadeh & Barakpour, 2021).

Resilience must be understood as a multi-scalar concept (Kirmayer et al., 2009; Koliou et al., 2020). Since changes and disasters occur at and impact different levels, resilience should not be examined at solely one level and in isolation from other levels (Sharifi, 2016). The interaction between these various scales requires a balanced approach to manage the dynamic relationships between them (Chelleri et al., 2015). According to Béné et al. (2013), resilience thinking highlights how actions taken at one level can influence outcomes at other levels, demonstrating that interventions at one scale can either support or interfere with other parts (see Meriläinen et al. (2022)).

In the majority of definitions, resilience is associated with *ability* or *capacity* (Magis, 2010; Norris et al., 2008). A particularly relevant factor is the community's capacity to act in a timely manner before, during or after a disaster, with the objective of reducing the community's vulnerability and the disaster's negative impacts (Manyena et al., 2019). In essence, resilience encompasses a community's ability to build strengths in anticipation of disasters and changes (Sherrieb et al., 2010), hence enhancing their ability to evolve in dynamic environments (Magis, 2010). The IPCC defines resilience as "[t]he capacity of social, economic, and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganising in ways that maintain their essential function, identity and structure, while also maintaining the capacity for adaptation, learning and transformation" (IPCC, 2022, p. 2920).

Resilience capacities represent an important concept in the IPCC's resilience definition. While disaster resilience refers to the process of coping with disasters, adapting to new situations and transforming, resilience capacity refers to the underlying conditions that make it possible to cope with disasters (Park & Kennedy Ochieng, 2024). In the past, many authors have concentrated on absorptive, adaptive and transformative capacities (see Asadzadeh, Kötter, et al., 2022; Bartelet et al., 2023; Béné et al., 2013, 2014; Cutter et al., 2008; Jeans et al., 2017; Malherbe et al., 2024; Park and Kennedy Ochieng, 2024; Reyers et al., 2022). Building on this literature Manyena et al. (2019) advanced a novel conceptualization of disaster resilience: Disaster Resilience Integrated Framework for Transformation (DRIFT). The conceptualisation incorporates two additional capacities, preventive and anticipative, to emphasise the link between sustainable development and disasters (Manyena et al., 2019). The DRIFT framework therefore amounts to a total of five capacities that contribute to disaster resilience: preventive, anticipative, absorptive, adaptive, and transformative capacities.

2.2.1 DRIFT Framework

The DRIFT framework consists of preventive, anticipative, absorptive, adaptive, and transformative measures. The preventive and anticipative capacities are of particular relevance in the period preceding a disaster, while the absorptive, adaptive, and transformative capacities represent approaches that are employed during and in the aftermath of a disaster to cope with the consequences (Moghadas et al., 2023). The DRIFT framework's five capacities represent underlying conditions that improve coping with disasters. Realising resilience capacities requires inputs and processes (Manyena, 2006). Learning, planning, organising, allocating resources, collaborating, networking, improvising, and innovation are considered inherent elements to enabling and managing these five capacities (Manyena et al., 2019).

The objective of *preventive* capacity is to reduce the vulnerability and exposure of communities or systems by minimising existing risks and avoiding new risks (Malec et al., 2022). Emphasis is placed on interventions that strengthen physical, human, social, financial, and political capital (Park & Kennedy Ochieng, 2024). This includes measures intended to prevent the occurrence of a disaster, including physical protection of infrastructure, environmental management or access to disaster education.

Anticipative capacity is concerned with foresight and timely recognition of future risks and potential disasters, and focuses on the questions of where, when and who the disaster will affect (Manyena et al., 2019). An important aspect lies in the understanding of risk and disaster scenarios, and leveraging this knowledge to formulate predictions and execute timely responses (Moghadas et al., 2023). Anticipative capacity incorporates strategies to identify and prepare for future shocks, including short-term prediction, long-term forecasting, scenario planning, monitoring critical processes and utilising of early warning systems (Lankford et al., 2023).

Absorptive capacity is the capacity realised once a disaster strikes. It is defined as the short-term response that aims to mitigate the initial adverse effects and to ensure the persistence of the system while seeking a quick recovery (Lankford et al., 2023; Mentges et al., 2023). It absorbs or buffers the immediate impact of disasters and enables the bouncing back after a disaster (Malherbe et al., 2024). It encompasses provision of support to victims, as well as implementation of short-term measures to address the consequences of a disaster, such as imposition of water restrictions during drought conditions.

If absorptive capacity is not sufficient to cope with the intensity of a disaster, *adaptive* capacity is required (Mentges et al., 2023). Adaptive capacity involves acceptance that changes and disasters are ongoing and unpredictable (Jeans et al., 2017) and involves the ability to make suitable adaptations to more effectively manage gradually changing situations (Béné et al., 2014; Gibson et al., 2016). Adaptation is perceived as the capacity to actively exploit new opportunities (Amirzadeh & Barakpour, 2021; Tiernan et al., 2019). It integrates coping strategies with medium-term strategies. Adaptive capacity emphasises learning from previous disasters and making incremental adjustments to new situations to maintain functionality, including the use of flood-resistant materials for buildings in flood-prone areas.

Transformative capacity goes beyond the previously mentioned capacities. Its objective is to establish alternative structures to those that cause vulnerability and risk, thereby challenging the status quo (Malec et al., 2022; Manyena et al., 2019). This entails implementing fundamental changes to the process or system, which may entail a transition from reactive to proactive measures (Asadzadeh, Khavarian-Garmsir, et al., 2022). Transformative capacity is not merely about recovering from a disaster, but about transitioning to a new state that facilitates more effective coping with disasters, or to a state in which the disaster is no longer a major threat (Moghadas et al., 2023; Schlosberg et al., 2017). Thus, it can be regarded as a long-term response to disasters. Examples include seeking alternative employment opportunities in different industries or relocating to more suitable areas.

2.2.2 Resilience in Different Contexts

There is a noticeable discrepancy in the attention given to sudden- and slow-onset disasters in the literature. While sudden-onset disasters are the subject of extensive research, slow-onset disasters receive comparatively less attention from academics and policymakers (Amirzadeh & Barakpour, 2021; Staupe-Delgado, 2019b). The systematic under-assessment of slow-onset disasters has resulted in critical gaps in the understanding of their risk reduction strategies (Cole et al., 2021; Staupe-Delgado, 2020). The neglect may be attributed to E.L. Quarantelli, a pioneering figure in the field of disaster sociology, who wanted to eliminate slow-onset disasters such as famines, epidemics, and droughts from the disaster category (Staupe-Delgado & Rubin, 2022). However, more recent research challenges this view. Staupe-Delgado and Rubin (2022) even argue that although hazards can appear sudden or slow, all disasters are ultimately slow-onset from a vulnerability perspective. A fundamental challenge in analysing slow-onset disasters lies in the temporality, as there is no obvious pre- or post-disaster phase, complicating the determination of a tipping point (Staupe-Delgado, 2020).

In the geographical context, the Global South has been neglected in resilience research, despite countries in this region often being highly vulnerable to disasters, for example, in south-west Asia due to flooding (Shukla et al., 2025). This gap is problematic, as an indicator for one country is not necessarily applicable in another country (Birkmann, 2007). Nevertheless, the majority of resilience tools have been developed in the context of the Global North, yet they are frequently implemented in the Global South (Meriläinen et al., 2022; Sharifi, 2016).

2.2.3 Resilience Discourse in the Media

The resilience discourse has been analysed in several papers in the past. Much of this research focuses on the discourse in countries in the Global North such as the United States, Canada or Australia. Choudhury and Haque (2018) have examined the resilience discourse in major Canadian daily newspapers in the context of disasters over the period of 1996 to 2017. Using a social constructivist approach, the authors performed a discourse analysis, assessing the trend of how and by whom the term was used and interpreted over the analysis period. The analysis revealed that the term resilience significantly increased during the 1990s in Canadian newspapers. Leitch and Bohensky (2014) examined the resilience discourse in Australian newspapers between 2006 and 2010. The authors focused on the stakeholders who used the term resilience and how they used it. The findings indicated that the term was often used by politicians and government agencies outside the affected community, and how the term could be undermined when used as a rhetorical device. Torres and Alsharif (2016) used a local newspaper to qualitatively analyse the resilience discourse in Broward County following Hurricane Wilma in 2005. They highlighted the importance of incorporating the most vulnerable groups in their pre- and post-disaster programs to reduce their vulnerability and involving community members in the development of planning strategies. Dhakal (2018) analysed the news coverage in local and foreign news media of the earthquake in Nepal on 25 April 2015, using a community capital framework including built, cultural, financial, human, natural, political and social capital. The author found that the topics discussed in local and foreign media can vary, with foreign media emphasising more on the aspects of financial capital.

2.2.4 Resilience Critique

The concept of resilience is subject to considerable criticism for its vagueness and theoretical weakness with multiple alternative meanings, which make it hard to identify relevant factors and apply the concept consistently (Manyena et al., 2019; Norris et al., 2008; Patel et al., 2017). Keating and Hanger-Kopp (2020) found in interviews with practitioners that the broadness of the resilience framework results in a lack of practical orientation. Further critiques highlighted the uncertainty surrounding the definition of the concept. Some definitions emphasise particular aspects of resilience, which may result in overconfidence and susceptibility to aspects that were not considered. Other definitions can be very extensive, leading to a highly complex model, which hinders its practical implementation at the local level (Patel et al., 2017). Due to the imprecise definition, the concept is jeopardised and sometimes manipulated to serve different interests (Aldunce et al., 2015).

Holton et al. (2009) argued that the concept may reinforce biases and stereotypes similar to those associated with the discourse in risk and protection. It can be used to blame communities for their adversities by alleging an inability to build resilience, which demonstrates a lack of comprehension of the complexity of the concept (Kirmayer et al., 2009). Resilience-oriented policies are criticised for placing responsibility on communities, even though many vulnerability factors originate from external sources and are caused by corruption at a higher level (Eitel, 2023; Lewis & Kelman, 2010). Bonds (2018) further criticized that resilience may be misused to govern and control communities. Another problem is that resilience is often promoted through non-participatory approaches, which can reinforce power hierarchies and social inequalities (Eitel, 2023). However, with the shift from resilience as a reactive concept towards a transformative concept, more focus is laid on improving underlying inequalities and problems (Sousa & Moss, 2022).

2.3 Natural Language Processing

NLP is a subfield of computer science and artificial intelligence that focuses on enabling computers to understand, produce and manipulate natural language (Ghasiya & Okamura, 2021; Hirschberg & Manning, 2015). It seeks to comprehend how humans understand and use language, leveraging this knowledge to engineer techniques that facilitate the processing of human languages by computer (Chowdhury, 2003). NLP employs various computational models that enable the translation of text to machine language, which can be provided to machine and deep learning algorithms (de Oliveira et al., 2021; Sadman et al., 2021). It builds the foundation for extracting relevant information from texts (Joshi, 1991), providing insights into topics hidden in large amounts of unstructured text data (Sodoge et al., 2023).

The field of NLP emerged in the 1950s as an intersection of linguistics and artificial intelligence. Since then, however, it has evolved to incorporate elements and methodologies from a multitude of disciplines (Nadkarni et al., 2011). It now draws on methodologies from computer and information sciences, linguistics, mathematics, electrical and electronic engineering, artificial intelligence, robotics, as well as psychology (Chowdhury, 2003).

NLP has become an essential tool in recent decades for processing the vast amounts of unstructured data generated daily (Ghasiya & Okamura, 2021). Its ability to analyse large text corpora makes it valuable in various domains, including public health, policymaking and climate change research (Stede & Patz, 2021). NLP enables researchers and policymakers to access information on multiple scales from sources ranging from social media to newspapers, policy documents and scientific literature (Ghasiya &

Okamura, 2021). These properties allow the identification of discourse trends and the timely response to discourse shifts (Stede & Patz, 2021).

To achieve these tasks, NLP employs a broad variety of tools, starting from simpler tasks including tokenization or part-of-speech tagging, to more complex tasks such as Named Entity Recognition (NER) or information extraction (Nadkarni et al., 2011). Tokenization is the process of splitting a text into smaller units, also referred to as tokens (Grefenstette, 1999). Part-of-speech tagging refers to the assignment of parts of speech (noun, verb, preposition, etc.) to each word (Hirschberg & Manning, 2015). In NER specific words or phrases, also referred to as entities are identified, such as names of persons, locations or companies (Nadkarni et al., 2011). Common NLP techniques encompass sentiment analysis, topic modelling, text summarisation as well as text classification (Ghasiya & Okamura, 2021).

2.3.1 Text Classification

Text classification can be divided into three approaches: supervised, semi-supervised and unsupervised learning (Thangaraj & Sivakami, 2018). Supervised learning requires training data that contains the label for each instance which is cost-intensive. This labelled set is used to build the classifier. In contrast, unsupervised learning tries to automatically identify underlying patterns in the data using modelling assumptions and properties of the texts (Grimmer & Stewart, 2013; Nadkarni et al., 2011) and hence does not require labelled data (Vlachos, 2011). Unsupervised learning is more challenging than supervised learning due to the absence of ground truth data to evaluate the results, and the difficulty of interpreting results due to the lack of labels (Padmanabha Reddy et al., 2018). Semi-supervised learning combines small amounts of labelled and large amounts of unlabelled data to train the model and is becoming increasingly important (Thangaraj & Sivakami, 2018). Its objective is to overcome the drawbacks of supervised and unsupervised learning, by reducing the amount of labelled data required and increasing interpretability (Padmanabha Reddy et al., 2018). The following thesis focuses on the supervised text classification approach.

Supervised classification is the process of "assigning predefined classes (labels) to an unlabelled text document" (Mirończuk & Protasiewicz, 2018, p. 39). It uses similarities between texts to assign a text to a group of labelled texts in the training set (Dien et al., 2019). Thereby, the text classifier learns the characteristics of examples of the predefined classes and compares them to the new text (Sebastiani, 2002). Supervised machine learning enables the classification of large volumes of data (Barberá et al., 2021), which would not be possible for humans in a reasonable timespan (Dadgar et al., 2016). It requires large datasets for training, which need to be manually coded by humans, and require features that are well balanced and represented in the text (Barberá et al., 2021).

Supervised learning methods apply three basic steps. First, a training set with labelled data needs to be created. This requires human coders to manually classify a subset of the text corpus into a previously defined classification scheme. Second, a supervised learning model is implemented, which aims to detect the patterns between features and classes in the training set and applies these patterns to the test set.

Third, the performance of the model needs to be validated. Validation for supervised learning methods is easier than for unsupervised approaches because it can draw from clear statistics (Grimmer & Stewart, 2013).

There are different approaches to text classification: binary, multi-class, multi-label and hierarchical classification. Binary classification is used for binary problems, where only two classes are available. The multi-class classification considers multiple classes and chooses the most accurate. In contrast, the multi-label classification allows multiple classes to be assigned to one element. The hierarchical classification is a combination between the multi-class and the multi-label classification (Mirończuk & Protasiewicz, 2018).

2.3.2 Uses of NLP for Disaster Resilience

NLP has been used in the past to analyse disaster-related discourses. Newspaper articles or social media such as Twitter are often chosen as sources of information. Lai et al. (2022) for instance, established a NER model to extract geographic locations from newspapers and locate flood risk reduction projects. Liu et al. (2018) used Chinese newspaper articles to extract locations and applied a rule-based approach to determine the hazard type for each article. In their study, Sodoge et al. (2023) implemented a supervised machine learning approach to classify the impact class for droughts using a large corpus of newspaper articles.

Other authors have focused on resilience-related topics as well. Lv et al. (2019) used scientific papers and public reports to implement a keyphrase extraction to identify phrases relating to disaster resilience of critical infrastructure. Zou et al. (2018) conducted an analysis with Twitter data before, during and after Hurricane Sandy. They applied a sentiment analysis to assess resilience. Fu et al. (2023) explored the use of topic modelling to analyse and extract key information from a large collection of resilience plans. Franceschini (2023) employed a deep learning classification approach based on a BERT model to detect landslide event-related tweets.

3 Methodology

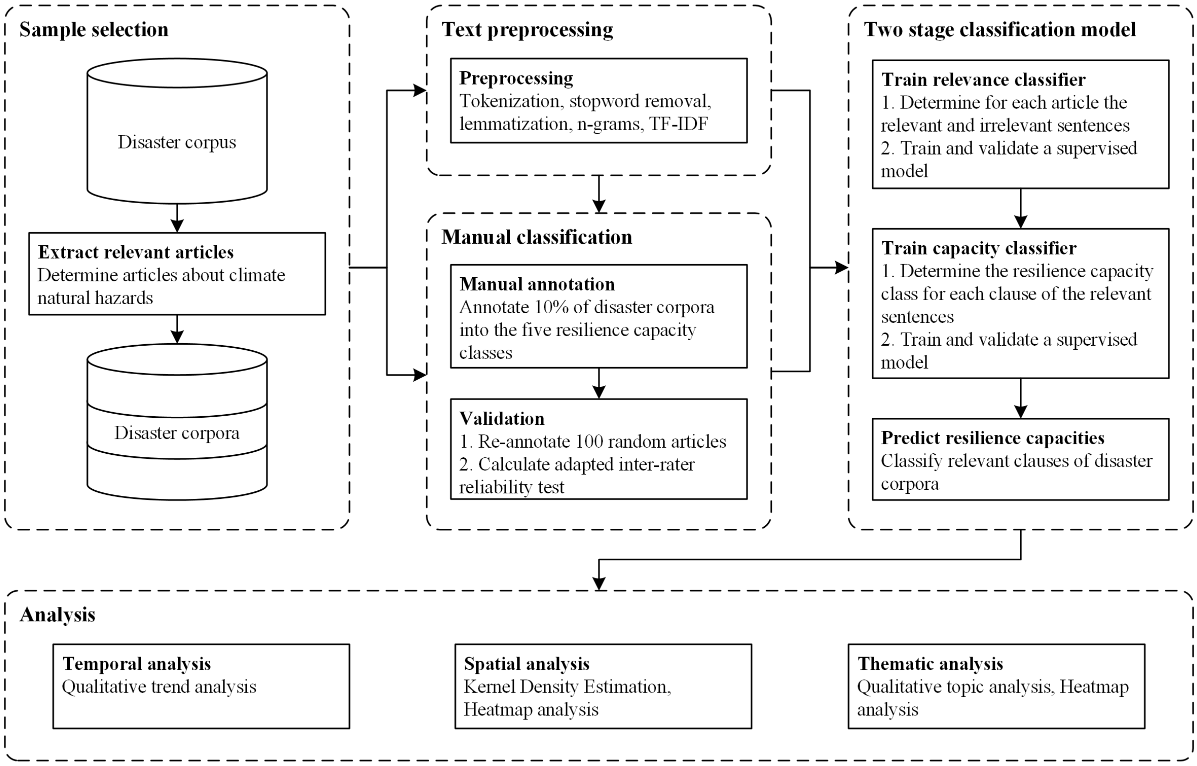

Figure 3.1: Methodological workflow of the study, consisting of sample selection, text preprocessing, manual classification, supervised classification, and subsequent analyses.

An overview of the multi-step procedure applied in this study is provided in Figure 3.1. The process is structured into five main stages. First, data collection involved extracting articles on climate-related natural hazards from a broader disaster corpus. This corpus was drawn from previous research by Kong and Purves (2025) and is described in detail in Section 3.1. Second, a manual classification was conducted on a subset of articles to annotate resilience capacities, with the annotation validated through inter-rater reliability tests (see Section 3.2). Third, multiple preprocessing procedures were implemented to clean the text corpus, as detailed in Sections 3.3 and 3.4. Fourth, a two-stage supervised classification model was trained: the first stage identified relevant sentences, while the second stage classified resilience capacities within relevant clauses (see Sections 3.5, 3.6 and 3.7). Finally, the classified data were subjected to temporal, spatial and thematic analyses to identify trends, patterns and topics in the resilience discourse, as outlined in Section 3.8.

3.1 Data Collection

The analysis draws upon an existing corpus of newspaper articles related to climate disasters, created for a previous study by Kong and Purves (2025). The corpus incorporated articles published over a period of 24 years, from 1 January 2000 to 31 December 2023, reporting on various climate disaster events.

Newspaper articles published in five major national newspapers in Great Britain were considered: The Daily Telegraph, Financial Times, The Guardian, The Independent and The Times. Nationally circulating newspapers were chosen due to their global orientation and information reach (Bohr, 2020), ensuring broader coverage of events and related topics.

The articles were collected from Nexis Uni, which is an academic digital archive providing access to different kinds of text data. To create the corpus with climate disaster-relevant data, all articles mentioning the keyword "climate change" either in the title or the text body were considered. Additionally, they had to include climate-related disaster types (i.e. flood, drought, heatwave, storm, hurricane, cyclone and wildfire) in the title. These disaster types were selected as they are highly relevant and predominantly used in IPCC reports (O'Neill et al., 2022). The corpus was cleaned by removing both duplicates and articles longer than 2,000 tokens, resulting in a final corpus consisting of 10,493 articles.

For this thesis, disaster-specific corpora were created to extract the relevant articles for each of the following climate disaster types: flood, drought, heatwave, wildfire, storm, hurricane, and tornado. For an article to be considered relevant, the disaster type had to be mentioned in the title and at least three times in the text body. This resulted in climate disaster-specific corpora including 6,003 newspaper articles (see Table 3.1). Some articles were classified in multiple disaster-type categories, as they reported on different events and disasters.

Table 3.1: Overview of newspaper articles related to disasters.

Disaster	Number of Articles	Percentage [%]
Flood	2,346	39.1
Drought	880	14.7
Heatwave	689	11.5
Storm	951	15.8
Hurricane	438	7.3
Tornado	68	1.1
Wildfire	631	10.5
Total	6,003	100

3.2 Annotated Dataset

3.2.1 Manual Annotation

Since the DRIFT framework already provided the topics to be classified, a supervised classification was chosen. A semi-supervised approach – which integrates limited labelled data with a larger unlabelled set – was not implemented, despite its potential advantage of requiring less labelled data for training. However, semi-supervised learning carries a risk if examples cannot be distinctly assigned to a single class or if class boundaries overlap. Numerous studies have shown that semi-supervised learning can result in a decline in performance when its assumptions are not met (van Engelen & Hoos, 2020). Furthermore, the propagation of errors can occur in self-training approaches. If the model generates incorrect pseudo-labels for the unlabelled data, these errors may be reinforced and amplified in subsequent training iterations (Arazo et al., 2020). Given the ambiguity in the labelling of resilience capacities and the partial overlap between classes, a supervised classification approach was selected to ensure more controlled learning performance.

A training set was created by manually annotating relevant clauses in newspaper articles. This training set comprised 10% of all articles from the disaster-specific corpora, which incorporated 10% of the articles for each disaster type. Articles for the training set were randomly sampled from each corpus, aiming to obtain a representative sample of the articles, and thus the disaster discourse in various newspapers (Grimmer & Stewart, 2013). Manual annotation was conducted using MAXQDA 24, a qualitative text analysis software (VERBI Software, 2025).

The classification scheme was established based on the DRIFT framework by Manyena et al. (2019), distinguishing the five disaster resilience capacities (hereafter, five resilience capacity classes): preventive, anticipative, absorptive, adaptive, and transformative. A hybrid approach combining deductive and inductive analysis was applied to build a codebook that serves as a guideline for manual annotation. Deductive data analysis describes the process that draws on pre-existing literature and theories to create a framework (Azungah, 2018). Inductive data analysis, on the other hand, derives categories from the data and integrates them into larger categories (Thomas, 2006). The combination of the two approaches brings advantages, as the deductive approach helps to consolidate the analysis with the help of existing research, while the inductive analysis also allows new patterns in the data to be recognised and integrated (Schadewitz & Jachna, 2007; Yuwono & Rachmawati, 2023).

The five resilience capacities served as the main categories for the deductive analysis. Additional literature was consulted to better inform the creation of subcategories for each resilience capacity (see Chivunga et al., 2024; Lankford et al., 2023; Malec et al., 2022; Moghadas et al., 2023). Examples and topics from previous research were used to summarise subcategories and develop a preliminary coding scheme. Inductive analysis was subsequently conducted on the first 5% of the training set, drawing on the coding scheme previously established in the deductive analysis. The codebook was continuously revised during the coding process, enabling subcategories to be created or changed based on newly emerging topics (Grimmer & Stewart, 2013) (see examples from the codebook in Appendix A.1). Once the coding scheme had been finalised, the whole 10% of the training set was coded using the elaborated coding scheme. It was found that there were hardly any entirely new examples when manually annotating the second 5%, which suggests that 10% of the data were sufficient to obtain a comprehensive picture of the capacity discourse. The automated text classification was only conducted for the five resilience capacity classes and not for each subcategory. The subcategories mainly served to guide the manual classification and the subsequent thematic analysis. Additionally, the coding scheme was discursively supplemented by incorporating knowledge obtained through regular consultation with an expert.

Table 3.2: Codebook for the five resilience capacities with associated subcategories and supporting literature.

Capacity	Subcategory	Sources from Literature
Preventive	DRM	Malec et al. (2022); Manyena et al. (2019)
	Structural Measure	Chivunga et al. (2024); Manyena et al. (2019)
	Governance & Policy	Chivunga et al. (2024); Manyena et al. (2019); Moghadas et al. (2023)
	Strategic Planning	Chivunga et al. (2024); Manyena et al. (2019); Moghadas et al. (2023)
Anticipative	Risk Awareness	Chivunga et al. (2024); Manyena et al. (2019); Moghadas et al. (2023); Park and Kennedy Ochieng (2024)
	Early Warning	Chivunga et al. (2024); Jeans et al. (2017); Malec et al. (2022); Manyena et al. (2019); Moghadas et al. (2023);
	Scenario Planning	Chivunga et al. (2024); Lankford et al. (2023); Manyena et al. (2019); Matoju et al. (2022); Park and Kennedy Ochieng (2024)
	Risk Transfer Mechanism	Chivunga et al. (2024); Manyena et al. (2019)
Absorptive	Resource Management	Béné et al. (2014); Chivunga et al. (2024); Malherbe et al. (2024); Manyena et al. (2019); Mentges et al. (2023); Moghadas et al. (2023)
	Operational Adjustment	Lankford et al. (2023); Malherbe et al. (2024)
	Support	Chivunga et al. (2024); Manyena et al. (2019); Moghadas et al. (2023)
	Preparation & Response	Bartelet et al. (2023); Béné et al. (2013); Béné et al. (2014); Chivunga et al. (2024); Jeans et al. (2017); Lankford et al. (2023); Malec et al. (2022); Malherbe et al. (2024)
Adaptive	Diversification	Bartelet et al. (2023); Béné et al. (2013); Béné et al. (2014); Chivunga et al. (2024); Lankford et al. (2023); Manyena et al. (2019); Matoju et al. (2022); Park and Kennedy Ochieng (2024)
	Learning	Bartelet et al. (2023); Jeans et al. (2017); Lankford et al. (2023); Mentges et al. (2023)
	Incremental Adjustment	Asadzadeh, Kötter, et al. (2022); Béné et al. (2014); Chivunga et al. (2024); Jeans et al. (2017); Lankford et al. (2023); Malherbe et al. (2024); Mentges et al. (2023)
	Institutional Adaptation	Asadzadeh, Kötter, et al. (2022); Manyena et al. (2019); Moghadas et al. (2023)
Transformative	Livelihood Transformation	Béné et al. (2013); Béné et al. (2014); Malherbe et al. (2024); Manyena et al. (2019); Matoju et al. (2022); Mentges et al. (2023); Staupe-Delgado (2020);
	Technical Innovation	Asadzadeh, Kötter, et al. (2022); Chivunga et al. (2024); Moghadas et al. (2023)
	Social Transformation	Béné et al. (2014); Manyena et al. (2019); Moghadas et al. (2023); Park and Kennedy Ochieng (2024)
	Governance Transformation	Asadzadeh, Kötter, et al. (2022); Lankford et al. (2023); Malec et al. (2022); Manyena et al. (2019); Moghadas et al. (2023)

The instances of resilience capacities were determined at the clause level. During manual annotation, it was observed that information related to resilience capacity was frequently only addressed briefly and only takes up part of the sentence. In certain cases, multiple capacities were mentioned in subordinate clauses within a sentence. Hence, the clause level was selected as the most appropriate unit of analysis.

The subcategories for each resilience capacity class from the final coding scheme are described in the following. Each subcategory is briefly explained and illustrated with examples, while the corresponding sources are listed in Table 3.2. Preventive capacity was divided into the four subcategories: DRM, structural measures, governance & policy and strategic planning. DRM incorporated comprehensive management strategies that addressed underlying disaster risks, including risk assessment, investment in disaster risk reduction, infrastructure maintenance, community education and training programmes for the population and personnel in DRM. Structural measures involved the construction, reinforcement, and retrofitting of physical infrastructure to withstand hazards, encompassing both engineered and nature-based solutions. Instruments and policies to deal with disaster risk constituted an element within governance & policy, for instance, the implementation of land-use regulations that prohibited settlements in high-risk zones. Strategic planning included the establishment of resilience capacity-building plans or guidelines, as well as guidelines for preparedness plans to enhance overall community resilience.

Risk awareness, early warning, scenario planning and risk transfer mechanisms were the subcategories elaborated for anticipative capacity. Risk awareness encompassed the capacity to identify threats in a timely manner, leading to better disaster preparedness due to increased understanding of disaster risks. It also included the forecasting of short-term and long-term situations. Early warning incorporated the detection and monitoring of hazards using systems that provided timely warnings, enabling early protective measures, such as harvesting crops before adverse effects occurred or relocating livestock. These systems could also activate emergency response mechanisms, for example, through automatic alerts. Scenario planning was defined as the strategy of implementing actions in advance based on the anticipation of future conditions and associated risks, including the establishment of strategic reserves, emergency shelters and evacuation routes. Risk transfer mechanisms mainly comprised insurance arrangements to allow predictable financing in the event of a disaster.

Absorptive capacity included resource management, operational adjustment, support and preparation & response. Resource management focused on preparatory actions that built redundancy to buffer disaster impacts, incorporating backup communication systems, electricity generators, additional water storage or stockpiling of critical assets. It further included the mobilisation of resources and the initiation of emergency preparedness and response plans. Operational adjustment consisted of strategies to reduce operational demands, such as implementing deficit irrigation, imposing hosepipe bans during droughts, or adjusting watering times to minimise water loss. Support incorporated financial, material or psychological assistance to victims through humanitarian aid, fundraising campaigns, and community solidarity. Preparation & response involved measures to absorb immediate effects of disasters, for instance relieving staff, restricting outdoor activities, or closing schools. Furthermore, it encompassed emergency responses such as declaring a state of emergency, organising evacuations and firefighting efforts.

Adaptive capacity was divided into diversification, learning, incremental adjustment and institutional adaptation. Diversification involved the ability to flexibly switch between adaptation strategies, for example diversifying income sources, changing farming practices, investing in improved seeds or farm machinery and adapting energy generation methods. Learning referred to the process of drawing lessons from past disasters or others' experiences. This included analysing historical data, learning from experiments or previous events and participating in self-help groups. Incremental adjustment consisted of gradual changes to existing practices, policies or infrastructure, for instance modifying agricultural techniques, improving water use efficiency, implementing sustainable soil management, or making marginal improvements to buildings, such as adapting house design by using flood-proof tiles or relocating sockets to higher locations. Institutional adaptation incorporated organisational and policy changes, such as incorporating medium-term risk levels into planning instruments, enforcing land-use regulations and government investment in socio-economic security, for instance by ensuring broader access to insurance for people exposed to hazards.

Livelihood transformation, technical innovation, social transformation and governance transformation were the subcategories elaborated for transformative capacity. Livelihood transformation incorporated household strategies to adapt to a new direction to secure livelihoods, for instance by relocating or migrating, shifting from one agricultural product to another, adding new income streams such as agritourism, or exiting sectors in favour of alternative employment opportunities. Technical innovation referred to investments in advanced technologies or the modernisation of infrastructure with the aim of rebuilding better systems than previous ones, or researching innovative developments. Social transformation encompassed behavioural changes, questioning values, or challenging established norms and assumptions that underpinned existing social systems. Governance transformation comprised deep structural changes to governance settings or planning systems. Examples included introducing new legal, regulatory or political instruments, incorporating multiple and higher levels of risk and uncertainty into planning processes and reorganising decision-making processes at the community or local institutional level to increase citizen participation.

3.2.2 Validation of Annotation

Since the manual classification was only conducted by the author, a validation measure was needed to ensure the persistence and robustness of the annotation. The principles of the inter-rater reliability tests were therefore integrated into the validation process. Inter-rater reliability tests determine the degree of agreement between classifications by independent annotators to ensure consistency in their results (McHugh, 2012).

For this thesis, the inter-rater reliability approach was adapted to determine the consistency of annotation by one person. One month after completing the initial round of classification, the classification was conducted again. 100 articles from the training set were randomly selected and recoded. The differences between the coding results for the two stages were analysed using the intercoder agreement function provided by MAXQDA 24 (VERBI Software, 2025). Two levels of analysis were applied to determine the coding agreement: the document comparison level and the segment comparison level. For the document-level approach, the agreement was calculated based on code frequency per document for the first and the second annotation round. An agreement was recorded when the same codes appeared with the same frequency in both annotation rounds. The segment-level approach assessed the overlap of coded segments, comparing the extent to which segments were assigned the same codes in both rounds (MAXQDA, 2025). The inter-rater reliability test was performed for the five resilience capacity classes, excluding the subcategories, as these are not required for the automatic classification process.

3.3 Preprocessing

As certain articles refer to multiple disasters, the disaster-specific corpora included the same articles multiple times. Consequently, these duplicates were removed, and the relevant disaster types were summarised and allocated to the respective articles. This resulted in a disaster corpus with release year and disaster types assigned to each article.

Manual annotation was performed at the clause level to capture only the most relevant information related to the resilience capacities. However, to reduce computational power and increase efficiency, the initial step in the classification pipeline involves identifying relevant sentences, not clauses. To create a training set for the relevance classifier, each annotated clause was mapped to its corresponding sentence. For each newspaper article, the text was segmented into individual sentences. The document number was then used to match annotated clauses with these sentences. Sentences that corresponded to an annotated clause were assigned the label relevant, while all others were labelled as irrelevant.

In NLP, text preprocessing is a crucial step. It serves the purpose of cleaning and preparing text data (Ghasiya & Okamura, 2021) and reduces non-informative and noisy features (Hartmann et al., 2019; Kayakuş & Açıkgöz, 2022). In text classification, preprocessing directly influences the performance (Uysal & Gunal, 2014) and the efficiency (Song et al., 2005) of the classifier. The text preprocessing was implemented using spaCy, an open-source Python library for building tools for NLP (spaCy, 2025). Several preprocessing steps were applied to clean the text. The first step was normalisation that included the removal of all orthographic features such as punctuation, special characters and digits, retaining only alphabetic characters (Ahuja et al., 2019). Next, the text was tokenized, meaning the segmentation of text into subunits referred to as tokens (Grefenstette, 1999), which can be words or phrases (Uysal & Gunal, 2014). For this thesis, the text was segmented into a list of words using the space character as a bounding criterion. Next, named entities were identified and removed from the text, including the names of organisations, people, locations or other entities (Sharma et al., 2022). Stop words, including articles, prepositions or conjunctions such as "I", "the", "and", "all" and "is" were additionally eliminated, as they are considered irrelevant for future text classification (Uysal & Gunal, 2014). The remaining tokens were lemmatized. Lemmatization uses morphological analysis to reduce a token to its dictionary form (e.g. was $\rightarrow$ be, droughts $\rightarrow$ drought, better $\rightarrow$ good) (Balakrishnan & Lloyd-Yemoh, 2014; Navigli, 2009).

3.4 Feature Extraction

Text data, in its raw form, lacks the structure necessary for computational processing. Feature extraction addresses this by transforming text into a machine-readable format. Bourahouat et al. (2024, p. 314) defines feature extraction as "the procedure of choosing and transforming raw data into a set of pertinent features that effectively represent and describe the data". Feature extraction methods therefore determine the most informative feature set (Wang et al., 2020) and convert words into vectors in a feature space (Tabassum & Patil, 2020).

Different approaches for feature extraction were tested using statistical features or static word embeddings (Bourahouat et al., 2024). Statistical feature extraction methods include Term Frequency-Inverse Document Frequency (TF-IDF) and Bag of Words (BoW) techniques. TF-IDF and BoW are traditional machine learning methods that rely on the frequency of word occurrences within a text corpus (Šilić et al., 2007). The BoW model counts the occurrences of words in a text and assumes that texts containing the same words are similar in context. The two main problems are that there are words with high frequency but little context and that longer texts have higher counts for each word. These drawbacks are addressed with TF-IDF. It defines the importance of a word by comparing how often it is used in the document and in the whole corpus. The frequency of the words is defined using normalisation by dividing the count by the length of the text (Tabassum & Patil, 2020). To capture short contextual patterns rather than isolated terms, both BoW and TF-IDF were implemented with N-gram vectorization. Liu (2011, p. 231) defines an N-gram as "a consecutive sequence of words of a fixed window size n". Instead of analysing each word individually, an N-gram model splits the text into sequences of consecutive words. In contrast to the frequency-based approaches, the static word embedding Word2Vec uses a semantic approach to determine the meaning and semantic relationship between words and represents them as continuous dense vectors (Bourahouat et al., 2024; Uysal & Murphey, 2017).

For comparability reasons, the model components – such as preprocessing steps and the classification model – were kept consistent to evaluate the most suitable feature extraction method. Among the tested methods, a combination of an N-gram vectorization model and a TF-IDF feature extraction approach performed best for both classification models, similar to Chotirat and Meesad (2021). The performance of the different approaches was evaluated using precision, recall, and F1 score (see Section 3.7.2).

3.5 Modelling Pipeline

To extract clauses related to the five resilience capacity classes from the newspaper corpus, a two-stage classification pipeline was implemented. The pipeline comprised two independently trained classifiers that were combined into a final pipeline. In the first stage, a relevance classifier identified sentences containing information pertinent to resilience capacities. This step employed a binary machine learning classification model to distinguish between relevant and irrelevant sentences. The sentences classified as relevant were segmented into clauses to align with the granularity of the capacity classifier. In the second stage, a multi-class text classifier assigned each clause a probability of belonging to one of the five resilience capacity classes. Unlike multi-label classification, where a single instance can be assigned to multiple categories, multi-class classification assumes mutually exclusive classes and requires assigning each instance to only one class. A multi-class approach was chosen over a multi-label classification for several reasons. First, it aligned with the labelling assumption that each clause primarily expresses one dominant resilience capacity. This simplified training, by using distinct, non-overlapping categories, and facilitated evaluation, by allowing the use of standard multi-class performance metrics (Mencía et al., 2018). Additionally, the assignment of a single capacity per clause enhanced interpretability. While some clauses arguably related to multiple capacities, a multi-class approach reduced semantic ambiguity by compelling the classifier to select the most relevant category in each instance. Individual decision thresholds were defined for each class, resulting in clauses falling below these thresholds being considered irrelevant and excluded from the final output. Both classifiers were independently trained and evaluated, as outlined in the subsequent sections. The Scikit-learn machine learning library in Python (Pedregosa et al., 2011) was used to implement the classifiers.

One key challenge that had to be addressed was the highly imbalanced distribution of classes, both in terms of distinguishing between relevant and irrelevant sentences, as well as in differentiating between the five resilience capacity classes. Class imbalance poses a well-known problem in classification tasks, as models tend to be biased towards the majority class and lack information about the minority class (Nguyen et al., 2008), which can lead to reduced performance, particularly for the under-represented classes. To mitigate this issue, a combination of resampling techniques, cost-sensitive learning, and threshold adjustment was applied, and model performance was evaluated using F1 score rather than accuracy (see Section 3.7.2).

3.5.1 Relevance Classifier

The first stage of the classification employed a relevance classifier to identify sentences containing information related to resilience capacities. The input for this model was the set of labelled sentences described in Section 3.3. To train the model, the dataset was split into training (75%) and test (25%) sets using stratified sampling, ensuring an equal distribution of relevant and irrelevant classes in both subsets, which is important for imbalanced data. Initially, a one-class classifier was considered to address the detection of relevant sentences. However, since labelled cases were available for both relevant and irrelevant classes, and the one-class approach yielded weaker performance than a supervised binary classification, it was not pursued further. Instead, different binary models were tested to build the relevance classifier, namely complement naive Bayes, random forest, support vector machine and XGBoost (Chen & Guestrin, 2016). The models were evaluated by assessing the F1 score, precision and recall (see Section 3.7.2). Among the tested models, complement naive Bayes performed best and was thus adopted to detect the relevant sentences for resilience capacities.

To determine the best parameters for the chosen model, a 10-fold cross-validation was conducted during training (see more details in Section 3.6). To evaluate the performance of the cross-validated model, a similar strategy to the one described in Mahajan et al. (2020) was implemented. Since the main objective of the resilience classifier is to extract all relevant sentences, the model was optimised for recall, to incorporate as many relevant sentences as possible. Additionally, a precision constraint was introduced to prevent the model from classifying most inputs as relevant, which could increase recall but harm the precision of the model.

To account for class imbalance in the relevance classification task, a combination of resampling techniques and threshold tuning was applied. The resampling strategy combined oversampling of the minority class using Synthetic Minority Over-sampling Technique (SMOTE) and undersampling of the majority class to reduce the disparity in class distribution (see Chawla (2005)). Undersampling randomly reduces instances in the majority class to balance the dataset, whereas oversampling randomly replicates instances in the minority class (Kumar et al., 2021). Only the training data were resampled, while the test data remained unchanged to maintain evaluation integrity. This was ensured using the imblearn Python package (Lemaître et al., 2017).

3.5.2 Capacity Classifier

For the second part of the two-stage classification pipeline, a disaster resilience classifier was implemented to assign relevant clauses to one of the five resilience capacity classes. Given the high class imbalance and the limited number of examples in some minority classes, particularly adaptive and transformative capacity, the manually annotated dataset was split into training (70%) and test (30%) sets (Kayakuş & Açıkgöz, 2022). The larger test set compared to the relevance classifier should ensure sufficient representation of all classes, especially the under-represented ones, in the test set. Several classification algorithms were evaluated, including random forest, naive Bayes, support vector machine, logistic regression and the AdaBoost classifier. Similar to the relevance classifier, the models were evaluated by calculating the F1 score, precision and recall. Logistic regression demonstrated the best performance and was used to determine the resilience capacity class for each relevant clause.

Due to the limited sample size, a 5-fold stratified cross-validation was applied during training to ensure a robust evaluation of the model's performance (see more details in Section 3.6). The data were split only into five folds to avoid under-representation of the minority classes, particularly the transformative category. A strategy analogous to that of the relevance classifier was applied for model evaluation. However, since the goal was to identify as many true examples of the five resilience capacity classes as possible, the model was optimised for precision. A recall constraint was implemented to prevent the model from being too conservative and only classifying a limited number of examples.

In order to address class imbalance, SMOTE was applied to generate synthetic samples for the two minority classes based on their feature space (see Chawla (2005)). Additionally, cost-sensitive learning was employed to penalise the misclassification of instances belonging to the minority class (Thai-Nghe et al., 2010). The concept of cost-sensitive learning involves applying higher misclassification costs to instances of the minority class (Araf et al., 2024).

An alternative approach to address the class imbalance – text augmentation – was tested. It has been demonstrated to facilitate the balancing of class imbalances by creating new instances of training data through the transformation of existing examples (Bayer et al., 2022). A series of experiments were conducted in order to assess the efficacy of a range of text augmentation techniques using the Python package NLPAUG (Ma, 2019). These approaches were based on synonym replacement and random insertion, where a word is either substituted with a synonym or a semantically similar word is inserted. These approaches generate alternative examples with similar semantic integrity and therefore increase diversity in the data (Khan & Venugopal, 2024). The method was discarded due to its inability to enhance performance.

3.6 Hyperparameter Tuning

To determine the optimal hyperparameter configuration for both models, a two-stage tuning strategy was implemented. Initially, a randomised search was conducted to explore the broad range of potential hyperparameter values. This preliminary search served to delimit the hyperparameter space. A more exhaustive grid search was then applied within the narrowed hyperparameter space to identify the best-performing hyperparameter settings.

To ensure robustness and generalisability of the selected configurations, cross-validation was integrated into the grid search. A stratified k-fold cross-validation was used to train and validate the model on different subsets of the data, providing a more reliable estimate of model performance. Cross-validation also mitigates the risk of over-fitting by avoiding learning from only one training set that might be biased or include noise (Grimmer & Stewart, 2013). By repeatedly training on different data splits, the model is trained on varying input, which enhances its ability to generalise (Nadkarni et al., 2011). The average of the validation results for each fold was then calculated to select the optimal hyperparameter values (van der Vaart et al., 2006).

3.7 Performance Measure

3.7.1 Gold Standard

In addition to evaluating the two models individually, the performance of the entire classification pipeline also had to be assessed. Since relevant sentences had already been manually annotated for each resilience capacity, a sentence-level ground truth was already available. This enabled the use of standard supervised evaluation methods, where predictions are compared to a predefined gold standard using metrics like precision, recall, and F1 score (Vlachos, 2011).

To establish the gold standard at clause level, all sentences were divided into clauses to match the output of the classification pipeline, regardless of their relevance. Since the capacity classifier works on clauses, this level was used as the analysis level for the gold standard. Next, all annotated segments were split into clauses to align them with those from the gold standard dataset. The clauses of the annotated segments were then matched with the clauses of the gold standard. If an annotated clause could be found in the gold standard, the clause received the corresponding resilience capacity label. If the clause could not be matched with any annotated clause, it was labelled irrelevant. Thus, a ground truth was available that indicated, for each clause in the subsample of the newspaper corpus, whether it contained irrelevant information or information related to preventive, anticipative, absorptive, adaptive, or transformative capacity. This ground truth was then compared to the result obtained by the classifier pipeline.

Due to the limited number of examples, no data was set aside specifically for the gold standard assessment. Instead, the same data were used for training and testing the two classifiers as well as for the gold standard. As this may lead to bias, given that some of the test data had already been seen during training, an evaluation was further conducted to assess the model's performance on 90% of the corpus. For each extracted clause, it was determined whether it was relevant to the capacity class to which it was assigned. This approach allowed the evaluation of the model's precision, but not of recall, as it is not known which examples were missed.

3.7.2 Evaluation Methods

Three performance metrics were used for the evaluation of the two-stage classification model. Due to the imbalance of the datasets, accuracy is not a suitable measure to determine the performance. Instead, the F1 score is typically used, being the best metric for calculating performance in this context (Ligthart et al., 2021; Palanivinayagam et al., 2023). Furthermore, precision and recall were calculated to get a better understanding of the performance for each class.

There are four possible outcomes of a classification. True Negatives (TN) refer to instances correctly identified as not belonging to the target class. False Negatives (FN) are cases in which the model fails to recognise an instance that belongs to the class. False Positives (FP) represent instances incorrectly assigned to the class, while True Positives (TP) are instances correctly classified as belonging to the target class (Chawla, 2005). These four outcomes form the basis for standard evaluation metrics such as precision, recall, and F1 score.

Precision captures the ratio of properly annotated clauses in comparison with all coded clauses for one class (Kadhim, 2019):

$$Precision = \frac{TP}{TP + FP} \tag{3.1}$$

Recall measures the proportion of properly annotated clauses compared to all clauses that actually belong to one class (Kadhim, 2019):

$$Recall = \frac{TP}{TP + FN} \tag{3.2}$$

F1 score is the harmonic mean of precision and recall, providing a balanced measure that mitigates extreme values of either metric (Kayakuş & Açıkgöz, 2022). A high F1 score indicates a good classification approach (Dadgar et al., 2016).

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{3.3}$$

During cross-validation, the performance of the models were calculated for each hyperparameter setting ten or five times for the relevance and the capacity classifier respectively. The performance metrics were recall with a precision constraint for the relevance classifier and precision with a recall constraint for the capacity classifier, as explained in the previous sections. The mean cross-validation score was determined for each hyperparameter setting and the best setting was used for the final model. The reported results of the three evaluation metrics precision, recall, and F1 score represent the performance of the model with the best hyperparameter settings on the testing datasets.

3.8 Analyses

To explore how disaster resilience is reported in British media coverage, a multifaceted analysis was conducted, including the temporal, spatial and thematic dimensions. In addition to a general assessment of the findings, the results were further contrasted between articles referring to the Global North and the Global South, as well as between those addressing sudden-onset disasters and slow-onset disasters.

To distinguish between articles reporting on countries from the Global North and Global South, the definition of Global South countries from the United Nations' Finance Center for South-South Cooperation was considered, also referred to as the Group of 77 (G-77) and China (G-77, 2025b). The group was established in 1964, starting with 77 countries, with the aim of providing "the means for the countries of the South to articulate and promote their collective economic interests and enhance their joint negotiating capacity on all major international economic issues within the United Nations system, and promote South-South cooperation for development" (G-77, 2025a). The G-77 and China currently includes 134 countries.

The definition for slow- and sudden-onset disasters was adopted from the UNDRR, where a slow-onset disaster is understood as a disaster that develops gradually over time (2017). Based on the disaster types analysed in this thesis, this included droughts. Heatwaves are not considered slow-onset disasters as they indicate a "sudden, significant and time-limited departure from average or recent environmental conditions" (Oppermann et al., 2021, p. 227). Accordingly, the disaster types analysed were categorised into sudden-onset disasters – including floods, storms, hurricanes, tornadoes, heatwaves and wildfires – and slow-onset disasters, limited here to droughts.

3.8.1 Temporal Analysis

The data were analysed to identify temporal patterns of disasters and the associated discourse on disaster resilience, revealing temporal trends in media coverage. This assessment enabled the identification of changes in the frequency of resilience thinking since the year 2000, as well as the contexts in which resilience topics were most frequently addressed. In particular, it was examined how often instances of the resilience capacities appeared in articles over time, allowing the detection of shifts in the discourse. In a more fine-grained manual assessment, the frequency of subcategories within each capacity was also evaluated to determine whether specific themes had gained or declined in prominence in recent years. Temporal developments of resilience capacities were visualised using time-series graphs to explore long-term trends and patterns.

3.8.2 Spatial Analysis

The spatial analysis aimed to identify geographical patterns in the discourse of disaster resilience in newspaper articles. Hence, geospatial information was extracted using the Python library Irchel Geoparser (Gomes et al., 2024), which is an integrated pipeline that uses spaCy's NER algorithm and a gazetteer to assign geographic coordinates and country information to each identified location. Since geographic references in newspaper articles are often scattered throughout the text and are not necessarily located next to content related to resilience capacities, all geographic information was extracted from entire articles that had been classified as resilience-relevant.

Based on the extracted country information, each article was further categorised according to whether it primarily referred to the Global North or the Global South. To determine the predominant geographic context of an article, each unique location mentioned in an article was assigned to the corresponding country and, for each country, it was determined whether it belonged to the Global North or the Global South. The region with the greater number of references was assigned as the article's primary geographical context.

To visualise and analyse spatial patterns in the disaster resilience discourse, Kernel Density Estimation (KDE) was applied to the geocoded locations extracted from the articles. KDE helps to detect hot spots by estimating point densities across a grid, revealing areas of high and low intensity within the spatial distribution (Kalinic & Krisp, 2018). Each geographic location was included only once per article to avoid overweighting places that were mentioned repeatedly within a single article. The KDE enabled the identification of regional clusters where discourse on disaster resilience was most concentrated, highlighting geographical hotspots of media attention within the British media landscape. This was particularly useful for analysing large countries such as the US or Australia, where media coverage may be concentrated in specific regions. This supports a deeper understanding of how resilience narratives are distributed spatially, providing a basis for comparing media attention across different disaster-prone regions.

3.8.3 Thematic Analysis

To complement the multi-class text classification that resulted in relevant clauses labelled for each of the five resilience capacity classes, a thematic analysis was conducted to systematically explore and understand the in-depth content within each class. The final analysis adopted a qualitative, human-guided topic analysis strategy. This involved a manual review of the extracted clauses, followed by classification into the subcategories within each resilience capacity class, summarised in Table 3.2. This approach enabled enhanced interpretability and a more nuanced understanding of the resilience capacity classes and their subcategories in the disaster resilience discourse.

In addition to this manual strategy, it was also tested whether automated methods could support the identification of thematic structures. Building on Huai and Van de Voorde (2022) and Rudra et al. (2018), keyword extraction and clustering methods were applied as a post-processing analysis. The approach integrated statistical keyphrase extraction using the RAKE algorithm, word embeddings via a pre-trained Word2Vec model, dimensionality reduction through Principal Component Analysis and t-distributed stochastic neighbour embedding, followed by K-Means clustering. While this methodology provided a robust technical framework, it ultimately lacked interpretability, which led to the preference for the human-guided, qualitative approach.

For the content analysis, all examples extracted with the pipeline were examined to determine their relevance to the capacity class and the subcategory to which they belonged. To graphically represent the results and determine which classes and subclasses dominate the resilience discourse, heat maps were created using the Python package seaborn (Waskom, 2021). These heat maps compared Global North and Global South, and slow- and sudden-onset disasters. As there were major differences in the frequency of topics mentioned between the Global North and the Global South due to higher media attention for the Global North, normalisation had to be carried out. Normalisation was performed for each column individually (i.e. for Global North and Global South) in order to identify the most frequent capacity classes and determine how the subcategory frequencies differed between them.

4 Results

4.1 Model Performance

4.1.1 Validation of Manual Classification

To ensure the reliability and consistency of the manually annotated dataset used for training and evaluating the classifier, an intercoder agreement analysis was conducted using MAXQDA 24. Two independent rounds of annotation were performed by the same annotator at different times to assess intra-annotator consistency. Agreement was evaluated in two ways: (1) by comparing the frequency of each class assigned to individual documents, and (2) by measuring the overlap of annotated text segments between the two annotation rounds.

Table 4.1 shows the agreement results based on code frequency per document. The overall agreement across all categories was 84%, with individual class agreement ranging from 80% (anticipative) to 90% (transformative). This indicates a high level of consistency in the identification and classification of content related to disaster resilience capacities at the document level.

Table 4.1: Intercoder agreement results based on code frequency in the document.

Capacity	Agreement	Disagreement	Total	Percentage [%]
Preventive	81	19	100	81
Anticipative	80	20	100	80
Absorptive	83	17	100	83
Adaptive	86	14	100	86
Transformative	90	10	100	90
Total	420	80	500	84

A more granular comparison was performed using the segment-level intercoder agreement approach, assessing the overlap between annotated text segments in the two annotation rounds. Using an 80% code intersection rate between annotations – for example, segments were considered a match if they overlapped by at least 80% – the agreement was 52.60%. Reducing the intersection rate to 50% increased the agreement to 74.94%, indicating greater alignment at a higher tolerance level. This suggests that, while the categories were reliably identified, the annotation varied in how precisely the span of text representing each category was delineated.

Table 4.2: Intercoder agreement based on minimum code intersection rate of 50% at the segment level.

Capacity	Agreement	Disagreement	Total	Percentage [%]
Preventive	176	61	237	74.26
Anticipative	156	49	205	76.10
Absorptive	192	44	236	81.36
Adaptive	86	52	138	62.32
Transformative	54	16	70	77.14
Total	664	222	886	74.94

4.1.2 Relevance Classification Model

The performance of the relevance classifier was evaluated using the three performance metrics precision, recall, and F1 score. Table 4.3 lists the results for the three metrics, including the macro as well as the weighted averages for both the relevant and the irrelevant classes. The results represent the model performance after adjusting the decision threshold to account for the high class imbalance in the dataset for relevant sentences. The classifier achieved high performance in identifying irrelevant sentences with a precision of 0.91, recall of 0.97, and an F1 score of 0.93. The relevant class achieved a precision of 0.56, a recall of 0.27, and an F1 score of 0.36. This shows that the classifier performs well in identifying sentences that are not relevant to disaster resilience. The macro average F1 score was 0.65, which treats every class equally regardless of class frequencies. The weighted average, which accounts for class imbalance, yielded an average F1 score of 0.88.

Table 4.3: Results for the three performance metrics for the relevance classification model after threshold tuning.

	Precision	Recall	F1 score	Data sample
Relevant	0.56	0.27	0.36	503
Irrelevant	0.91	0.97	0.93	4,015
Macro average	0.74	0.62	0.65	4,518
Weighted average	0.87	0.89	0.88	4,518

4.1.3 Resilience Capacity Classification Model

Table 4.4 shows the results for the three evaluation metrics of the capacity classifier for the five resilience capacity classes separately. The classifier achieved the highest F1 score of 0.82 for absorptive capacity, with a recall of 0.87 and precision of 0.77. Similarly, the anticipative capacity class showed robust performance with an F1 score of 0.75, indicating the model's effectiveness in identifying these categories. The preventive class also yielded good results with an F1 score of 0.70 and balanced scores for precision and recall. In contrast, the classifier did not perform as well for the adaptive and transformative classes. The adaptive capacity class yielded an F1 score of 0.44, while transformative capacity performed a little worse with an F1 score of 0.35, which is mostly driven by a low recall (0.26). The overall macro-averaged F1 score was 0.61, the weighted average F1 score 0.69. This suggests that the classifier performs reasonably well on average but is biased toward the classes with more examples per category.

Table 4.4: Results for the three performance metrics for the capacity classification model.

	Precision	Recall	F1 score	Data sample
Preventive	0.66	0.74	0.70	168
Anticipative	0.76	0.74	0.75	151
Absorptive	0.77	0.87	0.82	184
Adaptive	0.49	0.40	0.44	89
Transformative	0.58	0.26	0.35	43
Macro average	0.65	0.60	0.61	635
Weighted average	0.69	0.70	0.69	635

4.1.4 Two-Stage Classification Model

Table 4.5 shows the performance metrics for the entire classification pipeline of the two-stage classification model presenting the results for the five resilience capacity classes and the additional irrelevant class, using the same evaluation metrics. The results must be interpreted with caution, as there is the possibility of bias, given that the same data were utilised for both training and testing.

Table 4.5: Results for the three performance metrics for the whole two-stage classification model.

	Precision	Recall	F1 score	Data sample
Preventive	0.61	0.20	0.30	671
Anticipative	0.58	0.19	0.28	607
Absorptive	0.67	0.26	0.38	707
Adaptive	0.67	0.10	0.18	404
Transformative	0.72	0.10	0.18	172
Irrelevant	0.94	0.99	0.96	30,282
Macro average	0.70	0.31	0.38	32,843
Weighted average	0.91	0.93	0.91	32,843

The model demonstrated high performance on the irrelevant class, achieving a precision of 0.94, a recall of 0.99, and an F1 score of 0.96. Among the resilience classes, the absorptive class performed best, with an F1 score of 0.38. The preventive capacity class achieved an F1 score of 0.30. The anticipative, adaptive and transformative classes had F1 scores of 0.28, 0.18 and 0.18 respectively. The model performed quite well in retrieving instances relevant to each resilience capacity class with precision scores ranging between 0.58 and 0.72, though at the cost of recall. The adaptive and transformative capacities had the lowest recall of 0.10, indicating the challenge in retrieving relevant content for these minority classes. The macro average F1 score was 0.38, whereas the weighted average F1 score was 0.91, which is heavily influenced by the high performance of the irrelevant class. These results indicate that the two-stage classifier was highly effective at identifying and filtering irrelevant clauses. However, its performance with nuanced and less frequent resilience categories remained limited.

To complement the quantitative evaluation of the gold standard dataset, a manual precision evaluation was conducted to assess the performance of the two-stage classification model over the whole dataset. Table 4.6 shows that the overall precision across all classes was 0.76, indicating that the majority of extracted clauses were relevant. The precision was even higher for some capacity classes for the whole dataset than indicated by the gold standard dataset, for instance anticipative (0.81), absorptive (0.80) and preventive (0.73) capacities. In contrast, transformative (0.39) and adaptive (0.52) capacities performed worse.

Table 4.6: Results of manual evaluation of precision of two-stage classification model based on extracted clauses for each resilience capacity.

Capacity	Extracted clauses	Valid clauses	Precision
Preventive	2,512	1,826	0.73
Anticipative	2,248	1,831	0.81
Absorptive	4,005	3,190	0.80
Adaptive	534	277	0.52
Transformative	132	51	0.39
All classes	9,431	7,175	0.76

4.2 Summary of Manual Annotation

The 10% subset of all articles from the disaster-specific corpora comprised 565 unique articles. Of these, 426 articles contained information relevant to disaster resilience, which corresponds to approximately 75%. The manual annotation process yielded 2,115 text segments from this subset. These annotations were coded at the clause level and assigned to one of the five resilience capacity classes. Table 4.7 provides an overview of the distribution across the resilience capacity classes, revealing that absorptive capacities were mentioned most frequently (29.0%), followed by preventive (26.4%) and anticipative (23.8%) capacities, while adaptive (14.0%) and transformative (6.8%) capacities were less common. Selected examples of annotated clauses for each resilience capacity class are provided in Appendix A.1.

4.3 Summary of Automatic Extraction

The article-level analysis revealed that 5,069 unique newspaper articles were extracted from the disaster-specific corpora. Out of these articles, 3,352 articles contained at least one clause relevant to disaster resilience capacities, representing 66% of the original articles. Among these, 3,289 articles (98.12%) included geospatial references that allowed for further analysis of spatial patterns. A substantial imbalance was observed in the geographic focus of the articles: 2,796 articles (85.01%) primarily referred to the Global North, whereas only 493 articles (14.99%) focused on the Global South. Similarly, a notable discrepancy was evident in terms of disaster onset. Of the relevant articles, 2,751 (83.64%) addressed sudden-onset disasters, while 538 articles (16.36%) discussed slow-onset disasters. These distributions highlight underlying representational asymmetries in the reporting of disaster resilience, both geographically and by disaster type.

A more detailed analysis at the clause-level revealed that the text classification pipeline acquired 9,431 segments related to disaster resilience capacities, of which 7,175 were valid examples (see Table 4.6). The number of segments extracted per article varied considerably. In 25.6% of the cases, five or more segments were extracted from a single article, suggesting a considerable focus on disaster resilience, with some articles containing up to 22 segments. In contrast, 28.3% of the articles yielded only one relevant clause, indicating that disaster resilience was a subordinate topic in those texts.

When comparing the distribution of resilience capacity classes between the manually coded subset and the automatically extracted clauses, several notable differences emerge (see Table 4.7). In both datasets, absorptive, preventive and anticipative capacities were most frequently mentioned, indicating consistency in the thematic focus. Yet, absorptive capacities were more prominent in the automated results, accounting for nearly half of all extracted clauses (44.5%) compared to 29.0% in the manual annotations. In contrast, adaptive and transformative capacities were significantly under-represented in the automated results (3.9% and 0.7%), while appearing more frequently in the manually coded subset.

Table 4.7: Overview of annotated segments in the subset and the finally extracted segments per capacity class.

Capacity	Coded Segments	Percentage [%]	Extracted Segments	Percentage [%]
Preventive	559	26.4	1,826	25.4
Anticipative	502	23.8	1,830	25.5
Absorptive	614	29.0	3,190	44.5
Adaptive	296	14.0	277	3.9
Transformative	144	6.8	51	0.7
Total	2,115	100.0	7,175	100.0

A similar comparison was carried out for disaster types to examine whether the class imbalance of disaster types was reflected in systematic biases in automated extraction, similar to the capacity classes. Table 4.8 shows that the overall distribution across disaster types remains relatively consistent between the manual and the automated process. This suggests that the extraction process does not disproportionately favour or ignore particular disaster types. For most types, the percentage of extracted clauses aligned closely with the percentage in the manually coded data. Slight decreases were observed for drought (from 13.1% to 9.5%) and storm (from 18.6% to 14.0%), whereas flood and wildfire saw modest increases. These shifts are minor and suggest that the extraction model performs robustly across disaster types, without introducing significant bias in the output distribution.

Table 4.8: Distribution of annotated and automatically extracted clauses per disaster type.

Disaster	Coded Segments	Percentage [%]	Extracted Segments	Percentage [%]
Flood	1,241	44.3	4,106	48.4
Drought	366	13.1	806	9.5
Heatwave	218	7.8	654	7.7
Storm	520	18.6	1,190	14.0
Hurricane	162	5.8	458	5.4
Tornado	31	1.1	71	0.9
Wildfire	261	9.3	1,198	14.1
Total	2,799	100.0	8,483	100.0

4.4 Geographic Scope of Disaster Resilience Reports

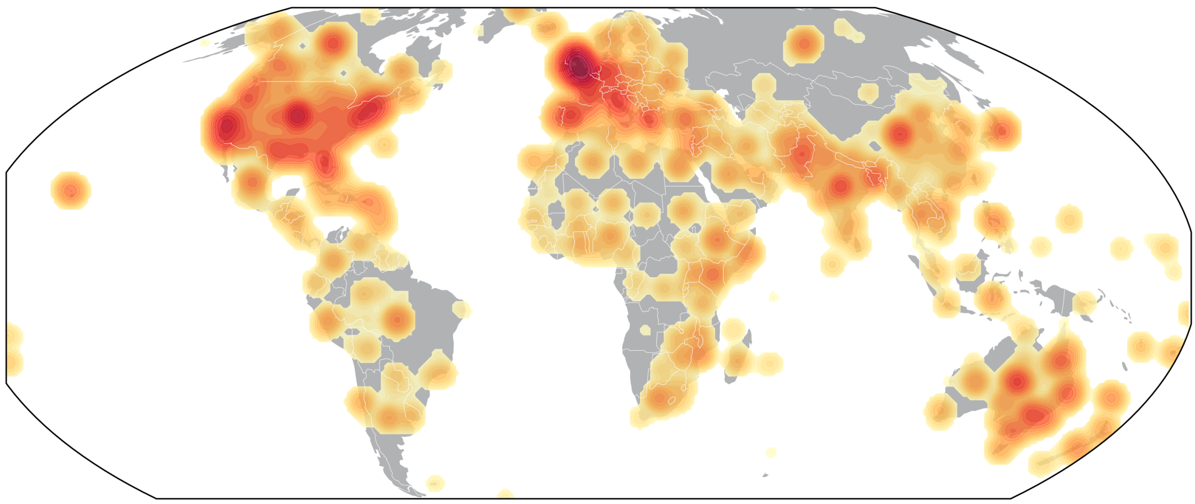

Figure 4.1: Normalised global spatial distribution of resilience reporting (Kernel density).

The geographic information retrieval returned 2,659 unique place names in 212 countries for the relevant newspaper articles. The media attention was biased towards the UK and the US, with 1,677 and 1,371 articles reporting on each country respectively, compared to 354 articles about Australia, the third most frequently mentioned country. Aside from these countries, the media most frequently reported on events in Europe (France, Italy, Spain, Germany, The Netherlands, Greece) besides China, India, Canada, and Pakistan.

The most pronounced hotspots in the US were California, Florida, New York, Washington, and Oregon, as well as the southern states of Texas and Louisiana. In the UK, England was mentioned most frequently followed by Wales, Scotland and Northern Ireland. Most reporting occurred for the cities of London, York, Leeds, and Carlisle. In Australia, the most pronounced regions were New South Wales, Queensland, and Victoria with frequent references to Sydney and Brisbane. In all three countries, region, county or state names and specific location names were frequently referenced to, unlike in many other countries.

Media attention in Asia focused on China, India, Pakistan, Bangladesh, and Japan next to some South-east Asian countries including the Philippines, Indonesia, Vietnam, and Thailand. In Africa, media coverage concentrated on East African countries such as Kenya, Ethiopia, Somalia, Mozambique, and Malawi. Other hotspots included South Africa, Egypt and Nigeria. South America tended to experience a lack of attention from British media in terms of resilience. Pronounced hotspots were Brazil, Argentina and Peru. Hotspots in Central America included Mexico, Puerto Rico, Cuba, the Bahamas, and Haiti.

In certain countries, such as the US and Australia, there were noticeable hotspots appearing in proximity to the geographical centre of the country. The occurrence of these hotspots cannot be attributed to the frequency of references to central locations; rather, it is a consequence of the manner in which the Irchel Geoparser processes country-level toponyms. When encountering a country name, the Geoparser assigns coordinates corresponding to a location in the vicinity of the country's centre. This can result in clustering of points in central areas that do not reflect actual mentions of places.

4.4.1 Geographic Disparities in Global North and Global South

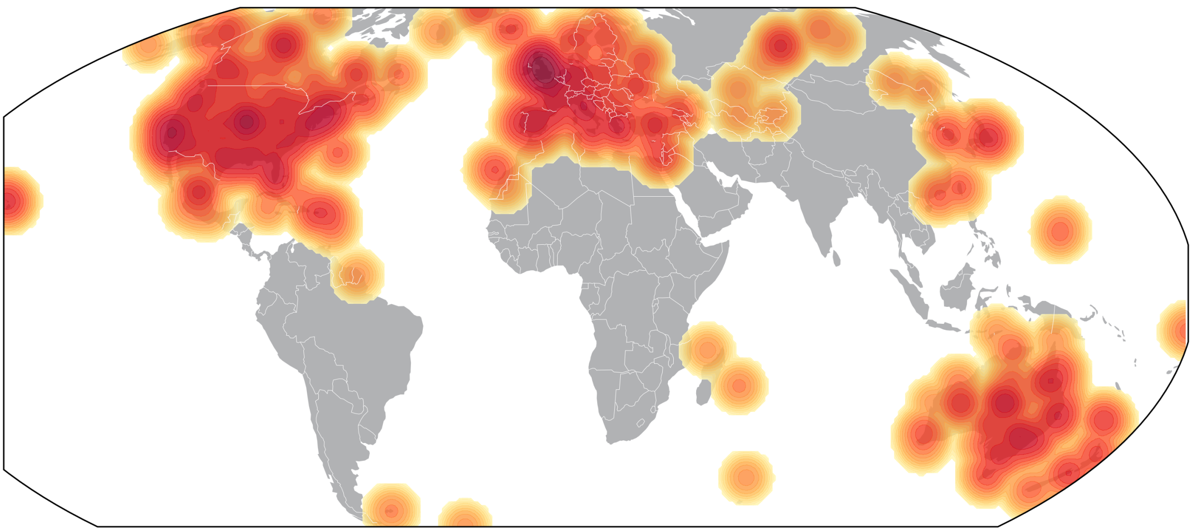

Figure 4.2: Normalised global spatial distribution of resilience reporting (Kernel density) for the Global North.

A disparity was evident in the geographic reporting level between the Global North (see Figure 4.2) and the Global South (see Figure 4.3). Media coverage in the Global North focused on country and county/

state/region levels, with mentions on the local geographic level being relatively common, while regional or local reporting was more rarely observed in the Global South. When focusing exclusively on media reporting in the Global North, the primary hotspots remained in the UK and the US. Furthermore, several countries in Europe, in addition to Australia and New Zealand, received increased media attention. Isolating reporting on the Global South, the media were primarily concentrated on Asia, followed by Africa, Central America and South America.

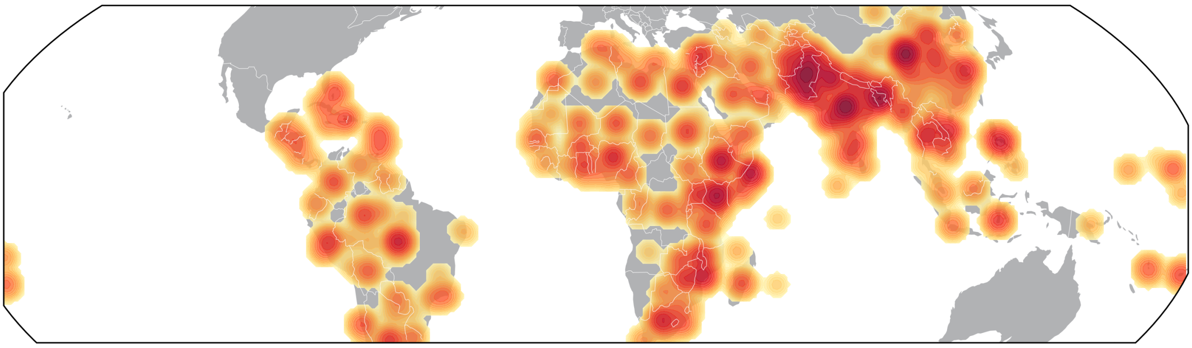

Figure 4.3: Normalised global spatial distribution of resilience reporting (Kernel density) for the Global South.

4.4.2 Geographic Disparities for Sudden- and Slow-Onset Disaster

A comparison of slow- and sudden-onset disasters shows that both share hotspots in Western Europe, North America and Australia, but slow-onset mentions were more geographically dispersed. In Africa, the Arabian Peninsula, Asia and Australia, reporting on slow-onset disasters was generally more widespread. However, in Canada, Alaska and Greenland sudden-onset disasters were more widespread.

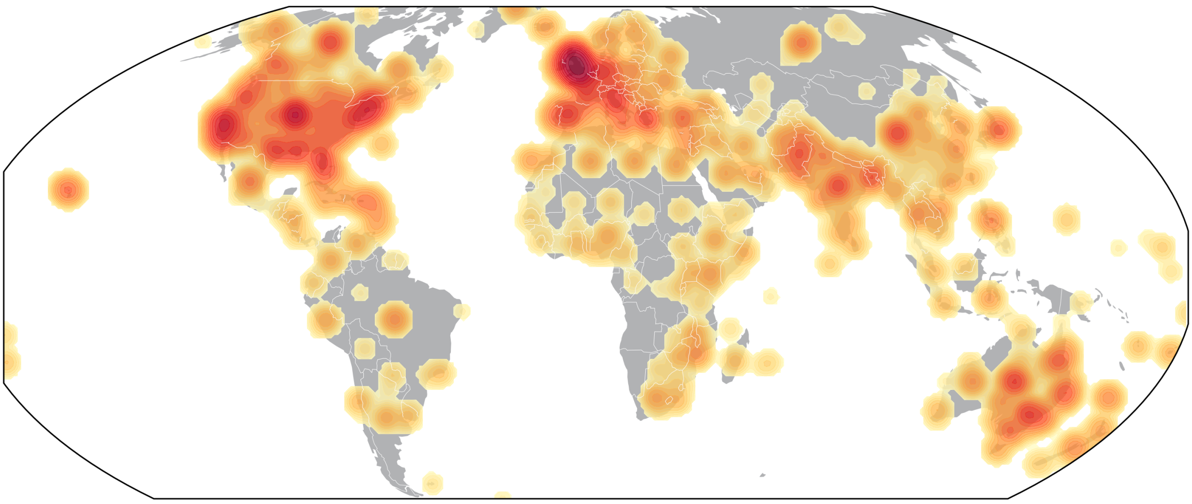

Figure 4.4: Normalised global spatial distribution of resilience reporting (Kernel density) for sudden-onset disasters.

When considered in relation to the global distribution of all disasters, a shift in media coverage of sudden-onset disasters towards other regions was observed. In the Asian context, the Philippines, Afghanistan, Thailand and Nepal received increased attention. In Africa, Algeria and Libya have attracted heightened attention and in South and Central America Puerto Rico, Cuba, and the Bahamas received increased media coverage. In the US, the focus shifted towards New Jersey, North Carolina and Pennsylvania. With regard to slow-onset disasters, a discernible transition was observed from Europe towards Africa, South America and some parts of Asia, including Indonesia, Israel and Syria. In Europe there was a noticeable shift towards Ukraine, while the southwestern states in the US, such as Arizona, Colorado and New Mexico, experienced an increase in media coverage.

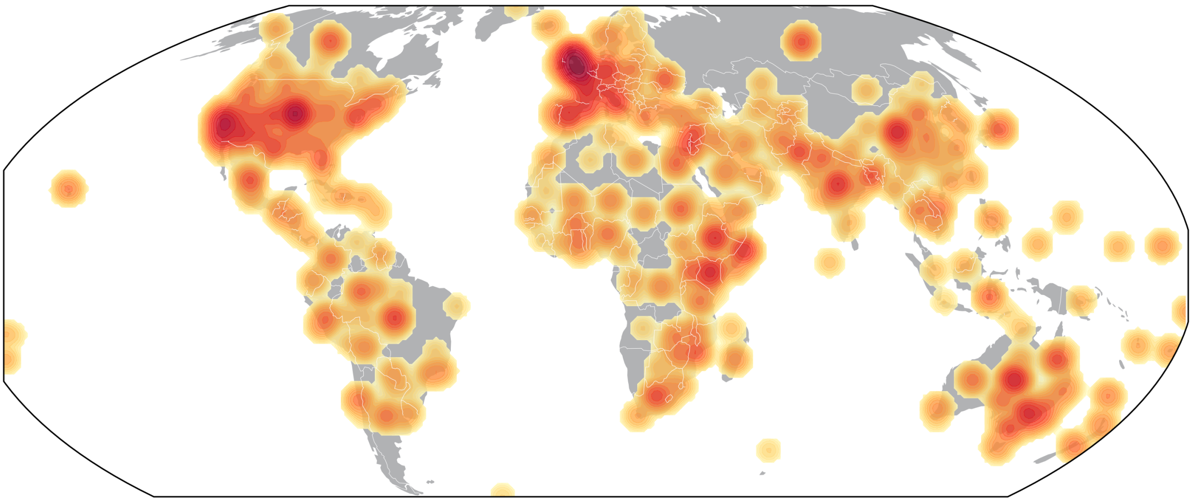

Figure 4.5: Normalised global spatial distribution of resilience reporting (Kernel density) for slow-onset disasters.

4.5 Thematic Content in Resilience Discourse

The following analysis examines the thematic content of disaster resilience reporting, focusing on the portrayal of preventive, anticipative, absorptive, adaptive and transformative capacities in the media.

Preventive Capacity

Within the preventive capacity, media placed strong emphasis on DRM, particularly highlighting the significance of financial investment. Economic considerations were the most recurrent topic across the articles, indicating that monetary concerns dominated the media discourse around preventive capacity. Articles often underscored the cost-effectiveness of proactive spending, noting that "for every £1 spent on flood defences, an estimated £8 is saved, from insurance and the cost of damage to homes and businesses" (The Guardian, 09.07.2014) and that "every $1bn invested in protection against coastal flooding leading to a $14bn reduction in economic damages" (The Guardian, 02.11.2023).

In the UK context, a considerable amount of attention was given to the government budgets spent on flood defences or other protection measures. Media reports frequently compared spending under different administrations, scrutinising cuts or increases, and revealing differences in spending in different regions in England. There was a recurring critique of Britain's "stop-start approach to flood defence funding" (Financial Times, 15.12.2015) due to changing interests of governments weakening long-term resilience. Some articles criticised that return on investment was often the primary factor in determining where defences were built, resulting in a disproportionate focus on urban areas and leaving rural communities more vulnerable.

Beyond financial topics, risk management practices were also discussed in practical terms, including the maintenance of infrastructure, such as routine inspections, repairs, as well as cleaning infrastructure such as pipes. Furthermore, strategies around natural resource management received increased media attention in recent years, with around two-thirds of reporting occurring after 2016. These management approaches included tree planting, wetland restoration, creating salt marshes or maintaining coral reefs and helped to decrease the impacts of floods or storms by capturing water upstream and buffering storm surges and were also very cost-effective. Forest management was described as an approach for wildfires, focusing on maintaining forest health and increasing tree diversity to prevent wildfires. The novelty of natural resource management approaches was emphasised by the lack of political engagement and willingness to support these projects: "the funding system in Scotland was set up to favour 'traditional' hard engineering works, such as walls, embankments and barriers, at the expense of natural solutions" (The Times, 23.09.2023).

Within the domain of DRM, education appeared as a less frequently discussed preventive measure. Important topics were the education of society on disaster risks and promoting preparedness, for example through "campaign[s] so people could prepare themselves ahead of time" (The Independent, 19.04.2023) and emphasised the importance of early education "starting as early as primary school" (The Guardian, 25.07.2022). In the context of wildfires, particular attention was given to educating both professional and voluntary fire services on new risk reduction strategies, including updated forest management practices.

With regard to structural measures, the need to construct new or fortify established hard-engineering solutions was most frequently reported on, encompassing large-scale engineering projects such as flood defences, sea walls, reservoirs and dams. Flood mitigation strategies were typically implemented with the objective of regulating the flow of water downstream. However, these measures often resulted in the diversion of water to elsewhere. The idea of deliberately breaching sea walls to allow water ingress at strategic locations was also explored, illustrating "two completely opposing flood defence techniques - one for keeping water out and the other for letting water in" (The Independent, 23.11.2000). In several articles, the validity of conventional measures was questioned, noting that "we will never be able to build enough defences to guarantee zero risk to everyone" (The Times, 14.12.2015). Structural measures were also discussed in relation to other hazards: for droughts, common responses included desalination plants, cooling systems or water storage solutions such as dams or rainwater harvesting systems. In the case of heatwaves, strategies included improved insulation, enhanced ventilation and the implementation of air conditioning systems.

While DRM and structural measures were the predominant topics, preventive strategic planning was also featured in the discussion of improving or renewing disaster plans or introducing new planning guidelines for defence structures. The importance of considering climate change in plans was already evident in the early 2000s: "And if we don't build climate change into our flood defence plans, we can expect a 65% increase in river flooding and a four-fold increase in coastal flooding in the second half of this century" (The Guardian, 16.05.2002).

Governance & policy was the least visible topic of preventive capacity and focused primarily on the regulation of land use and building standards. Articles called for stricter planning laws to prevent construction in high-risk zones, as well as more robust building codes to ensure structures were built to withstand future hazards. In the context of heatwaves, this included regulations to prevent overheating in new developments.

Anticipative Capacity

Early warning emerged as the central element in the resilience discourse for anticipative capacity. Recurrent topics were the issuing of warnings or alerts, ranging from local wildfire warnings to national drought and heatwave alerts. Early warning was portrayed as an essential tool for enabling communities and governments to prepare for and respond to impending disasters, including evacuation or emergency mobilization. One article described how fishers "moved their boats to safety when they were given 36 hours notice of two strong cyclones" (The Guardian, 17.05.2016), while another highlighted government preparedness as "emergency services were put on high alert, with police on standby in the areas thought to be most at risk, on the east coast" (Financial Times, 09.11.2007). These examples highlight the "importance of acting quickly in response to early warnings must be properly recognised for its powerful role in reducing the risk of repeated disasters and building resilience" (The Guardian, 17.05.2016). Alerts were spread across a variety of channels including text messages, emails, sirens, or public display boards. One article noted that "more than a million people now receive flood warnings by text or phone thanks to the new alert service" (The Daily Telegraph, 27.11.2012). The significance of early warning systems was repeatedly stressed, with the “UN aiming to reach everyone on Earth by 2028” (The Guardian, 02.11.2023) presented as a major global target. However, effectiveness was also contingent on public trust and responsiveness, as “a warning system that people ignore is next to useless” (The Daily Telegraph, 20.06.2022).

Closely linked to early warning is the use of monitoring systems, which were employed to observe river levels or track weather patterns. The information collected through monitoring processes proved to be important in the development of early warning systems. The implementation of monitoring systems and the subsequent availability of data resulted in enhancements in early warnings. Nevertheless, it was frequently highlighted that monitoring and tracking systems could still be improved to allow for more accurate predictions, which could result in improvements to warnings.

Besides early warning, risk awareness was a central topic in the anticipative capacity discourse. Disasters or findings from reports were often described as wake-up calls, leading public and political attention towards climate-related risks and the necessity of better preparation. For instance, one article stated that "the Foresight report should have been a wake-up call, with its warning that either governments provide high levels of flood protection to resist rising coastal threats, or they abandon large tracts to the sea" (The Guardian, 28.12.2015). Risk awareness was regarded as a crucial component of resilience, as it empowers individuals and communities. This perspective is reflected in a call to "develop consistent standards for flood and coastal resilience in England that help communities better understand their risk and give them more control over how to adapt and respond" (The Independent, 09.05.2019).

Forecasts, including both short- and long-term, played a major role in awareness building. Short-term forecasts helped communities and authorities to determine the scale of the expected impact and facilitate pre-emptive responses such as emergency preparations. Long-term forecasts, however, are crucial to underscore changing conditions under climate change. Articles often cited assessment reports that studied the impact and scale of disasters in the future. These forecasts not only increased situational awareness by leading attention to future risks and problems, they also contributed to shaping future planning strategies by identifying areas of increased risk and determining areas on which to focus.

Risk awareness was crucial for understanding and adapting to shifting conditions in the future due to climate change. The return period for which a defence structure was originally built was often discussed. However, as climate change alters the frequency and intensity of extreme events, the reliability of the return period is increasingly questioned: "current one-in-100-year high-water level on the east coast may be expected to be exceeded every 20 years, on average, by 2050" (The Guardian, 09.10.2002). When formulating future planning strategies these modifications need to be considered.

Scenario planning was reflected in the frequent reporting of anticipative measures informed by future risk projections. One article noted that authorities had "warned several times that climate change could mean drought is 'the new normal' for the UK and urged water companies to come up with long-term plans for saving water" (The Guardian, 12.03.2012). Media highlighted how both governments and individuals prepared for expected climate impacts, by reinforcing infrastructure or building water tanks "in anticipation of a prolonged drought" (The Independent, 19.04.2023). Risk mapping was often mentioned as a tool to guide decisions, allowing governments and communities to assess vulnerabilities.

The establishment of emergency response plans formed another important element of scenario planning. States and union territories in India were for example advised "to prepare heat action plans at state, city and district levels" (The Independent, 06.05.2022). In the US "many cities and states have put in place heat action plans, by setting up cooling centers and providing warnings to vulnerable people, such as the elderly" (The Guardian, 01.08.2023). However, articles also pointed out the lack thereof: "In 2019, the CCC [Climate Change Committee] repeated its warnings that the UK had no proper plans for protecting people from heatwaves, flash flooding and other impacts of the climate crisis" (The Guardian, 16.06.2021).

Risk transfer mechanisms were mostly portrayed through insurance schemes, with frequent emphasis on the need to maintain their affordability and accessibility. Media reports highlighted the rising demand for catastrophe and flood insurance in the context of climate change, while also noting that in high-risk areas households sometimes faced higher premiums, stricter conditions, or the need to demonstrate mitigation measures in order to obtain cover. Beyond insurance, risk transfer was also discussed in relation to direct financial transfers — including grants, cash payments, and disaster relief funds — that can strengthen resilience both before and after disasters. Such measures were often framed as particularly important for vulnerable communities, where insurance markets alone may not provide adequate protection.

Absorptive Capacity

A central component in the narrative of absorptive capacity was the strategic mobilisation of physical and human resources to absorb impacts of disasters. These resources included emergency vehicles such as helicopters, aeroplanes, or water trucks as well as emergency services including firefighters, paramedics, military personnel, and rescue teams. Stand-by forces including military or emergency services further strengthened absorptive capacity by allowing immediate deployment of aid when needed. Building redundancy and ensuring the availability of essential supplies such as food, water and power during disasters is also fundamental. In Africa, multiple governments have established "strategic food reserves to cope with ... emergencies" (The Independent, 06.07.2011) long before crises to enable governments to maintain basic supply chains during disasters. Others built additional water tanks to ensure enough water during droughts. Furthermore, proactively investing in specialised equipment for emergency response can improve emergency response. For instance, fire services in the UK have started acquiring off-road vehicles, drones, and backpack sprayers to better cope with increasingly intense summer conditions, alongside tools to help firefighters stay cool during operations. An other important measure was the provision of generators and fuel "to ensure the continued availability of backup power" (The Guardian, 18.02.2021). During a major drought, Barcelona needed "tankers to bring in drinking water" (The Independent, 29.11.2023).

Articles also emphasised the importance of international collaboration in resource management, particularly in response to wildfires. Numerous articles reported on the assistance from other countries by providing critical support including firefighting personnel, helicopters or planes to help affected countries in battling large-scale blazes.

Another approach to building redundancy involves modifying infrastructure to enhance its capacity to absorb extreme events. In flood-prone areas, for instance, authorities have adjusted water management systems to increase their ability to accommodate sudden inflows. One article reported that "Labor wants to amend Warragamba's operating rules so it can lower the height of the water behind the existing wall, giving it 'airspace' to absorb sudden inflows" (The Guardian, 17.08.2022).

Operational adjustment was often portrayed as legally enforced restrictions aimed at conserving scarce resources or reducing risks. Water restrictions during droughts were a recurrent measure reported on. Governments imposed hosepipe bans, prohibited the filling of pools, washing cars or running fountains. In France, it was mentioned that enforcement were very strict, with helicopters deployed to check misuse from the air. During wildfires, operational adjustments included bans of smoking outdoors, charcoal barbecuing and campfires as well as power cuts to prevent sparks from lines to start wildfires. Similarly, during floods, authorities often closed roads, rail lines or underground stations. Heatwaves prompted energy-saving efforts, with officials urging the public to reduce energy use during peak hours to prevent power outages. Additionally, hosepipe and barbecue bans were enforced.

Support included financial, material and community-driven contributions to help affected communities recover from disasters, whereby financial support was by far the predominant topic in support narratives. Support was normally provided from the federal government to certain affected regions within the country or from one country or international organisation to affected countries. Food, water, and medicine were among the frequently distributed forms of aid during and after disasters. Articles frequently reported on communities facing food insecurity, such as in Kenya, where "nearly 5m Kenyans require food aid, according to the United Nations World Food Programme, with nearly 23m people in need across east Africa, most notably in Ethiopia" (Financial Times, 29.10.2009). WaterAid, an international non-governmental organisation was "providing safe water and emergency sanitation access in two regions of Malawi and Mozambique, and in Mozambique [they] are also distributing hygiene kits containing water purification drops or tablets, a large water bucket, drinking mugs, soap, cotton cloth, toothbrushes and toothpaste, menstrual supplies and other essential items" (The Independent, 21.04.2019). In addition to basic needs, support often included materials and assistance in rebuilding critical infrastructure like shelters, latrines and sanitation facilities, health centres and schools was further provided to help communities return to normality. However, challenges in delivering international aid were also reported. It was criticised that international aid was sometimes complicated as "red tape is making it difficult for international aid workers to reach devastated areas" (The Independent, 22.11.2022), highlighting bureaucratic obstacles in emergency contexts. Debates also emerged regarding the most effective forms of aid provision. Some criticism was directed at direct food aid, which was argued to potentially undermine local and national resilience rather than strengthen it. Similar to the preventive capacity discourse, the reporting revealed a noticeable shift from reactive financial support towards investments in emergency preparedness aimed at reducing risk and mitigating the long-term impacts of disasters.

Community solidarity emerged as a vital form of support in the aftermath of disasters. Forms of community solidarity included monetary donations, the distribution of essential goods such as meals and clothing, and active participation in clean-up and rescue efforts. One town "where 120 homes were damaged, has quickly bounced back thanks to an exemplary community effort" (The Guardian, 08.01.2016). Fundraising initiatives, such as turning local festivals into donation drives, also exemplified community solidarity.

The capacity to absorb the impacts of disasters is contingent on timely preparation and the coordination of emergency responses. A pivotal mechanism is the declaration of a state of emergency, which facilitates streamlined decision making and unlocks financial resources. In Italy and Australia, these declarations have proven instrumental in expediting the deployment of emergency aid and reducing bureaucratic obstacles.

Prompt protective measures encompassing evacuations and the establishment of emergency shelters were vital to safeguard lives during and in the aftermath of disasters. Evacuees were relocated to temporary accommodations located in public spaces, such as sports arenas or government buildings, where they were provided with basic necessities. Concurrently, emergency services were deployed to manage the unfolding crisis. Response efforts included firefighting teams to contain wildfires, the deployment of helicopters for aerial rescues, the coordination of recovery teams tasked with the location and rescue of survivors, and the distribution of essential supplies.

In addition to these interventions, a variety of short-term adjustments were implemented to reduce harm including the closure of schools, the rescheduling of exams, the imposition of speed restrictions, the rerouting of transport services and the establishment of emergency cooling centres during periods of extreme heat. It has been demonstrated that even animals may receive care in the form of sun protection.

Adaptive Capacity

Adaptive capacity was dominated by discussions centred on incremental adjustment at both the household and the government level. Drought-related articles reported on various conservation strategies to reduce water consumption through rainwater harvesting, low-flow toilets and showers and greywater recycling. For flood adaptation, common strategies were river renaturalisation, greening of roofs and walls and permeable driveways, all designed to enhance ground infiltration, decrease surface run-off and relieve pressure on wastewater systems. The benefits of greening were that "every inch of soil you have on a green roof absorbs five per cent more water, so that’s five per cent less water that’s running off into drains" (The Independent, 26.06.2021) and that green roofs "act as giant sponges, soaking up water and letting it drain off more gradually" (Financial Times, 29.11.2010). The greening of urban environments not only helps with flooding but also results in local cooling during heatwaves. For flood-prone areas, adaptation measures for households included elevated electrics, water-resistant flooring, flood-resistant doors, and ground-floor garages. Some articles also highlighted nature-based solutions, such as beaver reintroductions, which "restore wetland habitats through dam-building and felling trees, slowing, storing and filtering water in the landscape, which attracts other wildlife and reduces [sic] flooding downstream" (The Independent, 17.03.2022) and "create thousands of ponds and lakes, at no cost to the taxpayer, and so hold back millions of gallons of rainwater" (The Independent, 17.01.2016).

Learning from insights from past disasters is a crucial asset of adaptive capacity enabling continuous improvements in preparedness and response strategies. Following Hurricane Katrina, the US government incorporated valuable lessons into their disaster response system such as "deferring to authorities on the ground and drawing on the knowledge of local volunteers" (Financial Times, 01.09.2017) and after Sandy, structural innovations were implemented such as "Kevlar-strengthened ’flex gates’ that can be pulled across subway entrances in minutes to prevent floodwaters cascading in" (The Independent, 09.07.2021). Learning also incorporated the exchange of knowledge and practices between countries. The Netherlands, a country renowned for its expertise in flood management arising from its topography, serves as a model of innovation in this field. The UK, which faces similar coastal challenges, has drawn on Dutch flood management strategies including increased investment in deepening and widening rivers, creating run-off channels, and subsidising the establishment of green roofs to improve urban rainwater absorption.

Diversification was portrayed both as a shift towards more resilient cultivation systems and a realignment of income strategies. Examples ranged from farmers switching from water-intense crops like wheat to drought-tolerant alternatives such as olives or almonds, to trials of genetically modified resistant varieties to drought or flooding. Techniques such as planting crops with deeper or more water-resistant root systems or planting closer together were emphasised. Beyond farming, diversification was framed as a strategy to switch to different fish species for catching, find alternative sources for firewood and turn to alternative income by changing from one sector to another. In wildfire context, the importance of tree diversity and natural regeneration to better adapt that post-fire species pools to future conditions was underlined.

Media perception of organisational adaptation centred on insurance discussions. This included strategies by the authorities to ensure that more people who are exposed to disasters receive insurance. Introduced strategies helped decrease people’s vulnerability by installing disaster-resilient infrastructure or by government increasing spending on better defence infrastructure.

Transformative Capacity

A recurring topic for transformative capacity was livelihood transformation, predominantly in the context of migration and relocation. Newspapers reported on cases where people had to leave their homes and migrate to cities or other countries as the impacts of disasters became excessive, or the possibility of return was extinguished following a disaster. In order to be able to support their families, some moved to the city. In other cases, growers were forced "to consider whether to shut down, relocate or otherwise alter their operations" (The Guardian, 01.11.2022), with some shifting to cooler climates. The driving forces for migration or resettlement were diverse. While in some examples families were relocated through government initiative, other requested resettlement from authorities. As one article put it, “migration should not be seen simply as a problem - in many cases, it is a sensible solution to the environmental changes caused by a warming climate, and can be managed if governments make adequate preparations” (The Guardian, 20.10.2011). The media also emphasised the importance of cooperation across government levels as a crucial element of transformation. Enhanced coordination between state, federal and regional actors was portrayed as being pivotal for the reconstruction and support of affected populations. This coordination should encompass the cutting red tape, the alignment of federal funding with local rebuilding visions, and the guarantee of effective delivery of assistance. Another approach for livelihood transformation was to change agricultural practices, such as switching from planting to dairy farming or from corn to rice. Most livelihood transformation examples originated in the last ten years, with hardly any reporting in previous years.

Media also covered technical innovation as a means of transformative capacity. This included novel design approaches such as floating houses or cities, designated flooding spaces or "sand motor" dune systems. The "sand motor" was a coastal engineering project in the Netherlands where a large sand peninsula was constructed in front of the coast. Over time, natural forces like waves and currents gradually distributed the sand along the shoreline, reinforcing the coast and reducing the need for frequent artificial replenishment. Designated flooding spaces can be implemented in multiple ways, for example by creating recreational grounds that serve as both leisure areas and temporary flood zones during flood events. Similarly, buildings can be designed with ground floors intended to safely absorb flooding, minimizing damage to the infrastructure.

Over time it was recognised that infrastructure needed to be redesigned for both resilience and flexibility. This paradigm shift would require the use of "construction materials and methods that can withstand extremes" (Financial Times, 03.07.2021). Another approach would be to design buildings to better cope with disasters for example by implementing optimally thermoregulated houses or train tracks that are not susceptible to heat. Flexible building styles require designs to move buildings more easily away from cliffs, or to construct houses on rising stilts. Flexibility was also reported as an important asset of flood defences, such as portable flood defences.

At the institutional level, transformative capacity was framed through the rethinking of urban planning and governance resulting in smart building concepts. News articles pointed to a transition from traditional hard-engineering flood protection toward greener, more integrated approaches: "where hard engineering has been used at scale, for example, in Japan, there is a movement now towards actually trying to move away from those hard structures towards a more holistic natural flood management approach to try to deal with a problem at the source" (The Guardian, 07.11.2023). The evolution towards embedding climate change considerations into planning processes and to redesign cities with more green infrastructure to mitigate flooding and urban heat was evident. Examples of social transformation were largely absent in the media. While there were some indications of a shift from reactive to preventive risk cultures – particularly in the context of floods – a few articles explicitly addressed deeper changes in social norms, values, or power structures as part of building resilience.

Indicators across Capacities

Across the different capacities, certain words appeared frequently and proved to be highly indicative of particular subcategories. For instance, preventive capacity was strongly associated with terms such as "spend" and "invest", while anticipative capacity was often linked to expressions like "alert" or "warning". Absorptive capacity frequently co-occurred with references to "support" or "help". These words provided clear markers for the classifier, yet they also introduced ambiguity, as they were occasionally used in unrelated contexts, for example, "spend" in the sense of spending time rather than spending money. By contrast, adaptive and transformative capacities lacked such distinctive markers, relying more on broader contextual patterns than on specific keywords.

4.5.1 Thematic Content in Different Regions

Figure 4.6 presents the differences in the emphasis on disaster resilience reporting across the five capacities from the Global North and the Global South. The values were column-normalised to highlight the intra-regional priorities. The dominant resilience capacity was absorptive capacity for the Global North as well as for the Global South. Preparation & response and support received the highest media attention in both contexts. While support measures received more media coverage in the Global South, reporting in the Global North was dominated by preparation & response.

In the context of the Global South, support during disasters was primarily framed around international aid, often provided by foreign governments, charities, NGOs or international organisations such as the

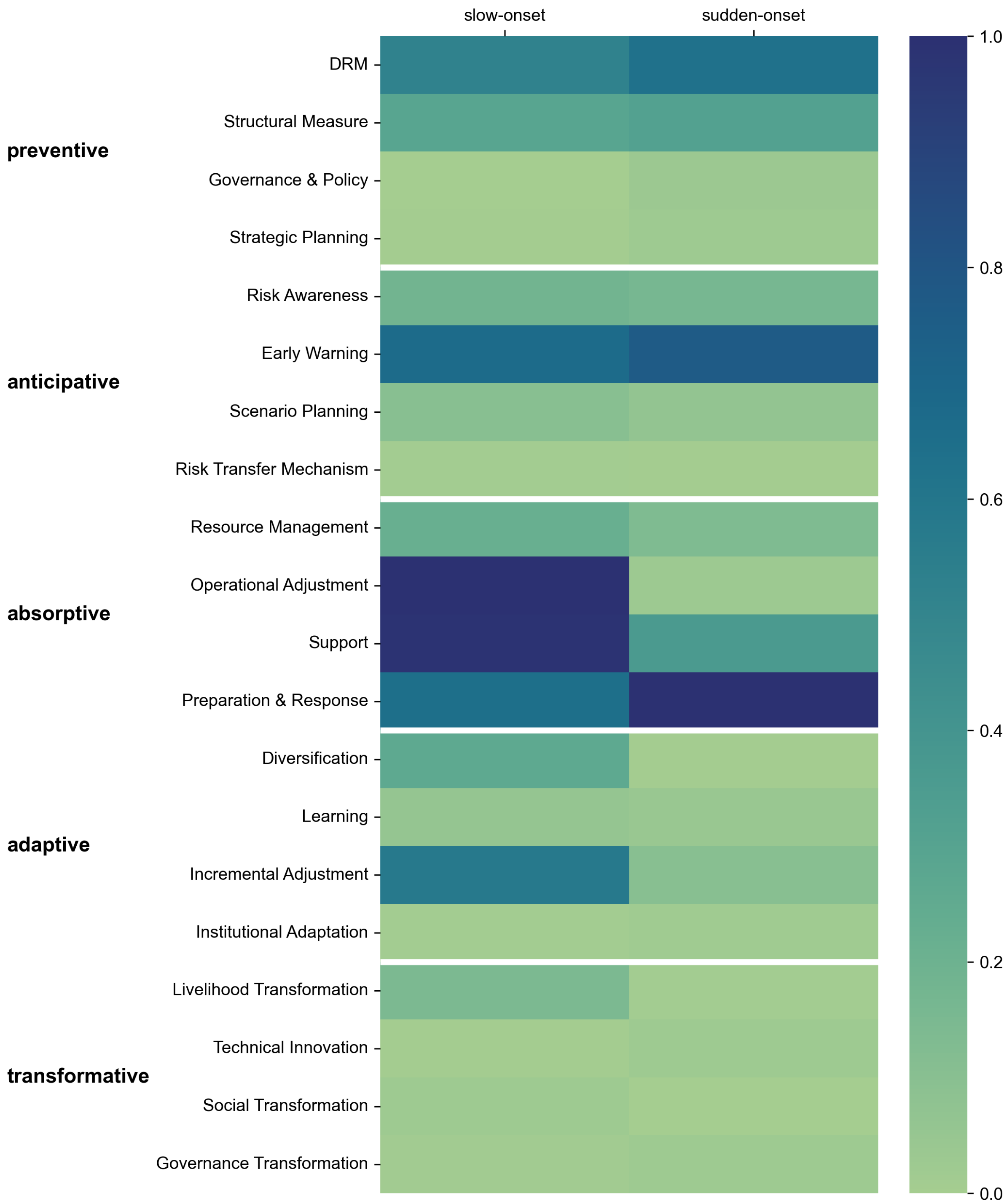

Figure 4.6: Normalised heat map for differences in disaster resilience mentions for the Global North and Global South.

UN. The provision of assistance frequently encompassed the allocation of financial resources, the provision of food and potable water, the distribution of medical supplies and other essential goods. In the Global North, support primarily included regular state-provided aid, alongside the distribution of food and other supplies. In addition, the Global North focused more frequently on the importance and existence of community solidarity as "a community will lift up and help each other in a time of emergence [sic]" (The Guardian, 09.03.2022). This community solidarity aspect was hardly evident in the reporting on the Global South. Further disparities were revealed with regard to preparedness & response. The Global North has focused more on evacuation strategies, whereas the Global South has placed greater emphasis on shelter provision. Operational adjustment was portrayed as measures taken to ration or restrict water or power usage. However, while there were concrete measures given for the Global North encompassing hosepipe bans, restrictions on filling swimming pools or fountains and prohibition on barbecues, specific examples were generally lacking in the Global South.

In the Global North, preventive capacity was the second most frequent class, followed by anticipative. In terms of preventive capacity, substantial emphasis was placed on DRM and structural measures. Regarding anticipative measures, early warning is predominant as well as risk awareness. In contrast, in the Global South a greater focus was on anticipative capacity, followed by preventive. Anticipative capacity was mainly reported as early warning. For preventive capacity the dominant topics were DRM as well as structural measures.

In the context of DRM, financial aspects played a role in both the Global North and the Global South, although the financial aspects were much more strongly represented in the Global North. In the Global South, however, the importance of disaster education was frequently noted, focusing, for example, on which strategies farmers should learn in order to farm better or to teach children what impact climate change can have on natural hazards and how to protect themselves from natural hazards. In the Global North, the management of disasters and natural resources such as forests and water, and the maintenance of important infrastructure, also played a prominent role. There was frequent talk of inspecting and checking infrastructure such as water defences or pipes to ensure that everything is in good shape and functioning properly in the event of an upcoming natural hazard. In the context of structural measures, there were differences in the complexity of the projects described. Projects in the Global South were often simpler, often discussing bolstering, raising and strengthening flood defences, whereas large projects in the Global North were described in more detail. In addition, the Global North referred more frequently to soft measures that can be used for disaster reduction, whereas this hardly played a role in reporting on the Global South. There were hardly any examples for governance & policy and strategic planning for the Global South.

For anticipative capacity, the majority of risk awareness was focussed on forecasts. The forecasts in the Global North ranged from short and medium-term statements to long-term predictions. In the Global South, on the other hand, predictions mainly covered medium to long term. In addition, the idea of a wake-up call was used more frequently in the Global North. Issuing warnings was an important topic in both the Global North and the Global South, in the context of early warning. In the Global North, however, this was reported in more detail with information on the number of warnings and the warning level frequently provided. In contrast, early warning systems played a greater role in the Global South, where the discussion pointed out that new early warning systems are needed or that the existing systems should be improved. In the Global North, however, dominant narratives were how society can be warned with the help of early warning systems, for example through emails or phone messages. Evacuations played a much more important role than early warning systems in the Global North, but were only of secondary importance in the Global South. While risk transfer mechanism in the Global North relied on obtaining insurance, the Global South emphasised providing finance to countries so they can better prepare in anticipation of future disasters.

Adaptive and transformative capacities were the least mentioned capacity categories for both the Global North and the Global South. In the Global North most emphasis was placed on incremental adjustment in terms of adaptive capacity, followed by learning. Transformative capacity was presented as technical innovation and governance transformation. Focusing on the Global South, incremental adjustment was also dominant in adaptive capacity, however, diversification and learning received similar attention as well. In terms of transformative capacity, livelihood transformation was much more important than in the Global North, accounting for a significant proportion of the reporting.

In the case of adaptive capacity, both Global North and Global South emphasised the diversification of crops and plants, particularly the adoption of drought-, water-, and salt-resistant varieties to cope with changing environmental conditions. In the Global South, crop diversification was accompanied by income diversification, which included the development of new skills to secure alternative livelihoods in the long term. In contrast, the Global North adaptive capacities encompassed the promotion of resilient adaptations in gardens. Learning in both cases was about learning lessons from past disasters, which in the case of the Global North often includes insights for management, but also learning and implementing solutions in other countries and cities. In the case of incremental adjustment, the focus in the Global North is on the greening of infrastructure to better cope with large amounts of water as well as high temperatures. This also includes the increased integration of nature in the disaster management process.

Livelihood transformation played an extremely important role in the Global South. It often involved migration to other countries or moving to cities in search of better opportunities for oneself and one's family. A common reason for such migration is the desire to find new jobs in order to provide for the family. In the Global North, livelihood transformation is also a relevant topic, however, relocations and resettlements were more common, while migration was rarely mentioned. This may involve farmers considering relocating their farms to areas with better climatic conditions, as their current location is no longer economically viable for farming. In the Global South, technical innovation tends to focus on floating villages or houses whereas in the Global North, much of the innovation centred on providing resilient infrastructure, often highlighting innovative projects such as the sand motor. Governance transformation in the Global South is expressed through the integration of climate change impacts into urban planning. In the Global North, there is a strong emphasis on the importance of incorporating green infrastructure into planning mindsets. The importance of cooperation between different levels of government as well as the involvement of communities were also frequently stressed.

4.5.2 Thematic Content Regarding Disaster Onset

The relative emphasis of disaster resilience across the five resilience capacities is illustrated in Figure 4.7. Similar to the comparison between the Global North and the Global South absorptive capacity was the most frequently mentioned for both slow- and sudden-onset disasters. However, in terms of sudden-onset disasters preparation & response was the predominant topic, followed by support measures. For slow-onset disasters, the media focused on operational adjustment and support, whereas preparation & response was less dominant. For resource management within absorptive capacity, media reports on sudden-onset disasters highlighted the mass mobilisation of people and equipment, alongside the activation of redundant resources such as back-up generators. These efforts aimed at immediate stabilisation in response to sudden impacts. In contrast, slow-onset disasters were associated with more strategic resource planning, such as refilling reservoirs, drilling boreholes, and trucking in water, with the goal of maintaining basic supply over extended periods of scarcity.

Operational adjustment was relevant in both disaster types but with different emphases. For sudden-onset events, measures included temporary restrictions like power reductions, travel speed limits and campfire bans, often applied at local or regional levels to reduce immediate risks. For slow-onset disasters, adjustments such as hosepipe bans were typically implemented at a larger scale, sometimes nationally, aiming to conserve water and safeguard supply stability over time. Support measures were also present in both contexts. While both disaster types involved financial aid, sudden-onset disasters more frequently highlighted the distribution of food, clothing and emergency shelter, and placed stronger emphasis on community solidarity and mutual assistance. In contrast, slow-onset disasters focused more on institutional or governmental aid, with less attention to community-level action. For preparation & response, both slow- and sudden-onset disasters saw frequent emergency declarations. However, sudden-onset disasters were associated with a wider variety of response actions, including evacuations, rescue missions, and the deployment of firefighters, military personnel and emergency shelters. By contrast, such operational responses were rarely mentioned in the context of slow-onset disasters, where declarations remained largely administrative.

For sudden-onset disasters preventive and anticipative capacities received roughly equal levels of media attention followed by adaptive capacities. For slow-onset disasters however, adaptive and anticipative capacities were very prominent followed by preventive capacity. Preventive measures focused on DRM and structural measures for both disaster typologies. For DRM, sudden-onset disasters were primarily associated with financial investments, discussing the availability and distribution of funding, often raising concerns about underinvestment in critical defence structures and its consequences. In contrast, DRM in slow-onset disasters was also education-oriented. The focus lied on capacity building, such as teaching children and farmers how to better adapt to environmental changes. Regarding structural measures, sudden-onset disaster coverage strongly emphasised large-scale physical defences, such as the Thames Barrier, Delta Works, and the MOSE project, as well as dams, embankments, sea walls, and levees. These were portrayed as essential but also insufficient on their own, with critical voices highlighting the limitations of hard infrastructure: “We cannot expect to build our way out of future climate risks with infinitely high walls” (The Times, 06.05.2020). In contrast, structural measures in slow-onset disasters

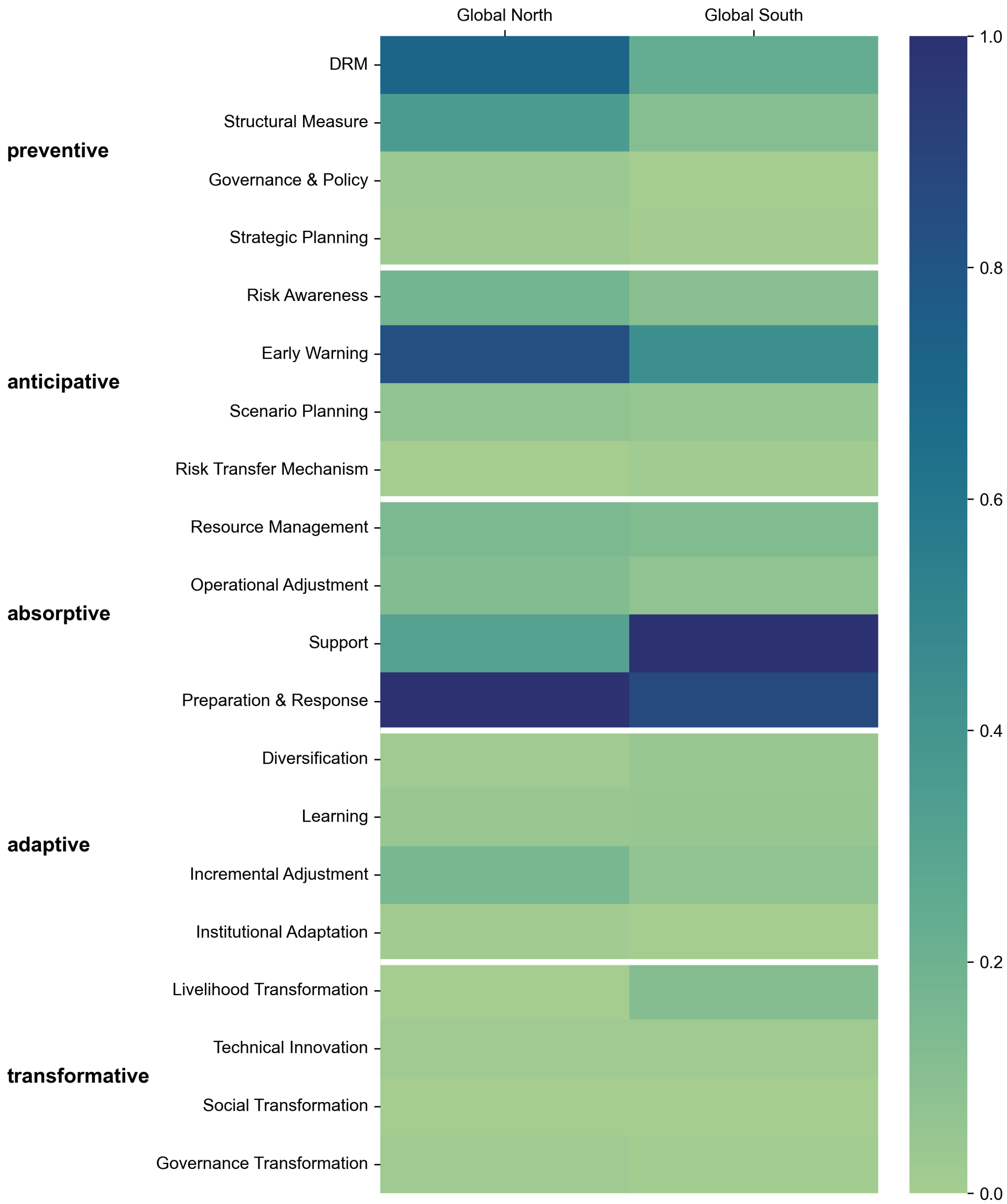

Figure 4.7: Normalised heat map for differences in disaster resilience mentions for slow-onset and sudden-onset disasters.

focused on sustaining basic supply under prolonged stress, including reservoirs, desalination plants, and water storage systems.

With respect to anticipative capacity, early warning was dominant in both contexts, yet differed in application. Sudden-onset disasters were closely linked to evacuation orders and real-time alerts. In slow-onset disasters, evacuations or monitoring were rarely discussed. For risk awareness, media narratives about sudden-onset disasters were often framed as a wake-up call, arising in response to dramatic events or extreme weather forecasts. In contrast, risk awareness for slow-onset disasters focused on longer-term forecasts focusing a lot on the implications of climate trends. Similarly, scenario planning for slow-onset disasters tended to include more medium- to long-term strategies, for example focusing on medium-term strategies such as hosepipe bans or long-term strategies with establishing climate action plans whereas in sudden-onset disasters the main focus lay on shorter-term actions although medium- and long-term strategies were also visible. Finally, risk transfer mechanisms were similarly represented for both disaster typologies, focusing on insurance or preventive disaster funds in anticipation of future disasters.

Adaptive capacity was more strongly associated with slow-onset disasters. It was dominated by incremental adjustment and diversification whereas sudden-onset disasters mainly focused on incremental adjustment and learning. With regard to incremental adjustment, sudden-onset disasters tended to focus on physical modifications and design adaptations. Examples included raised electrics, water-resistant floor tiles, or revised building techniques that reduce future impacts. Media also covered some behavioural changes, though to a lesser extent. In slow-onset disasters, incremental adjustment was far more behaviourally and socially focused. Strategies included water-saving habits, such as using water butts, recycling greywater, or altering everyday routines such as not running taps while brushing teeth. Across both types, there was a shared interest in nature-based solutions and integrated water management. In terms of diversification, both disaster types focused on increasing ecological and agricultural resilience, particularly through the use of resistant plant varieties, crops, and trees. However, for slow-onset disasters, the diversification of income sources was also a recurrent topic, providing greater flexibility and economic stability. Learning was portrayed similarly by learning from past events, using the knowledge from prior disasters for future preparedness. Finally, institutional adaptation received limited attention for slow-onset disasters. For sudden-onset disasters, media occasionally discussed the role of governments and institutions in ensuring that insurance systems remain viable in future crises.

Transformative measures were the least reported on in newspaper articles for both slow- and sudden-onset disasters. While in case of sudden-onset disasters the focus lied on technical innovation and governance transformation, for slow-onset disasters it was mainly on livelihood transformation. Livelihood transformation was represented similarly across both disaster typologies. Media reports highlighted how affected individuals changed their economic strategies to adapt to deteriorating environmental conditions or migrated to escape them. In the context of sudden-onset disasters, social transformation was portrayed as a reconsideration of relationships with risk and the built environment. Examples included rethinking how communities prepare for and live with disasters, how daily life can be adapted to a changing climate, and how cities are designed. In contrast, slow-onset narratives were more behavioural, typically centred on rethinking individual habits, such as water use and consumption patterns. Governance transformation showed greater prominence in sudden-onset disaster coverage. Media discussions frequently highlighted the integration of climate change into planning, the modification of building regulations, and the emergence of greener urban environments. By contrast, slow-onset disaster coverage contained only scattered references to governance, usually emphasising the importance of multi-level cooperation and the inclusion of local communities in planning processes. Technical innovation was hardly visible for slow-onset disasters.

4.6 Temporal Development of Resilience Discourse

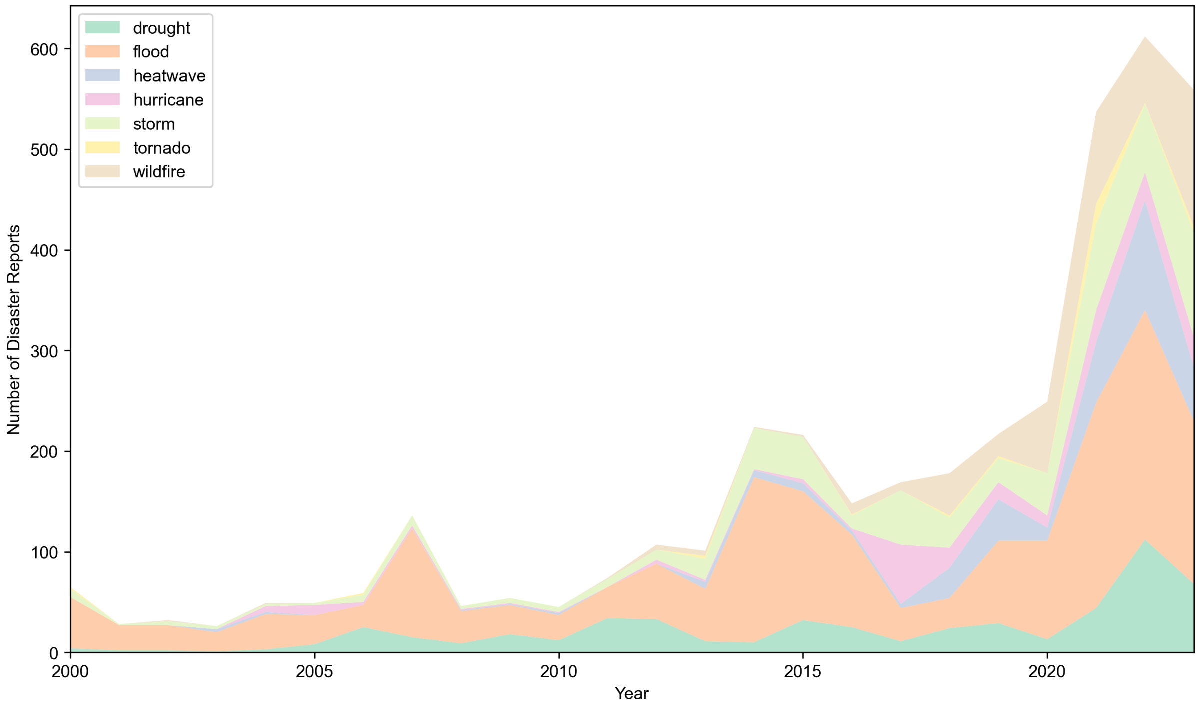

Figure 4.8: Annual distribution of newspaper articles by disaster type containing references to at least one resilience capacity.

Figure 4.8 presents the yearly number of articles reporting per disaster type mentioning at least one resilience capacity. While flood events have consistently dominated media coverage with noticeable spikes in certain years, their relative share has decreased as other disaster types including drought, heatwave, and wildfire events have become more prevalent. Drought-related reporting has increased since 2005, and heatwave and wildfire coverage has surged since 2015, after being nearly absent previously.

The increased media coverage in certain years is often linked to major events in the UK or US. The year 2007 was dominated by reports of flood events in the UK. Most of the articles were from June and July, when major floods hit the UK and many major cities were flooded. Reporting in 2012 was characterised by a period of drought in the UK in March and further severe flooding in July. Hurricane Sandy in the US, which occurred during October and November, also featured prominently in the media. 2014 started with many articles about the winter floods of 2013/2014 in the UK. Affected areas included Norfolk and Worcester, which were increasingly cited in the newspapers. The reporting in 2015 was dominated by flood and storm related events in December, especially the storms Desmond and Eva. 2021 was characterised by articles of Hurricane Ida in the US in August and by forest fires in Canada, mainly in British Columbia and in the US, in multiple states. Reporting in 2022 was influenced by Storm Franklin in the UK in February, the August and November floods in the UK, Hurricanes Fiona and Ian in the US and further floods in Australia and Pakistan in March and April. 2023 was dominated by various storms in the US, drought in Spain and recurring forest fires in Canada and the US in California and Hawaii.

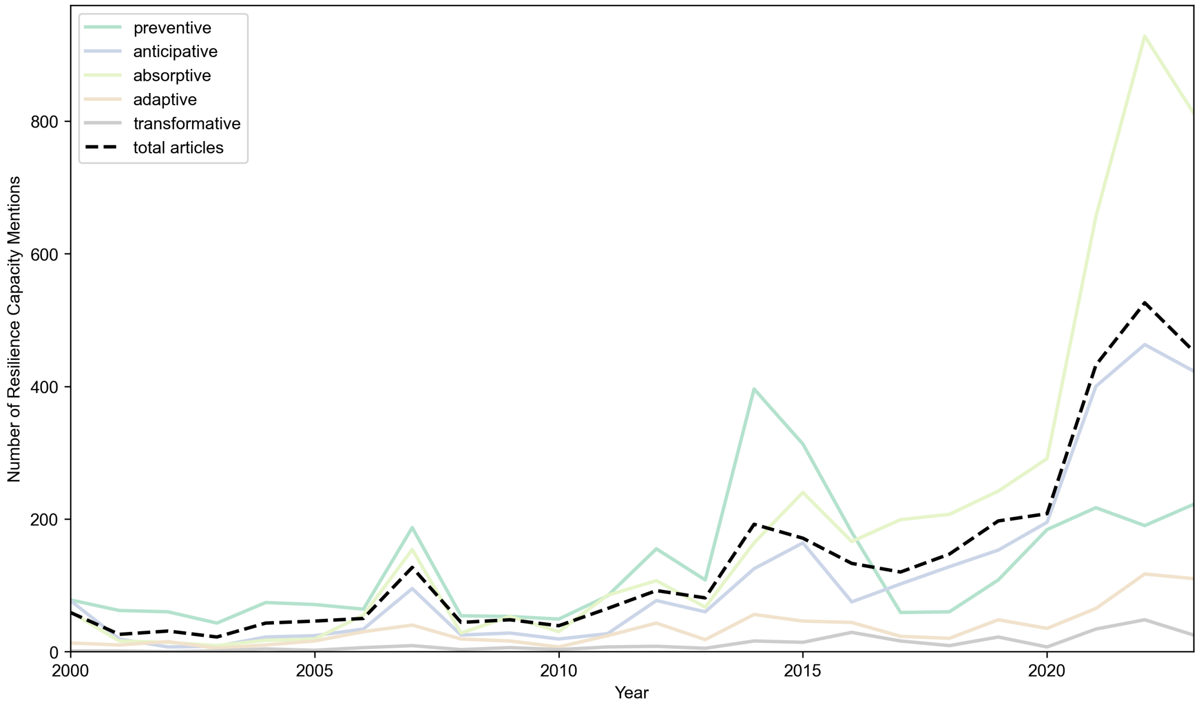

Figure 4.9: Annual mentions of resilience capacities compared to total disaster-related articles.

In general, there were more mentions of resilience capacities-related topics in the past decade, particularly for preventive, anticipative and absorptive capacities. This growth may also be partly attributed to the increased reporting on disasters in the last years (see Figure 4.9). Until 2017, preventive capacity had been the predominant topic in the resilience discourse in British newspapers. However, there has been a decrease in attention to preventive measures afterwards. Instead, absorptive topics gained markedly in coverage, especially after 2020. Anticipative measures have gained attention since 2010 and have been discussed more frequently than preventive capacity in recent years. Adaptive topics have long received similar attention to anticipative capacities, however, since 2013 anticipative topics have gained relevance, whereas adaptive topics have remained at a similar level. Transformative capacity remained at a low level in recent decades, although there has been a slight increase in recent years.

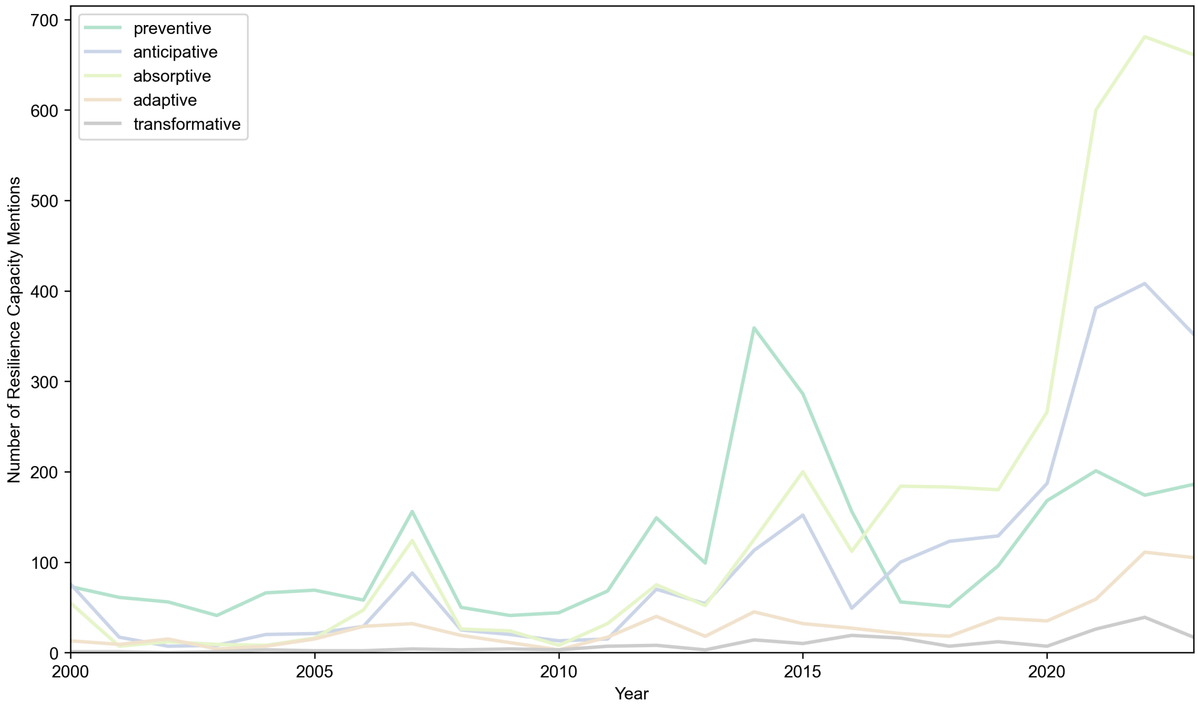

Figure 4.10: Temporal distribution of media coverage of disaster resilience in the Global North.

4.6.1 Temporal Development across World Regions

Since 2010, all disaster resilience capacities in the Global North have received increased media attention, largely attributable to the higher number of disaster-related articles being released. For transformative capacity, there was a slight increase of relevant topics after 2020, however, this declined again in 2023, making it unclear whether this represented a lasting trend or a short-term anomaly.

Media coverage reflected these growing attention on disaster resilience over the last two decades, with peaks in certain years, which can often be attributed to a higher number of disaster-related articles being published in those years that correlated with events in the UK or US discussed in the previous section. The significant increase in preventive topics in 2014 was primarily linked to a series of major flood events in the UK, during which newspapers concentrated on debates about financing new flood defences. The increase in absorptive topics in 2021 and 2022 originated in an increase in topics of preparation & response with newspapers focusing on evacuations and the declaration of emergencies as well as firefighting. The rise in anticipative capacity in these years was mainly the consequence of an accumulation of reports of warnings. Between 2021 and 2023, transformative capacities gained more visibility, primarily through reporting on technological innovation alongside governance transformation. Smart building designs and floating homes were increasingly discussed, as well as a new approach to city planning that involved reimagining cities to be more environmentally friendly and resilient to disasters.

Resilience capacities were mentioned only sporadically in the context of the Global South, with only a few annual reports until 2005. Absorptive capacity was the most frequently mentioned capacity, while transformative discussions remained at a consistently low level. In 2007, increased emphasis was placed

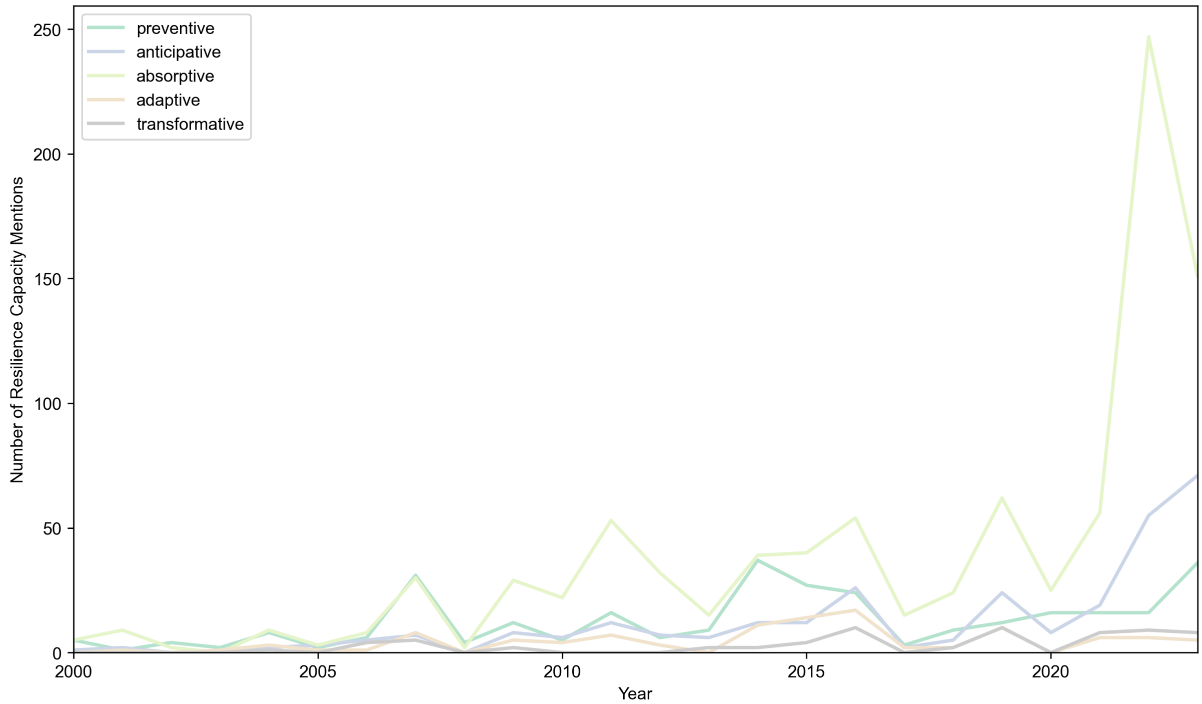

Figure 4.11: Temporal distribution of media coverage of disaster resilience in the Global South.

on preventive and absorptive capacities, particularly in connection with the floods in South Asia that year. Preventive capacities focused on educating the population about floods and absorption capacities primarily concerned the support provided. There was an accumulation of mentions for all capacities in 2011 in connection with the East African drought, where support was also an important topic. There was another peak in 2019 due to floods in South Asia, where media focused on rescue efforts, evacuations and support in terms of absorptive capacity, but also on migration and behavioural changes to build more sustainably in the context of transformative capacity. In 2022, there was an increase in preventive, anticipative and absorptive topics related to floods in South Asia.

Comparing the temporal development of disaster resilience capacity reporting in newspapers preventive capacities played a crucial part in the Global North until 2017. Afterwards, absorptive topics became increasingly important. In the Global South, absorptive capacity has always been one of the dominant capacities, focusing mainly on support, but in recent years also increasingly on preparation & response. Preventive capacity reporting has been on a comparable level but has not increased as much in recent years as absorptive capacity. Adaptive and transformative topics tended to be the least mentioned topics in both regions.

4.6.2 Temporal Development across Disaster Typologies

Figure 4.12 illustrates the evolution of media coverage of resilience capacities in relation to sudden-onset disasters. The data revealed a trend towards increased attention for all five capacities, including several peaks related to flood events in the UK and US. Until 2017, preventive capacity dominated the

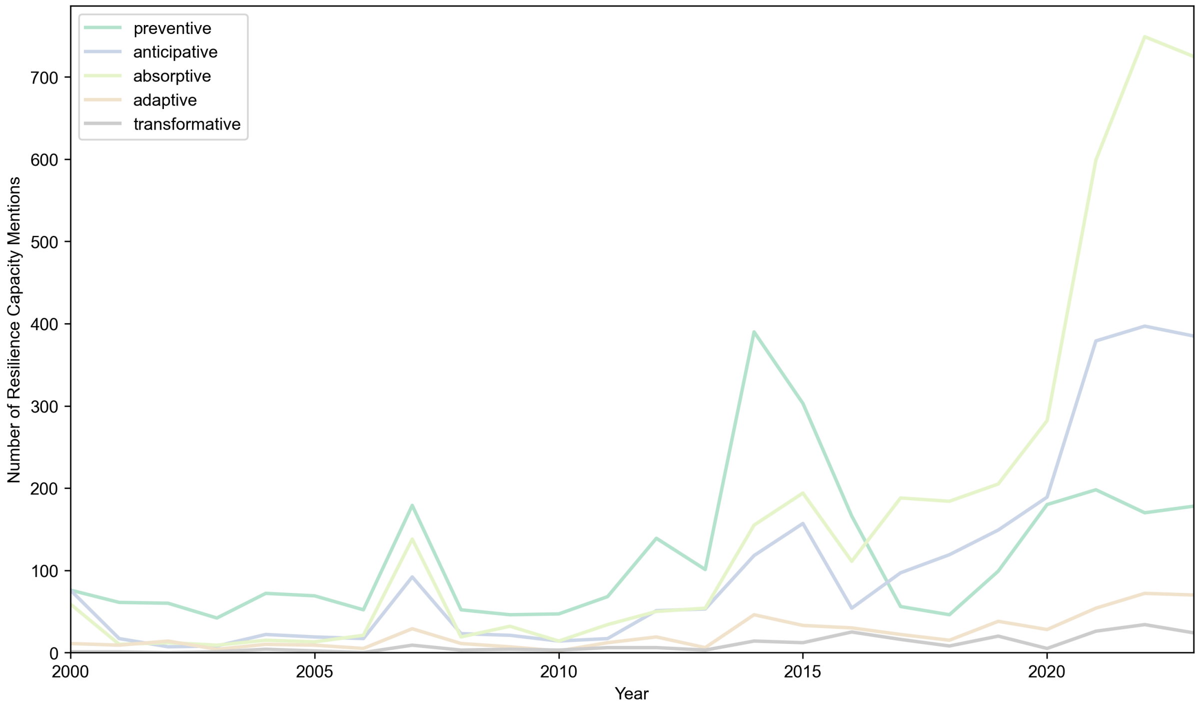

Figure 4.12: Temporal distribution of media coverage of disaster resilience for sudden-onset disasters.

disaster resilience narrative, showing a similar pattern to the temporal development in the Global North. Starting around 2017, there was a noticeable shift with preventive attention decreasing significantly and absorptive capacity becoming the predominant capacity. All other capacities gained attention after 2010 as well. Transformative capacity remained the least prominent capacity throughout the analysis period, with a small increase visible in recent years.

Over the past decades, media coverage of disaster resilience in the context of slow-onset disasters has shown a fluctuating but overall increasing trend. Before 2005, there were hardly any mentions of slow-onset disasters. A noticeable surge in attention was observed after 2020, when mentions across all five resilience capacities rose sharply.

Throughout the entire observation period, absorptive capacity was the most frequently cited capacity. In 2022, the main focus was on operational adjustments, including widespread reporting on restrictions or rationing of water use, such as hosepipe bans or prohibitions on filling pools. Anticipative capacity, while less prominent in the early 2000s, has gained significant traction since 2017. In 2022, media often highlighted early warning systems and the provision of timely alerts, underscoring a shift towards proactive risk management. Adaptive capacity remained consistently relevant throughout the period and received similar attention to preventive and anticipative capacities. Although transformative capacity was the least reported overall, it exhibited a modest but steady increase beginning after 2015 until 2023.

The temporal analysis revealed that for sudden-onset disasters preventive capacity was a frequently used topic until 2017. Afterwards it was overtaken by absorptive topics but still remained one of the most frequently mentioned capacities. For slow-onset disasters preventive topics were only discussed on a very

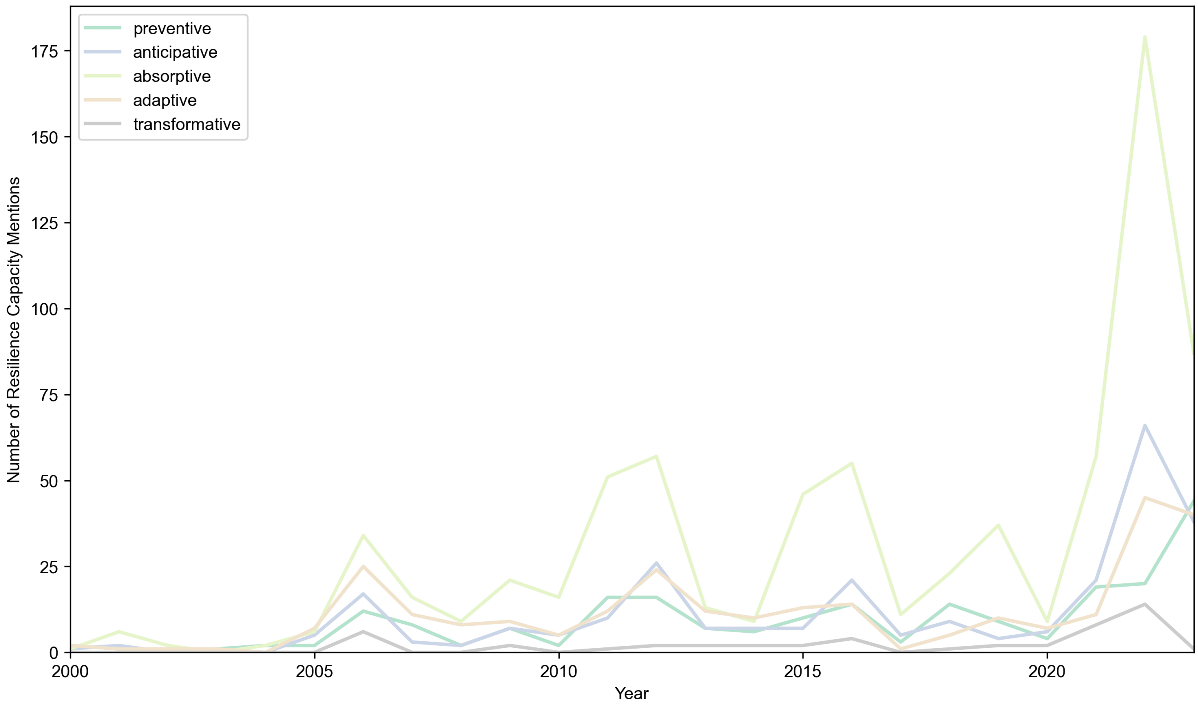

Figure 4.13: Temporal distribution of media coverage of disaster resilience for slow-onset disasters.

low frequency level. Other capacities such as absorptive and anticipative have a much higher importance in newspaper articles. Another significant difference was that adaptive capacity was one of the most frequently mentioned capacities for slow-onset disasters, whereas it was of lower importance for sudden-onset disasters. For both disaster types, transformative capacity was the least frequently mentioned capacity class.

5 | Discussion

5.1 Model Performance

The results from the document-level and segment-level intercoder reliability tests indicate a high degree of consistency in the classification of clauses over time, with agreement rates of 84% and 74.9% respectively. This suggests a relatively stable interpretation of the coding scheme and supports the consistency of the annotation process. However, further analysis revealed variations in the precise spans of annotated clauses for each class. The more granular comparison of the segment-level intercoder agreement demonstrated that the agreement rate with a 50% overlap was significantly higher than with an 80% threshold, indicating that discrepancies were primarily related to the exact extent of the annotated clauses rather than the category selection. These findings suggest a lack of robustness in defining the span of segments representing a category. To enhance consistency in future annotation efforts, clearer guidelines or annotation tools that support more precise segment boundaries would be beneficial.

The results of the two-stage classification pipeline evaluation must be interpreted with caution, as the same dataset was used for both training and evaluation, introducing the risk of overfitting. Nonetheless, the comparison with the manual precision evaluation showed that the evaluation measures for preventive, anticipative and absorptive capacities are plausible, and in some cases, even slightly superior to those assumed by the gold standard evaluation. The model performed well in identifying resilience capacity-related clauses, achieving a weighted average F1 score of 0.91. The high precision and recall scores for the irrelevant class indicated robust identification of irrelevant content. The high precision across most capacity classes suggests that many of the extracted examples for the resilience capacities are correctly classified. However, the low recall scores revealed that this happened at the expense of recall, meaning that there were many cases for the different capacity classes that were missed. This was especially problematic for adaptive and transformative capacities, as indicated by the low recall scores of 0.1. The manual evaluation furthermore showed that the precision values were overestimated by the gold standard evaluation. Therefore, the model performed well in identifying irrelevant clauses, as well as preventive, anticipative, and absorptive capacities, but was less effective in recognising adaptive and transformative clauses.

The decreased performance for the two minority classes could be attributed to several factors. Their strategies are often similar to strategies of other classes. They are inherently more context-dependent, often requiring broader situational understanding for accurate classification. As Lankford et al. (2023, p. 11) have stated: "one farmer may have learnt from the last drought and installed drip irrigation (which is adaptation), but their neighbour may install drip in readiness for the next drought (which is anticipation)". This semantic overlap leads to ambiguity and contributes to misclassification. Adaptive and transformative strategies further tend to be more diverse than other capacity classes, making it difficult for the classifier to detect consistent linguistic patterns. The limited number of training examples also contributed to the challenge, restricting the model's ability to learn patterns. While the classifier performs well for the majority and irrelevant classes, its performance on minority categories remains limited, underscoring the need for more balanced datasets and potentially more context-aware modelling approaches.

5.2 Disaster Resilience Capacity in the Media

5.2.1 Spatial Distribution of Disaster Resilience Reporting

The spatial analysis revealed a strong bias in media attention towards countries in the Global North, particularly the UK and the US. This disproportionate focus does not necessarily reflect a geographical imbalance in resilience reporting, where events in the Global South receive less detailed coverage. Rather, the Global South is frequently under-represented in British media coverage of disasters, with a disproportionate focus on wealthy nations (Kong & Purves, 2025). This suggests the issue lies less in the neglect of resilience discourse in these regions and more in the overall patterns of disaster reporting.

A discrepancy was observed in the geographical reporting levels between the Global North and the Global South. While articles concerning the Global North frequently incorporated local or region-level locations, in the Global South locations were rarely stated below the regional level. One possible explanation for this disparity is that media discourses in the UK tend to centre around more familiar, proximate regions in the Global North. In contrast, certain regions within the Global South are less prominent, resulting in a paucity of media coverage. Moreover, the discrepancy in the number of reporting may emerge as disasters in geographically distant regions often engender lower political salience, unless similar events could also occur (Staupe-Delgado, 2019a).

Regional differences in reporting on slow-onset and sudden-onset disasters can be explained by the geographical distribution of the hazards themselves. Warmer and drier regions in Africa, South America, parts of Asia, or Ukraine, for example, are more prone to droughts, while sudden-onset disasters such as storms and floods occur more frequently in other climatic contexts. This pattern is consistent with the findings of Caretta et al. (2022) on the spatial distribution of climate-related hazards. Thus, the observed shifts in reporting reflect underlying hazard distribution rather than changes in reporting patterns alone.

5.2.2 Temporal Trends in Disaster Resilience Reporting

The temporal analysis revealed that, over the past two decades, preventive, anticipative, and absorptive capacities have increased more strongly than adaptive and transformative capacities. Much of this increase can be attributed to the increased media attention on disasters in general. In some years, this rise in media coverage was driven primarily by major disasters occurring in the UK or the US. The lack of mention of adaptive and transformative capacities is in contrast to the fact that they are becoming increasingly important in scientific discourse (Asadzadeh, Khavarian-Garmsir, et al., 2022). One possible explanation would be that transformative measures are more difficult to implement than the others. Keating and Hanger-Kopp (2020) interviewed NGO staff members working on resilience building in the Global South and found that transformative activities require long-term investment. However, time often poses a constraint, as NGOs typically do not remain in one location for extended periods. Another reason could be that adaptive and transformative capacities are not reported directly in relation to disasters, which is why they do not appear in the disaster corpus, as articles were only included if they have a strong focus on a climate disaster type.

A comparison of the Global North and Global South showed distinct emphases in resilience reporting. In the Global South, absorptive capacity was the most frequently mentioned category throughout the analysis period, largely centred on international support and, to some extent, emergency response. This aligns with findings by Khawaja et al. (2025), who similarly observed that international aid represents a dominant framing of resilience in media outlets covering the Global South. In contrast, preventive capacity dominated in the Global North, especially in the early years of the analysis. This could be attributed to the stronger institutional and financial capacities of countries in the Global North, where media attention often focused on government spending on prevention measures such as flood protection and planning guidelines, rather than on immediate post-disaster relief support.

Looking at the temporal development of slow- and sudden-onset disasters, slow-onset events received little to no media attention before 2005. This could be attributed to the absence of drought-related articles in the corpus. By contrast, sudden-onset disasters were already present in reporting prior to 2005, predominantly framed through preventive capacities, which mirrors the patterns observed in the Global North.

5.2.3 Thematic Discussions in Disaster Resilience Reporting

The resilience discourse was dominated by reports on absorptive capacity, followed by preventive and anticipative capacities, whereas adaptive and transformative capacities were rarely mentioned. The classifier's recall for adaptive and transformative capacities was lower than for the other classes, indicating that many relevant examples were missed. Nonetheless, as observed during the manual annotation process, these two capacities were indeed in the minority, though not to the extent suggested by the extracted examples. As adaptive and transformative capacities are essential for effective resilience building, enabling communities to "bounce forward" rather than merely recover, it is important that media cover them to shape public discourses. However, it remains unclear whether their low representation reflects a genuine lack of adoption in practice or simply a lack of media coverage.

Financial aspects and physical infrastructure were the dominant narratives in media coverage for preventive capacity. Media reporting on preventive capacity centred on DRM, with a strong emphasis on economic considerations. Articles frequently highlighted the cost-effectiveness of proactive investment in flood and coastal protection, while also criticising inconsistent and urban-biased government spending. This strong focus on financial topics has been documented in previous research. Houston et al.

(2012) evaluated disasters in the US between 2000 and 2010 and revealed that the cost of disasters received considerable attention in the media. Additionally, Dhakal (2018) analysed discrepancies in local and foreign news reports and found that foreign newspapers placed significantly more emphasis on financial capital. The media often equated preventive capacity with increased investment in infrastructure designed to protect communities from disasters. They frequently highlighted the economic benefits of investing in preparedness, which is also reflected in publications such as Hernantes et al. (2017). This shift towards proactive investment is also evident in absorptive capacity, where reporting reflected a transition from reactive financial support to greater investment in prevention (Sheehan et al., 2023). Literature has shown that in the past international development "has been severely dominated by a focus on crises response and ex-post recovery following disaster events, neglecting ex-ante risk reduction" (Keating & Hanger-Kopp, 2020, p. 2) but more recent trends indicate a gradual shift towards greater emphasis on preparedness.

Education was not a dominant topic in media coverage, yet it was emphasised that early education and awareness campaigns are crucial for society to improve risk management. These findings align with Yang et al. (2024), who similarly recognised education as a central component of resilience building. Closely related, media narratives also stressed the importance of risk awareness as a core element of anticipative capacity. Academic literature supports this view and underscores that promoting a culture of resilience can be achieved through awareness campaigns on disaster preparedness and climate change, particularly by integrating relevant topics into educational programmes for children and young people (United Nations International Children's Emergency Fund, 2014).

Media covered the emergence of natural resource management approaches in recent years, despite a lack of political support at times. One explanation for this limited support could be the continued reliance on traditional measures such as grey infrastructure approaches including pipes, tunnels or dykes. These consist of hard-engineered materials that create a false sense of security but enjoy a high level of trust. However, these measures leave communities inadequately prepared in the event of failure (Vojinovic et al., 2021). Yet, studies have demonstrated the effectiveness of nature-based solutions: for instance, Wu et al. (2023) have shown that wetland conservation and restoration can mitigate extreme floods and droughts, thereby enhancing resilience. Hjerpe et al. (2024) highlighted that forest restoration efforts, such as thinning and prescribed burning, can reduce wildfire risk. Furthermore, they have found that these strategies offered substantial cost benefits by avoiding wildfire costs. Recent comparative studies indicate that the effectiveness of natural resource management approaches varies by scale and design, with large-scale or hybrid combinations with traditional infrastructure considerably reducing risks (Vojinovic et al., 2021).

Media reports highlighted risk transfer mechanisms, such as insurance, as important tools within anticipative capacity. This aligns with the academic literature, which identifies insurance as essential assets for spreading financial risk and incentivising early investment in disaster preparedness (Sheehan et al., 2023). Media coverage also pointed to the involvement of governments and individuals in promoting anticipative measures. This reflects findings in the literature, which emphasise the importance of diverse stakeholders – including policymakers, insurance companies and local communities – in investing in resilience (Hernantes et al., 2017).

Monitoring systems were reported to be important components of early warning systems and of data collection. Early detection of hazards enables early warning of the population, allowing them to prepare more effectively and minimise the potential damage from disasters. Early detection is one of the main challenges of disaster management and requires accurate data (Sarker et al., 2020). However, monitoring disaster resilience extends beyond mere hazard identification to include tracking socio-economic factors, coping strategies and other factors that influence vulnerability and responsiveness (Staupe-Delgado & Rubin, 2022). Robust data are critical for disaster planning, as it influences preventive measures, guides response strategies and aids recovery (Cole et al., 2021). Having reliable data systems in place is a prerequisite for improving disaster response and emergency management, as well as strengthening overall resilience.

A crucial mechanism for absorptive capacity is the declaration of a state of emergency, which releases financial and material resources and reduces bureaucratic hurdles. However, this mechanism also highlights the common approach of reactive disaster management, where laws prevent the proactive release and mobilisation of resources (Staupe-Delgado, 2019b). This dilemma is exemplified by Staupe-Delgado et al. (2018), who observed that although task forces responsible for disaster preparedness in the event of an El Niño existed in the Philippines, plans could only be implemented once a state of emergency had been declared.

Learning was a central aspect of adaptive capacity, with past disasters playing a pivotal role in shaping future preparedness. As Krishnan (2017) illustrated, communities in flood-prone regions developed shelter designs based on lessons learned from previous interventions. After severe erosion in India, affected populations were able to quickly dismantle their shelters, relocate to safer areas, and rebuild their homes. These strategies were developed and adapted across generations to cope with flash floods. This example underscores the importance of incorporating lived experience and knowledge into planning, as it builds the foundation for more sustainable forms of adaptation. Moreover, it has been demonstrated that disasters frequently precipitate novel forms of innovation, as evidenced by Boossabong (2017), who documented the advent of floating gardens, rooftop farming, and traditional soil-repair techniques during protracted periods of flooding.

Resettlement and migration were common topics in media coverage of transformative capacity. Resettlement can be regarded as a significant strategy for resilience, but it requires profound interventions in the lives of individuals and communities and should thus be considered as a measure of last resort (Cernea & Maldonado, 2018). The success of resettlement initiatives depends on the extent to which the affected population is involved in the planning and decision-making processes. As Staupe-Delgado (2020, p. 1019) argued, "it is not uncommon for resettlement projects to fail due to lack of community participation, which in turn means that many households are often left without livelihood opportunities". In order to maintain social cohesion and avoid significant disruption to existing community structures, it is essential that resettlement processes are inclusive and participatory. The preservation of community structures during relocation is further crucial in ensuring long-term success and stability (Staupe-Delgado, 2020). One newspaper article described how residents in Kenya had actively requested to be relocated in exchange for their land. This suggests that community-initiated resettlements are already being practised, albeit only in a few cases.

Not only are collaboration and coordination essential in the context of resettlement, they also play a critical role in broader planning and response processes by facilitating the sharing of information, financial resources and human capital (Hernantes et al., 2017). Effective disaster management requires the involvement of various stakeholders, including representatives from different levels of government, as emphasised in one of the newspaper articles. By integrating the local population into participatory processes, measures can be adapted to local conditions, which contribute to strengthening resilience (Oxley, 2013). Instead of implementing top-down solutions, resilience strategies should be based on local knowledge and capacities (Amirzadeh & Barakpour, 2021). This participatory approach enhances the contextual relevance, acceptance, and ultimately the effectiveness of the measures implemented. The risks of neglecting participatory processes are illustrated by the case of New Chaitén, a relocation project in Chile, which stagnated due to discrepancies between planners and local residents (Sandoval et al., 2017). In a similar vein, Boossabong (2017) highlighted that discourses on resilience are frequently intertwined with local cultural interpretations and livelihood practices that may differ from institutional definitions of resilience shaped by Western academic frameworks.

Discussions in Global North and Global South

Across both the Global North and Global South, absorptive capacity – particularly support measures and preparation & response – received the most media attention. In the Global South, support was framed mainly through international aid, whereas the Global North emphasised state assistance and community solidarity. The latter was under-reported in the Global South despite its documented importance (Krishnan, 2017; Meriläinen et al., 2022). Preventive capacity was more prominent in Global North reporting, often focusing on infrastructure and disaster risk management, while anticipative capacity, especially early warning, dominated in the Global South. Transformative capacity was the least reported but differed by region: the Global South focused on livelihood change and migration, while the Global North emphasised technical and governance innovations. These findings highlight clear regional and thematic imbalances in how resilience is portrayed in the media.

Risk transfer mechanism concentrated on insurance-related topics in the Global North, while they were hardly present in the Global South. This can be attributed to the fact that in some countries in the Global South, including South Asian countries such as India, Pakistan and Bangladesh, the insurance industry is in its nascent phase of development (Shukla et al., 2025). A similar trend can be observed in many African countries, where insurance markets are also underdeveloped. Furthermore, in low-income areas people cannot afford insurance or lack trust in financial providers and hence decide not to obtain cover (Horvey et al., 2024).

In the Global South, absorptive capacity, mostly support, was the most frequently mentioned topic, with international aid from countries in the Global North often being highlighted. This aligns with previous research showing that communities in the Global South are frequently framed as victims of disasters, portraying local communities as powerless and dependent on external assistance (Bennett & Daniel, 2002; Das, 2019). Such framing tends to overshadow narratives of local resilience, downplaying the capacity of communities to respond to and recover from crises (Khawaja et al., 2025).

While community solidarity was a recurrent theme in media coverage in the Global North, it was notably absent in reporting on the Global South. This absence is in contrast to the finding of academic literature, which highlights the critical role of community-based support systems in the Global South during disasters. Research has demonstrated that in the aftermath of disasters, individuals frequently prioritise seeking assistance from family or community members over relying on formal institutional responses (Romo-Murphy et al., 2011). For instance, Meriläinen et al. (2022) described how support from extended families and friends reached earthquake-affected communities in Nepal faster than aid from government or international organisations. Similarly, Krishnan (2017) documented how elderly and women-headed households in Assam, north-east India, relied on social networks for essential needs like food, water and sanitation during floods. The absence of media attention to such community resilience in the Global South may be indicative of a framing bias that favours international responses over informal coping mechanisms. This discrepancy suggests a need to critically reflect on how disaster resilience is portrayed across regions and to consider the implications such narratives may have on shaping global understandings of resilience.

Moreover, a critical view on global resilience strategies reveals how measures implemented in the Global North can undermine resilience in the Global South. For example, policies promoting electromobility in northern cities contribute to increased lithium extraction in Chile, exacerbating water scarcity for indigenous communities (Agusdinata et al., 2018). Such cases emphasise the need for multi-scalar perspectives in resilience planning.

Discussions for Slow- and Sudden-Onset Disasters

The media coverage revealed significant differences in how resilience capacities are framed across slow- and sudden-onset disasters. Absorptive capacity dominated both contexts, though sudden-onset reporting focused on emergency response and community support, while slow-onset disasters emphasised operational adjustments and institutional aid. Preventive and anticipative capacities were equally present in sudden-onset disasters, highlighting infrastructure and early warning systems, whereas slow-onset disasters focused more on long-term planning and forecast-based awareness. Adaptive capacity played a greater role in slow-onset disasters, particularly in behavioural change and livelihood diversification. Transformative measures were mentioned least frequently overall, with the transformation of livelihoods being discussed more in the context of slow-onset disasters and technical or governance-related innovations being addressed mainly in relation to sudden-onset disasters.

Preventive capacity strategies were mentioned less frequently in the context of slow-onset disasters, with other capacities – particularly absorptive and anticipative – receiving greater media attention. One potential explanation for this relative absence can be found in the political and temporal dynamics associated with prevention. As Staupe-Delgado and Rubin (2022, p. 8) argued, "the political price of terminating the creeping disaster will be paid now while the benefits might be reaped in the future". This suggests that political actors often lack incentive to invest in preventive actions whose outcomes may not be visible within their term in office. Furthermore, once a slow-onset disaster reaches a critical level of severity, interventions become more expensive and the benefits unclear due to the advanced impacts, hence threatening political legitimacy.

There were considerable differences in the timeliness of early warning reports for slow- and sudden-onset disasters. In the case of sudden-onset disasters, early warnings were frequently issued as real-time alerts characterised by a pronounced urgency. In contrast, warnings of slow-onset disasters were typically framed as forecasting future conditions and were perceived less urgent. This phenomenon has been extensively documented in the academic literature. Several scholars have discussed the inherent difficulty of issuing timely warnings for slow-onset disasters, largely due to the ambiguous nature of their onset and the gradual development of their impacts (Staupe-Delgado & Rubin, 2022). In the literature, a recurrent pattern is what Lautze et al. (2012) described as "early warning, late response". This phenomenon implies that although early indicators of slow-onset disasters are frequently detected, these warnings are not immediately heeded. Responses usually only occur once the situation has already become critical (Amirzadeh & Barakpour, 2021), undermining the advantages of the extended lead time slow-onset disasters provide. Consequently, emergency measures are frequently developed under time pressure, despite the theoretical opportunity for early intervention (Cole et al., 2021). United Nations Office for the Coordination of Humanitarian Affairs (2011, p. 4) observed that “the international community waits until a slow-onset event reaches the acute phase and then needs to be dealt with using the tools created for a rapid-onset disaster” thus demonstrating how a lack of timely response can lead to the inappropriate application of short-term crisis mechanisms. This disparity between early warning and action not only reduces the effectiveness of anticipative measures but also reflects a deeper challenge in disaster governance: how to generate political and societal urgency in response to slow-onset disasters.

Adaptive capacity was comparatively more significant for slow-onset disasters than for sudden-onset disasters. The former was often centred on diversification, for which there were almost no examples in sudden-onset disasters. One possible reason is that for instance crop diversification is an important factor in making seeds resilient to slow-onset disasters, as Le et al. (2024) have also observed. This diversification is important, as slow-onset disasters are a long-term condition, whereas sudden-onset disasters are often short-lived. Furthermore, there are generally fewer examples of slow-onset disasters, so the additional examples of adaptive capacity are more significant.

5.3 Limitations

Several limitations can be identified within this study. The first pertains to the manual annotation of clauses into the different resilience capacity classes within the subsample corpus. This task was solely conducted by the author, who is susceptible to subjective bias. Manyena et al. (2019) acknowledged that, although the DRIFT framework presents the five resilience capacities as distinct elements, there are some overlaps between these resilience capacities in practice. Since the chosen classification approach was a multiclass classification, it was determined that each clause could belong to only one class. This ensured that the capacity classifier was trained with clear classes. In the case of borderline cases, however, a certain degree of subjectivity flowed into the annotation and different annotators might have judged certain cases differently. This limitation was mitigated by including information from previous studies that implemented the DRIFT framework or employed a comparable resilience capacity approach. This ensured the inclusion of different interpretations of the concept, which formed the codebook. Additionally, 100 articles were annotated a second time to evaluate the consistency of the manual annotation process. This analysis confirmed that the manual annotation remained consistent over time in terms of relevant clauses for each capacity class.

A second limitation concerns the nature of the available data. The classifiers were trained on data that was provided during the training process. Hence, as most articles had a focus on floods, or most examples were provided for absorptive capacity, the two-stage classifier performs best in identifying absorptive topics. This is also shown in Table 4.7, where the proportion for absorptive capacities increased significantly between the manual annotation phase and the automated classification. This indicated a bias of the classifier towards these topics. Examples for adaptive and transformative capacities were much more diverse than for the other capacities when they were manually annotated. This complicated the process of learning linguistic patterns, making it harder for the classifiers to extract relevant clauses. Since strategies for resilience capacities can vary between disaster typologies and geographical regions, it could be beneficial to train a classifier for each capacity class and disaster onset or region individually. However, this was restricted due to the low number of cases in the minority classes. Thus, training each individual classifier would not have been possible due to a lack of examples. In a subsequent study, it would be interesting to gather additional data for under-represented resilience capacities to get a more comprehensive picture of the discussed topics.

The observed differences in resilience capacity reporting between manual annotation and automated classification across disaster types are likely due to the presence of more distinctive language in certain categories, which made it easier for the classifier to detect patterns. For instance, in the case of wildfires, a commonly observed absorptive strategy was the intervention of firefighting services. These references were frequently captured in the automated classification dataset, presumably as they contained explicit lexical markers that the model could easily identify.

In addition to these annotation- and data-related constraints, several alternative methodological approaches were tested but ultimately not used due to performance issues. While these were not part of the final analysis, their outcomes helped to contextualise the chosen methods and highlight potential areas for improvement in future research. The deep learning-based approach for feature selection, particularly Word2Vec, which uses word embeddings, consistently underperformed compared to the simpler traditional machine learning methods. Word embedding models can either be trained on the data itself or adapted from large-scale pre-trained models (e.g. Google News Word2Vec). However, training an effective embedding model requires a substantial amount of high-quality, domain-relevant data. Given that the disaster corpora used for this thesis were rather small and the number of relevant clauses was even more limited, there was insufficient data for the deep learning models to effectively learn the underlying characteristics. Alternatively, the use of pre-trained embedding models also proved suboptimal. These models are trained on large, generic text corpora, that do not adequately replicate the specific vocabulary, context or linguistic patterns of the disaster-related corpora. As a result, the pre-trained models failed to accurately represent the semantic nuances and the relations within the dataset.

In contrast, traditional approaches such as count vectorizer and TF-IDF are directly based on the term distribution of the actual dataset. These methods capture the inherent characteristics of the text and assign importance to terms based on their contextual frequency. This alignment with the dataset's internal structure may explain the comparatively stronger performance of TF-IDF-based models in this case. One drawback of the traditional approach is that these models are not good at learning the context of a text compared to deep learning models. However, as previously mentioned, deep learning models require a huge amount of data to learn patterns, which was not available in this study. For further research, it would be interesting to test word embedding models, which account for semantic relationships, with a larger disaster resilience corpus, and to see whether adaptive and transformative capacities can be better recognised, as these require a particularly large amount of contextual background.

The chosen approach for addressing class imbalance was over- and undersampling, however, data augmentation was also tested but neglected as it did not improve the results. One possible reason could be that the variations created by the various text augmentation techniques did not provide useful results that would enrich the meaning of the clauses. According to Longpre et al. (2020), text augmentation is only helpful if it generates linguistic patterns that have not been seen previously.

Beyond the technical aspects, the results were also dependent on the geographical and temporal context of the data. As Dhar and Khirfan (2017) emphasised, the focus of disaster resilience strategies varies depending on the locality and temporality. One drawback of the machine learning-based classification approach was that it did not take background or surrounding information into consideration when classifying a clause. Some strategies that are adaptive or transformative for one location may already be state of the art for other communities and would be considered preventive or anticipative there. Similar limitations occur for the temporal analysis. Strategies and technologies have emerged over time, and an approach regarded as extraordinary at the beginning of the 2000s might not be considered revolutionary any more. This limitation could be mitigated by dividing the analysis period into multiple sections. However, the training data was limited by the availability of relevant examples which challenged the training process of the classification.

Though the chosen newspaper have international coverage, there is a clear tendency towards English speaking countries, especially the UK and the US. This influenced the results, as there are far more examples for the Global North than for the Global South. Further research should include articles from newspapers in other countries, for example from the Global South, and assess how they contribute to the disaster resilience discourse.

6 Conclusion

This thesis used articles from five major British newspapers to explore the discourse of disaster resilience, focusing on the representation of resilience capacities across global regions and disaster typologies. By applying a computational, supervised two-stage classification, key strategies and coping mechanisms for communities were identified. The DRIFT framework, elaborated by Manyena et al. (2019), was used to systematically evaluate the media discourse across the five resilience capacities. The analysis revealed that absorptive capacities dominated the resilience discourse, followed by preventive and anticipative measures, with adaptive and transformative capacities being under-represented. The thesis further revealed a strong focus on the Global North, particularly the UK and the US, and on sudden-onset disasters.

Over time, the resilience discourse has shifted from a reactive focus on post-disaster recovery towards more proactive approaches, including disaster risk financing, risk transfer mechanisms, and emergency planning. This transition reflects a growing recognition that the long-term costs of inaction frequently exceed the investments required for proactive measures. Media reporting was strongly oriented towards financial and infrastructural narratives. While traditional measures, such as the protection of infrastructure are crucial, they are limited in effectiveness. As climate change increases the frequency and intensity of hazards, more comprehensive approaches are needed, integrating nature-based solutions, community education and land-use regulations, with a focus on avoiding constructions in areas susceptible to disasters.

In this context, adaptive and transformative capacities represent essential attributes of disaster resilience. Their limited coverage in the media suggests a missed opportunity to communicate more sustainable pathways and shape public discourse around these strategies. Community participation is essential for these capacities, as local populations often possess valuable knowledge of regional hazards and culturally appropriate coping mechanisms. Involving communities in planning enhances the social acceptance of interventions and thus their long-term success. Given the agenda-setting power of the media, greater emphasis on adaptive and transformative strategies is crucial for fostering long-term resilience and encouraging more inclusive forms of risk reduction.

Media coverage revealed thematic imbalances between the Global North and the Global South. Absorptive capacity dominated across both regions, but narratives differed: the Global North emphasised government support and community solidarity, while the Global South focused on international aid, under-reporting community solidarity despite its documented importance in the scientific literature. Financial aspects were a central topic globally, yet the accessibility of mechanisms such as insurance varied widely.

In terms of slow- and sudden-onset disasters, long-term planning was more prevalent in slow-onset disasters, whereas preventive measures were discussed less frequently, partly due to political disincentives to invest in actions whose benefits extend beyond the scope of immediate political cycles. A recurring pattern found in both the media and the literature is the "early warning, late response" phenomenon, where slow-onset disasters are recognised early, yet action is only taken once the impacts become severe. This delay reduces the effectiveness of early intervention and often leads to the inappropriate use of short-term crisis mechanisms.

The imbalance in class distribution limited the automated classification approach, particularly for adaptive and transformative examples. This restricted the classifier's ability to learn linguistic patterns for these capacities. Contextual dependence also complicated the classification process. Future research should consider training classifiers that are sensitive to regional and temporal variation. Expanding the dataset to include a wider range of sources, such as non-British newspapers and newspapers from the Global South, would also help to reduce existing biases and enable a more comprehensive understanding of the global discourse.

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A Appendix

A.1 Appendix A

Table A.1: Sample of manually annotated clauses by capacity and subcategory.

Capacity	Subcategory	Annotated Clause
Preventive	Disaster Risk Management	’train the next generation of federal land managers, park rangers and other stewards of our natural resources’ (The Independent, 20.09.2023)
		’launch of a public inquiry to examine flood responses’ (Financial Times, 09.02.2019)
		’campaign so people could prepare themselves ahead of time’ (The Independent, 19.04.2023)
		’Government is to spend £294 million on flood risk management this year’ (The Daily Telegraph, 04.03.2013)
		’annual inspection and maintenance by local authorities’ (The Times, 21.11.2009)
	Structural Measure	’nonflammable roofing material and siding for houses, not using wooden decks, installing fine mesh screens on roof vents, and planting fire-resistant vegetation close to houses’ (The Guardian, 24.07.2018)
		’Authorities are contemplating desalination units on the beaches’ (Financial Times, 13.01.2007)
		’planting thousands of coconut trees in the sand, hoping the palms will defend the coastline against the encroaching sea’ (The Guardian, 15.11.2021)
		’new homes are being built with pricey hurricane-resistant features’ (The Independent, 09.08.2023)
	Governance & Policy	’CCC [Committee on Climate Change] said it had been recommending new building regulations to ensure homes, hospitals and schools do not overheat’ (The Guardian, 07.01.2020)
		’Avoiding risky locations is the first step’ (Financial Times, 27.02.2021)
		’new coastal defence policy is expected in the next few years, prioritising which areas will be defended’ (The Guardian, 09.10.2002)
	Strategical Planning	’master plan is being drawn up for the Natural History Museum’ (The Times, 04.12.2021)
		’include the creation of new flood protection standards for major infrastructure projects built with federal money’ (The Guardian, 19.08.2013)

Table A.1 continued from previous page

Capacity	Subcategory	Annotated Clause
Anticipative	Risk Awareness	’London is forecast to be worse off than places in the north of Scotland’ (The Independent, 07.03.2023)
		’summer will also bring an increased risk of heatwaves and bushfires, he said, as evidenced by soaring temperatures already sweeping across Queensland’ (The Guardian, 26.10.2018)
		’companies are gaining a better understanding of the risks posed by severe weather events’ (Financial Times, 20.04.2009)
		’more violent storms were forecast overnight’ (The Daily Telegraph, 31.05.2018)
	Early Warning	’employ our early warning-early action system to put the communities who are worst affected by natural disasters in the driving seat’ (The Guardian, 17.05.2016)
		’Sahib Din has set up a control room to monitor the situation’ (The Independent, 30.05.2019)
		’heat-health alert requires social and healthcare services to take specific action to protect high-risk groups, such as older people, children and babies’ (The Guardian, 20.07.2021)
		’people have heeded warnings to flee from the predicted path of the hurricane’ (The Times, 30.08.2021)
	Scenario Planning	’made important decisions based on those forecasts’ (The Guardian, 18.09.2017)
		’built a water tank two years ago in anticipation of a prolonged drought, and now shares his supply’ (The Independent, 19.04.2023)
		’information is key to assess multiple hazards and prioritise efforts to reduce risk and increase the resiliency of atoll islands’ communities around the globe’ (The Independent, 26.04.2018)
	Risk Transfer Mechanism	’most people should still be able to get flood cover’ (The Daily Telegraph, 27.10.2001)
		’demand for catastrophe insurance in Europe was growing as concerns about the dangers of climate change rose’ (Financial Times, 11.01.2022)

Table A.1 continued from previous page

Capacity	Subcategory	Annotated Clause
Absorptive	Resource Management	’activated the State Emergency Operations Center on Thursday evening to provide support to affected communities’ (The Independent, 25.08.2023)
		’importing electricity from the UK and other nations including Spain to plug the gap’ (Financial Times, 21.07.2021)
		’Hawaii National Guard had mobilized Chinook Helicopters to help with fire suppression as well as search and rescue efforts’ (The Independent, 10.08.2023)
	Operational Adjustment	’utilities blacked out entire swathes of the state in an effort to prevent more blazes’ (The Guardian, 28.10.2019)
		’Last year began in drought with hosepipe bans for 20 million people’ (The Daily Telegraph, 04.03.2013)
		’farmers and industry were already being asked to take measures to save water, including watering crops at night to stop evaporation and repairing leaks’ (The Daily Telegraph, 01.12.2011)
	Support	’got $125 (£75) in compensation to try to rebuild her life’ (The Guardian, 18.08.2009)
		’inspired by the thousands of Vermonters, businesses and organizations who have reached out, wanting to help’ (The Independent, 15.07.2023)
		’spending my time working on getting relief and government help for the victims’ (The Daily Telegraph, 13.09.2021)
	Preparation & Response	’police unit turned water cannon usually used against rioters on city trees to cool them down’ (The Guardian, 28.06.2019)
		’Multinomah county opened three 24-hour cooling centres, nine cooling spaces’ (The Independent, 07.07.2021)
		’Emergency aid and equipment was sent to staging areas around the impact zone’ (The Times, 30.08.2021)

Table A.1 continued from previous page

Capacity	Subcategory	Annotated Clause
		’62 municipalities have declared states of emergency’ (The Guardian, 27.10.2010)
		’nearly 14,000 firefighters are combatting the Mendocino blaze’ (The Independent, 07.08.2018)
		’announce flexible working hours to allow municipal employees to avoid the hottest periods of the day’ (The Guardian, 18.07.2022)
Adaptive	Diversification	’increase planting of sorghum, which is drought resistant and requires less water in the brewing process than barley’ (Financial Times, 26.11.2012)
		’plans to target coho salmon from Oregon, which is doing well enough to be fished unlike the coho in California’ (The Independent, 24.03.2023)
		’have to diversify their sources of income’ (Financial Times, 12.12.2009)
	Learning	’learn from the past and see what we can integrate today” (The Daily Telegraph, 18.04.2022)
		’children here are taught about the importance of conserving trees and water to stop history from repeating itself’ (The Guardian, 17.11.2016)
		’After Iwa, new homes had to have their roofs secured to their walls’ (The Independent, 09.08.2023)
	Incremental Adjustment	’best bet is a more sophisticated early-warning system’ (The Guardian, 15.01.2005)
		’Stockholm Resilience Centre said the greening of the Sahel was also the result of changes in farming practice’ (The Times, 02.06.2015)
		’built stilt houses that stand on columns to fight tidal floods’ (The Independent, 18.04.2023)
		’We have had the whole ground floor tiled to swimming pool standards’ (The Daily Telegraph, 27.10.2001)
		’Beavers are being brought back to London for the first time in more than 400 years to help restore nature and river habitat and reduce the risk of flooding’ (The Independent, 17.03.2022)

Table A.1 continued from previous page

Capacity	Subcategory	Annotated Clause
	Institutional Adaptation	’map will cover the whole country, about 600,000 homes could either benefit from cheaper insurance or get cover that was unobtainable before’ (The Daily Telegraph, 06.03.2004)
		’adaptation will have to involve the farmers who look after two-thirds of the country’s land, but many have felt left out of changing approaches to flood management’ (The Guardian, 11.01.2014)
Transformative	Livelihood Transformation	’forcing growers to consider whether to shut down, relocate or otherwise alter their operations’ (The Guardian, 01.11.2022)
		’have emigrated to Iran to work as labourers’ (Financial Times, 15.09.2021)
		’school has been relocated to safe ground’ (The Independent, 02.01.2016)
	Technical Innovation	’new buildings will be designed to be easier to move back as the cliff disappears’ (The Guardian, 07.02.2017)
		’Netherlands Residents can live in an amphibious building on a platform that can float if necessary’ (The Times, 30.04.2022)
		’artificially creating rain by seeding clouds with silver iodine in an attempt to put out more than 200 fires’ (Financial Times, 24.07.2021)
	Social Transformation	’encourage water saving as a general practice, not just in response to direct appeals’ (Financial Times, 09.10.2006)
		’Environment Agency (EA) has promised a "complete rethink" of flooding preparedness’ (The Guardian, 29.12.2015)
	Governance Transformation	’Providing "cool routes" through areas where the density of buildings poses a particular problem will also be a priority’ (The Guardian, 23.07.2021)
		’reimagine cities complete with greener streets and more resilient transport networks to help the country withstand future heatwaves’ (The Times, 20.07.2022)

Table A.1 continued from previous page

Capacity	Subcategory	Annotated Clause
		’Green New Deal does exactly this, changing the system to put people, community and protection of our countryside first, right at the heart of policy making where it should be’ (The Independent, 13.11.2019)

Personal declaration

I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

I further declare that I used DeepL and ChatGPT for rephrasing and grammar improvement. ChatGPT was also used to assist with troubleshooting certain coding issues. Nonetheless, I assume full responsibility for the content of this thesis.

Zurich, 24 August 2025 Laura Haus