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Navigating Climate Risk for Resilience: A Roadmap of Research Patterns and Emerging Trends

Abstract

Climate risk has become a defining challenge for business strategy, yet its research landscape remains fragmented across disciplines. This study maps the intellectual structure of climate risk research through a bibliometric analysis enriched with Latent Dirichlet Allocation (LDA) topic modeling of 2,715 peer-reviewed articles. Our analysis first identifies six consolidated research patterns: (1) climate adaptation and community resilience, (2) climate risk and insurance mechanisms, (3) climate finance and green investment, (4) climate extremes and scenario modeling, (5) climate impacts and agricultural resilience, and (6) climate mitigation and energy transition. Analysis of the 2020-2024 literature reveals four emerging trends: urban climate adaptation, climate risk and financial stability, extreme climate events and climate modeling, agriculture, food security and household security. The findings indicate a shift towards integrated approaches connecting the physical, social, and financial dimensions of climate risk. The resulting roadmap identifies converging risks and strategic priorities for organizational resilience while providing policymakers with an evolving evidence base to support climate governance and informed decision-making under deepening uncertainty.

JEL Classification: Q54, C55, G32, C88, Q01

Keywords: Climate Risk; Natural Language Processing (NLP); Latent Dirichlet Allocation (LDA); Bibliometric Review; Research Trends; Climate Finance

1. INTRODUCTION

Climate risk has emerged as one of the most consequential challenges of the twenty-first century—not just an environmental concern, but a systemic force that is reshaping economies, financial markets, and corporate strategy. From physical disruptions caused by extreme weather events to major shifts in decarbonization policies, climate-related hazards are increasingly recognized as significant drivers of business performance, investment risk, and societal resilience (Giglio et al., 2021; Stroebel & Wurgler, 2021; Bouri et al., 2023).

Acute and chronic physical risks threaten assets, supply chains and operational continuity (Skinner, 2021). They also affect financial conditions: climate-adjusted sovereign credit ratings indicate downward pressure on creditworthiness from as early as 2030 (Klusak et al., 2023), while climate vulnerability is already increasing borrowing costs in developing economies (Cevik & Tovar-Jalles, 2022). Transition risks arising from policy changes, technological disruption and shifting investor preferences can render assets obsolete, impair fossil-fuel-related loans and make human and physical capital redundant (Agarwala et al., 2021; Skinner, 2021). Physical and transition risks therefore create interconnected exposures that challenge conventional risk management.

These challenges have prompted a surge in interdisciplinary research across finance, management, macroeconomics and environmental science, addressing asset pricing, corporate adaptation, systemic shocks and ecological impacts (Pástor et al., 2021; Bartram et al., 2022; Ren et al., 2022; Bauer et al., 2023; Cepni et al., 2023; Guesmi et al., 2023; Naseer et al., 2024).

However, the literature remains fragmented across disciplines, sectors and methodologies, limiting the identification of connections between research domains and

the development of an integrated evidence base for researchers, business leaders and policymakers.

This study addresses that gap through a bibliometric analysis of 2,715 peer-reviewed articles on climate risk indexed in the Web of Science database. Our approach is distinctive in two respects. First, we combine traditional bibliometric techniques with natural language processing (NLP) and latent Dirichlet allocation (LDA) topic modeling. This methodological innovation allows us to systematically and scalably identify thematic structures across a large corpus (Syed & Spruit, 2017; Ribeiro et al., 2024). Second, our analysis is conducted in two complementary phases. The first phase identifies consolidated research patterns that constitute the established intellectual landscape. The second phase detects emerging trends in the most recent literature (2020–2024) to reveal where the field is heading.

Accordingly, the study aims to:

i. Map the core domains by identifying and categorizing the consolidated research patterns that have shaped the literature on climate risk.

ii. Identify emerging frontiers by characterizing novel research trends that signal the future trajectory of the field.

iii. Highlight conceptual linkages and methodological innovations that connect previously separated subfields.

iv. Propose a research agenda that addresses critical gaps and leverages interdisciplinary opportunities.

The study contributes by providing academics with a structured account of the field and its research opportunities, translating the findings into strategic implications for business resilience, and clarifying the evolving evidence base available to policymakers and regulators.

Relative to prior bibliometric reviews of the climate risk literature, which typically stop at describing publication trends, co-authorship networks or keyword clusters, this study's theoretical contribution lies in coupling that descriptive mapping with topic-modelling evidence to derive a structured taxonomy of research patterns and emerging trends, and in translating each pattern into an explicit strategic blind spot rather than leaving the mapping purely descriptive. Its managerial contribution follows directly from this taxonomy: each blind spot is linked to concrete implications for managers, investors and regulators, offering a decision-relevant account of where climate risk research currently falls short of practice.

The remainder of the paper is organized as follows. Section 2 presents the theoretical background, and Section 3 describes the methodology. Sections 4 and 5 report the consolidated research patterns and emerging research trends, respectively. Section 6 discusses the findings, strategic blind spots and future research directions, and Section 7 concludes.

2. MOTIVES FOR CLIMATE RISK MANAGEMENT

Climate risk has become a material consideration in asset valuation and capital allocation. Physical and transition risks increasingly influence asset prices, although their incorporation into financial valuations remains incomplete (Giglio et al., 2021). Transition risks appear to affect the predictability of returns in energy markets more strongly than physical risks, while ESG equities and bonds may provide some protection

against climate risk, with effectiveness varying across asset classes (Bouri et al., 2023; Cepni et al., 2023). Sustainable investing and green bonds have also become important vehicles for channelling capital towards low-carbon transitions (Pástor et al., 2021; Si Mohammed et al., 2024)[1].

At the corporate level, climate exposure can affect both financial performance and market valuation. Extreme heat, for example, reduces revenues and operating income, but financial analysts tend to underestimate these effects (Pankratz et al., 2023). Governance and ESG disclosure practices therefore influence how organizations identify and manage climate-related exposures (Mouti et al., 2025). Firms face increasing pressure from shareholders, regulators, customers and the public to adopt sustainable practices (Clare et al.,2025). Board independence, diversity, and environmental oversight are associated with stronger carbon performance and higher-quality sustainability reporting (Jizi, 2017; Cucari et al., 2018; Todaro et al., 2021; Khatib, 2024), supporting more proactive risk management and potentially improving corporate value and stakeholder perceptions (Goto & Sueyoshi, 2020; Clare et al., 2025).

Regulatory pressure constitutes a second major motive for climate risk management. Supervisory authorities worldwide are increasingly incorporating environmental and climate risks into their core mandates, responding to the shortcomings of traditional backward-looking risk models in capturing non-linear climate dynamics (Battiston et al., 2017; Chenet et al., 2019). Climate stress testing has emerged as a critical forward-looking tool for assessing the resilience of banks and insurers, while disclosure requirements and prudential measures seek to integrate climate risk into financial

[1] A recent study by Rebelo and Vieira (2024) has highlighted that climate risk has become a key concern for regulators and financial institutions, especially since the Paris Agreement in 2015, when nearly 200 governments committed to limiting the rise in global temperatures to 1.5 °C above pre-industrial levels.

decision-making and supervision (Battiston et al., 2017; Neisen et al., 2021; Bingler et al., 2022). These developments affect corporate compliance, strategic planning and competitive positioning.

Climate risk also generates societal and economic disruptions with direct implications for organizations. Droughts and floods amplify vulnerabilities and generate cascading impacts that challenge traditional single-hazard risk frameworks (Zscheischler et al., 2018). Synchronised crop failures across major agricultural regions pose systemic threats to food security, raw material availability, and social stability (Kornhuber et al., 2023). Climate-related migration, immobility and resettlement may also affect labor markets, consumer demand and operational stability in vulnerable regions (Boas et al., 2019, 2022).

Together, these financial, organizational, regulatory and societal pressures explain why climate risk management has become strategically important. However, the relevant evidence remains dispersed across disciplines (Giglio et al., 2021; Ren et al., 2022), reinforcing the need for an integrated analysis of the field.

3. METHODOLOGY

A comprehensive search was conducted using the term “climate risk” within the Abstract, Title, and Keyword fields of the Web of Science (WoS) database, which is widely recognized for its broad coverage of peer-reviewed academic literature (Kumpulainen & Seppänen, 2022; Vandagriff, 2023). Review articles and conference proceedings were intentionally excluded from the dataset, given their frequent lack of original empirical data and their occasional omission from rigorous peer-review processes typical of journal publications. This procedure yielded a total of 2,715 unique research papers.

3.1 Descriptive Overview of the Dataset

Prior to topic modelling, a descriptive bibliometric analysis was conducted using VOSviewer (van Eck & Waltman, 2010), following the B-SLR framework proposed by Marzi et al. (2025) and the guidelines of Donthu et al. (2021). The analysis covers 2,497 English-language journal articles indexed in the Web of Science Core Collection and published in complete years up to 2024. It examines publication trends, leading journals, author productivity and geographical output. The detailed figures are presented in Appendix A.

Publication Trends Over Time

Scientific output increased markedly, particularly after 2020. Annual publications rose more than elevenfold, from 55 articles in 2015 to 621 in 2024, demonstrating the rapid expansion of climate risk research. As shown in Figure A.1.1, this descriptive evidence does not indicate that the increase is the result of any specific policy or institutional event.

Distribution of Articles Across Journals

The leading outlet is Climate Risk Management, with 101 articles, followed by Sustainability (73) and Climatic Change (54). The 11 leading journals account for only 20% of the dataset, indicating that the literature is dispersed across several disciplinary domains rather than concentrated in a small number of outlets (see Figure A.1.2).

Most Productive Authors

Author productivity is dispersed as well. Ji and Mushtaq each contributed 12 articles, followed by Keller and Bresch with 11 each. This relatively narrow distribution among the leading authors suggests that no single scholar numerically dominates the field numerically (see Figure A.1.3).

Geographical Distribution of Research Output

The United States has the largest publication presence, followed by China, England, Australia and Germany. Although this confirms the field's international reach, research output remains concentrated in a limited number of national research systems. These affiliation-based counts indicate where research was produced, rather than the geographical contexts examined (see Figure A.1.4).

This geographic concentration constitutes a limitation discussed in Section 6, as findings may not fully generalize to emerging economies where institutional capacity and data availability differ significantly.

Search Strategy, Eligibility Criteria and Sensitivity Analysis

These eligibility criteria reflect the established recommendations of Donthu et al. (2021) and Fan et al. (2022) concerning the transparent and consistent delimitation of literature reviews and bibliometric corpora. The criteria are also consistent with the applied bibliometric and topic modeling research of Parsons et al. (2024), which defines the corpus according to database, language, and document type.

Our analysis was restricted to English-language articles to ensure linguistic consistency during text preprocessing and LDA estimation. To assess the quantitative effect of this criterion, a supplementary search was conducted using the same eligibility criteria but without the language restriction. This search identified only 24 additional articles in relation to the corpus of 2,715 articles used in the LDA analysis. Therefore, including non-English publications would have increased the corpus by less than 1%. This indicates that the language restriction had only a minimal quantitative impact on the records retrieved from the Web of Science Core Collection.

To evaluate how sensitive the retrieved literature is to the terminology used, a supplementary search-term sensitivity analysis was conducted. Starting with the initial

corpus based on the term "climate risk," alternative terms such as "climate vulnerability," "climate adaptation risk," "environmental risk," "transition risk," and "climate finance" were incorporated one by one using the Boolean operator OR. The search field and eligibility criteria remained constant, ensuring that only the search terms were altered.

As shown in Appendix C (Table C.1.1), the initial corpus consisted of 2,715 articles. Adding “climate vulnerability” increased the number of records to 3,473 records, representing a 27.9%, relative to the initial corpus. The subsequent inclusion of “climate adaptation risk” produced only one additional record. A substantially larger effect occurred when “environmental risk” was incorporated, increasing the total from 3,474 to 24,665 records. Finally, the inclusion of “transition risk” and “climate finance” increased the total to 25,620 records.

Overall, the fully expanded search yielded approximately 9.4 times more records than the initial corpus. This increase was primarily due to the term “environmental risk”, which suggests that it encompasses a much broader and partly distinct body of literature. Therefore, the analysis supported retaining “climate risk” as the primary search expression. IT also demonstrated that the resulting corpus represents research explicitly framed through climate-risk terminology rather than the entire body of literature addressing adjacent concepts. This supplementary analysis evaluates retrieval sensitivity but does not test the stability of the topics generated by the LDA models.

The analysis focused on the abstracts of research papers as the primary textual corpus. This methodological choice has several advantages (Syed & Spruit, 2017; Kim & Kim, 2022). Abstracts provide concise summaries of a study’s central themes, objectives, and key findings. They are typically presented in standardized English, which ensures linguistic consistency and enhances the efficiency of preprocessing and analysis using Natural Language Processing (NLP) techniques. Additionally, abstracts are generally

accessible and publicly available, making them a practical and cost-effective data source for scholarly research.

Latent Dirichlet Allocation (LDA), an unsupervised machine learning algorithm, was used to reveal the underlying thematic structures in the research literature. LDA conceptualizes each abstract as a probabilistic mixture of topics, where each topic is characterized by a specific distribution of words (Blei et al., 2003). This approach enables underlying thematic patterns to be identified through the analysis of word frequency and co-occurrence (Goyal & Kashyap, 2022). Owing to its scalability and methodological robustness, LDA has become a standard tool for large-scale literature analysis: It has demonstrated superior performance relative to alternative topic modeling techniques in identifying and categorizing research themes across diverse academic disciplines (Ribeiro et al., 2024)[2].

To guide model selection, performance was evaluated using two complementary metrics: the Coherence Score (Cs) and the Perplexity Score (Ps). The coherence score measures the semantic interpretability and internal consistency of the generated topics, with higher values indicating clearer and more meaningful thematic structures (Röder et al., 2015). The perplexity score measures the model's predictive fit on held-out data, with lower values indicating stronger generalization capacity (Kretinin & Nguyen, 2022; Rüdiger et al., 2022). However, following Chang et al. (2009), who showed that lower perplexity does not reliably correspond to more interpretable or human-coherent topics, perplexity was used solely as a boundary screening criterion to exclude models at the extremes of the search space, those producing severely underfitted (overly broad) or overfitted (fragmented and unstable) topic distributions. Within the feasible region so defined, the

[2] See Appendix B for further details on the LDA protocol.

coherence score served as the operative selection criterion. Final model selection was subsequently validated through a structured qualitative review, described below.

Following quantitative model selection, a structured qualitative validation was conducted to assess substantive interpretability. This involved: (i) systematic inspection of the highest-probability terms associated with each topic; (ii) review of representative abstracts assigned high topic-weight scores to verify thematic coherence; (iii) assessment of thematic distinctiveness across topics to ensure minimal conceptual overlap; and (iv) iterative topic labelling by the research team, based on convergent interpretation of the dominant terms and associated documents. This qualitative appraisal provided the primary interpretive basis for the final model choice and for the thematic labels assigned to each pattern and trend.

To present a comprehensive understanding of the intellectual landscape of climate risk research, two interrelated yet distinct analyses were conducted. The first analysis focused on identifying and examining established research patterns to delineate foundational themes, prevailing theoretical frameworks, and mature domains that have consistently shaped scholarly discourse. This analysis aimed to reveal the field's core intellectual structure, characterized by recurring topics and enduring conceptual paradigms.

The second analysis examined emerging trends in the literature, to capture the dynamic and evolving nature of climate risk scholarship. This involved identifying nascent themes and innovative research areas that signal the field's prospective directions. The five-year period from 2020 to 2024 was chosen to capture the most recent developments in the field, ensuring that the identified trends reflect current and emerging research priorities rather than historical patterns. By systematically analyzing these developments, the study draws attention to shifts in thematic focus, the emergence of interdisciplinary linkages, and areas that remain underexplored and warrant further investigation.

Together, these analyses provide a nuanced picture of both stability and evolution in climate risk research. By synthesizing insights from established and emergent strands of the literature, the study provides an integrated perspective that serves as a strategic roadmap, mapping the current state of the field while highlighting key destinations for future inquiry and decision-making[3].

To ensure terminological consistency, Appendix C (Table C.1.2) distinguishes the statistical outputs of the LDA models from their substantive interpretation. In this study, "topic" refers exclusively to the probabilistic output generated by LDA, whereas "research pattern" and "emerging research trend" refer to the authors' interpretation of the topics identified in the complete corpus and in the 2020-2024 subset, respectively.

3.2 Topic prevalence and representative articles

To strengthen the empirical basis of the interpretation of the topic, two complementary forms of model-derived evidence were examined. First, topic prevalence was calculated by assigning each article to the topic with the highest posterior probability, then reporting the resulting number and percentage of articles. This dominant-topic classification indicates the relative prevalence of each topic within the corpus but does not imply exclusive association with a single topic. Second, representative articles were identified from the document-topic distribution as those with the highest topic proportions within each topic. These articles were selected algorithmically, not based on subjective assessments of thematic affinity.

[3] The analysis was carried out using Python-based tools and libraries. Preprocessing procedures were carried out with the Natural Language Toolkit (NLTK), version 3.8.1 (Bird et al., 2009). Topic modeling was performed using the Gensim library, version 4.1.2 (Rehurek & Sojka, 2010), which facilitated the application of the Latent Dirichlet Allocation (LDA) algorithm. Data management and manipulation were conducted using Pandas, version 1.4.4 (McKinney, 2010), while data visualizations were generated using matplotlib, version 3.7.2c, (Hunter, 2007), and seaborn, version 0.11.2 (Waskom, 2021). All computational processes were executed on a scalable computing platform to ensure efficiency and reproducibility.

Two authors examined the highest-probability terms and highest-loading abstracts jointly. Therefore, topic labels therefore remain an interpretive synthesis rather than a direct output automatically assigned by the LDA model. Prevalence results and representative articles were used to strengthen the transparency and empirical basis of this interpretation. In the results section, model-derived evidence is presented before the subsequent comparisons with and contextualization through the broader literature.

To improve readability, the complete results concerning topic prevalence, document-topic proportions and the articles with the highest-loading for the consolidated research patterns and emerging research trends are reported in Appendix C (Tables C.1.3 and C.1.4). The main findings are summarized and interpreted below.

4. STUDY 1 – RESEARCH PATTERNS IN CLIMATE RISK LITERATURE

To identify consolidated research patterns within the climate risk literature, the LDA algorithm was applied to the full corpus of 2,715 research papers previously identified. A grid search procedure was conducted to determine the optimal model specification, resulting in the estimation of 675 different LDA models.

Model selection was guided by two complementary evaluation metrics: the Coherence Score (Cs) and the Perplexity Score (Ps). The coherence score assesses the semantic interpretability and internal consistency of the generated topics, with higher values indicating clearer and more meaningful thematic structures (Röder et al., 2015; Gupta et al., 2022). In contrast, the perplexity score evaluates the model's predictive performance, with lower values suggesting stronger generalization capacity and better out-of-sample predictive ability (Kretinin & Nguyen, 2022; Rüdiger et al., 2022).

Figure 1 presents the average coherence and perplexity scores across different topic numbers. The results reveal a clear trade-off between interpretability and predictive fit.

Models with fewer topics tend to under-cluster the corpus, producing overly broad thematic groupings, whereas models with a larger number of topics generate noisier and less stable topic distributions.

The six-topic solution (K = 6) trained for 110 passes with $\alpha = 0.5$ and $\beta = 0.4$ was identified as optimal within the feasible region defined by perplexity-based boundary screening, achieving the highest coherence score (Cs = 0.5157) among all candidate models that did not exhibit signs of underfitting or overfitting. As noted in Section 3, the coherence score was the operative selection criterion; perplexity served only to delimit the search space. The interpretability of this solution was further confirmed through the qualitative validation procedure described in Section 3. This configuration achieved the highest coherence score within the search space (Cs = 0.5157) while maintaining a near-minimal normalized perplexity (Ps = 3.12e−3 + 1). Consequently, the six-pattern topic model was selected as the optimal representation of the thematic structure underlying the climate risk literature.

For transparency, detailed trajectories of coherence and perplexity across the full set of tested models are provided in Appendix D (Figure D.1.1) illustrating the robustness of the model selection process.

Figure 1: Average Coherence and Perplexity Scores by Number of Topics (Full Corpus, Six-Pattern Model)

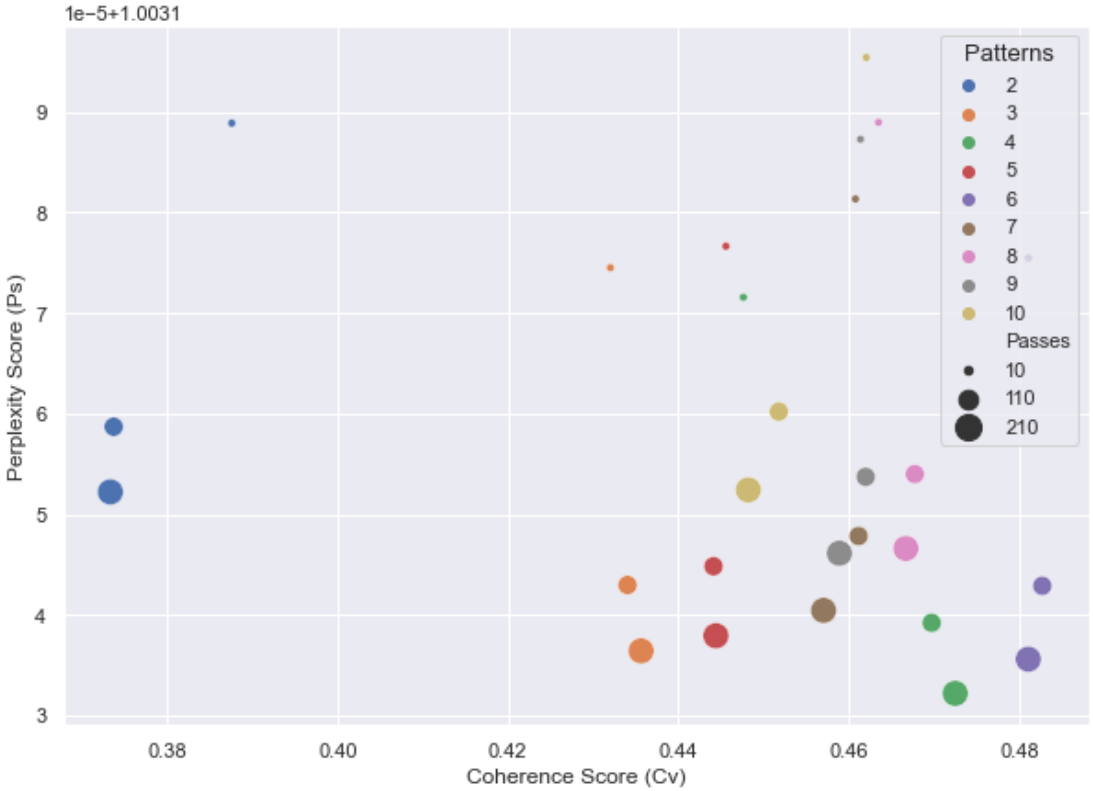


Table 1 presents the term–topic matrix for the six-pattern model. Each pattern represents a distinct domain of research focus within the climate risk literature, characterized by the most probable terms associated with each topic.

Table 1. Six-Pattern Model Term-Topic Matrix.

Pattern	Terms expressed as lemmas									
1	Climate	Change	Adaptation	Risk	Vulnerability	Policy	Management	Community	Local	Assessment
	0.046	0.019	0.015	0.011	0.008	0.007	0.007	0.007	0.005	0.005
2	Insurance	Flood	Heritage	Hurricane	Safety	Home	Diversification	Worker	Damage	Coverage
	0.041	0.010	0.007	0.006	0.005	0.004	0.004	0.004	0.004	0.004
3	Climate	Financial	Market	Green	Risk	Effect	Policy	Impact	Change	Investment
	0.038	0.013	0.012	0.011	0.010	0.009	0.009	0.009	0.009	0.008
4	Climate	Change	Temperature	Scenario	Region	Extreme	Future	Index	Increase	Using
	0.034	0.015	0.012	0.010	0.009	0.009	0.008	0.007	0.007	0.006
5	Farmer	Yield	Production	Agricultural	System	Household	Agriculture	Strategy	Water	Variability
	0.028	0.025	0.016	0.013	0.012	0.010	0.009	0.007	0.007	0.007
6	Forest	Carbon	Energy	Emission	Power	Mitigation	Renewable Energy	Solar	Fossil	Plant
	0.019	0.019	0.017	0.017	0.011	0.009	0.008	0.007	0.007	0.006

Note: terms are organized in decreasing order of probability within each topic.

4.1 Pattern 1: Climate Adaptation and Community Resilience

Top Terms: Climate, Change, Adaptation, Risk, Vulnerability, Policy, Management, Community, Local, Assessment

This pattern focuses on community-level vulnerability assessments and policy responses that aim to strengthen adaptive capacity. The prominence of the terms "adaptation," "vulnerability," and "local" reflects the growing recognition that climate change manifests as both global and local systemic risk (Giglio et al., 2021). Cities and communities concentrate populations and assets that are particularly vulnerable to climate hazards. Compound events, such as simultaneous droughts and heat waves, amplify these risks (Zscheischler et al., 2018).

Policy integration is central to this literature. Researchers have highlighted the potential and pitfalls of local climate policies, including the unintended consequences of industrial relocation (Bartram et al., 2022) and policy uncertainty following natural disasters (Guesmi et al., 2023). The emphasis on "community" highlights that adaptation involves context-specific social processes rather than merely technical solutions (Boas et al., 2022). Importantly, community-level vulnerabilities can aggregate into systemic financial instability, linking local adaptation to macroprudential concerns (Sun et al., 2022).

4.2 Pattern 2: Climate Risk and Insurance Mechanisms

Top Terms: Insurance, Flood, Heritage, Hurricane, Safety, Home, Diversification, Worker, Damage and Coverage.

This pattern focuses on risk transfer mechanisms and loss management for climate-induced disasters. The prevalence of terms such as "insurance," "flood," "hurricane," and "damage" highlights the sector's historical role in providing compensation for

catastrophic losses. However, the inclusion of terms such as "safety," "home," "worker," and "diversification" indicates a shift towards household protection, occupational security, and spreading risk at the portfolio level.

Insurance is increasingly viewed as a proactive adaptation tool rather than merely a compensatory mechanism (Mills, 2004; Surminski, 2013). Research emphasizes that integrating insurance with broader governance frameworks can incentivize risk reduction and strengthen resilience (Keskitalo et al., 2014).

At the systemic level, diversification across sectors, regions, and instruments enables insurance to stabilize financial systems under climate stress (Sun et al., 2022). Thus, insurance emerges as a financial instrument and societal safeguard, providing coverage for catastrophic risks and contributing to household security and systemic stability.

4.3 Pattern 3: Climate Finance and Green Investment

Top Terms: Climate, Financial, Market, Green, Risk, Effects, Policy, Impacts, Changes and Investment

This pattern illustrates the intersection of climate risk and financial market dynamics. The co-occurrence of "financial," "market," and "investment" alongside "green" and "risk" reflects a paradigm shift. Climate change is now considered a core factor in asset pricing, portfolio allocation, and systemic stability, rather than an external environmental constraint (Giglio et al., 2021).

Research in this area shows that climate risks are increasingly influencing returns, correlations, and diversification strategies across asset classes (Khalfaoui et al., 2022; Bouri et al., 2023). The prominence of "policy" and "impact" indicates the transformation of environmental shocks into financial and regulatory outcomes. Studies emphasize that

financial stability and regulatory coordination are essential for effective climate action (Bartram et al., 2022; Sun et al., 2022).

Green bonds and ESG equities have thus transitioned from niche instruments to strategic tools that enhance resilience, facilitate transition finance, and accelerate decarbonization.

4.4 Pattern 4: Climate Extremes and Scenario Modelling

Top Terms: Climate, Change, Temperature, Scenario, Region, Extreme, Future, Index, Increase, Using

This pattern focuses on scenario-based modelling and quantifying climatic changes. The prominence of the terms "scenario," "extreme," "temperature," and "region" reflects a focus on projecting future climate trajectories and assessing their differential impacts across regions.

Scenario analysis has become essential to climate risk research. Traditional, backward-looking models fail to capture the nonlinear dynamics of the climate, making forward-looking approaches essential (Battiston et al., 2017; Chenet et al., 2019). Frameworks developed by the IPCC (2021) and the NGFS (2022) now allow policymakers and financial institutions to stress-test vulnerabilities under different emissions scenarios (Bingler et al., 2022).

Research shows that compound events, such as simultaneous droughts, heat waves, and floods, produce cascading risks that amplify vulnerabilities across regions and sectors (Zscheischler et al., 2018; Kornhuber et al., 2023). These risks translate into measurable financial signals that affect sovereign ratings and bond spreads (Cevik & Tovar-Jalles, 2022; Klusak et al., 2023). Stress testing has transitioned from academic modelling to core prudential regulation, as evidenced by central bank exercises (ECB, 2021; Bank of England, 2021).

4.5 Pattern 5: Climate Impacts and Agricultural Resilience

Top Terms: Farmer, Yield, Production, Agricultural, System, Household, Agriculture, Strategy, Water, Variability

This pattern focuses on agriculture, the sector most directly affected by climate variability. The prominence of terms such as "farmer," "yield," "production," and "household" highlights the risks to food security and rural livelihoods.

Already, rising temperatures, shifting precipitation, and extreme events have reduced yields of major staple crops. Nonlinear temperature effects have caused disproportionately large losses (Schlenker & Roberts, 2009; Lobell et al., 2011). These risks are systemic and threaten household incomes and global food security (Stern, 2006).

Compound events amplify these impacts. For example, synchronized crop failures across major agricultural regions, driven by jet stream variability, pose systemic threats that are often underestimated in current models (Zscheischler et al., 2018; Kornhuber et al., 2023). Beyond biophysical dimensions, vulnerability is intertwined with social and institutional inequalities. Rural households respond with complex adaptation strategies that link agricultural resilience to broader questions of equity and institutional support (Boas et al., 2022).

4.6 Pattern 6: Climate Mitigation and Energy Transition

Top Terms: Forest, Carbon, Energy, Emission, Power, Mitigation, Renewable Energy, Solar, Fossil, Plant

This pattern illustrates the dual focus of climate mitigation research on natural carbon sinks and the transformation of energy systems. The co-occurrence of "forest," "carbon,"

"energy," "emission," and "renewable" reflects the convergence of ecological and technological approaches to achieving net zero.

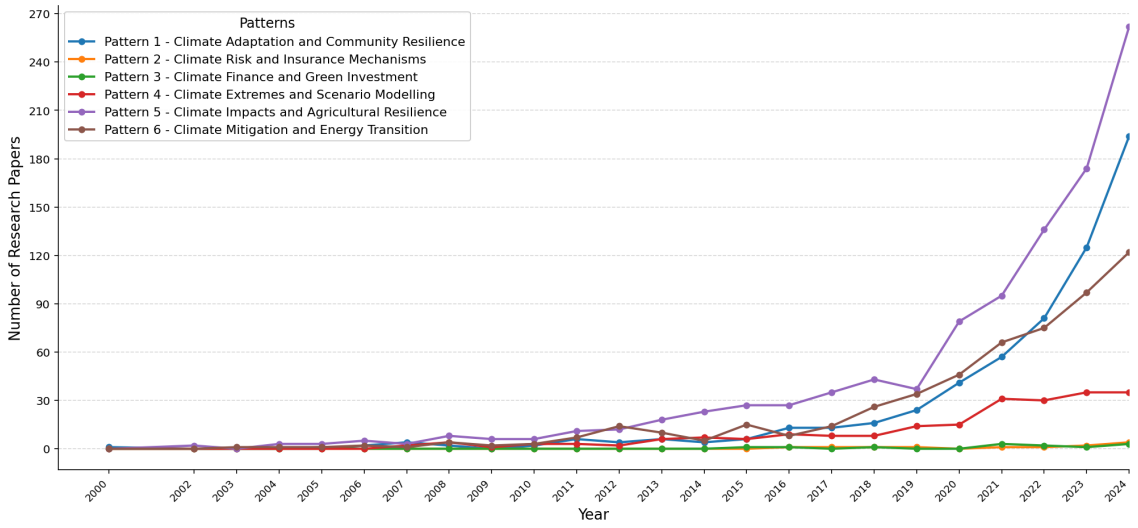
Forests and soils naturally sequester carbon, thereby maintaining ecosystem balance (Beillouin et al., 2023). Concurrently, decarbonizing energy systems by reducing fossil fuel dependence and scaling renewable energy sources represents the technological foundation of mitigation (Bouri et al., 2023).

The financial dimension is equally critical. Stable financial systems are necessary to mobilize long-term investment in renewable infrastructure and support a sustainable transition (Sun et al., 2022). Thus, this pattern characterizes the convergence of ecological, technological, and financial strategies required to stabilize the climate and sustain low-carbon development.

4.7 Evolution of Research Patterns over Time

Figure 2 shows a marked increase in publication activity across the six research patterns, particularly from the late 2010s onwards, although their growth trajectories differ in scale and intensity.

Figure 2. Annual distribution of the six research patterns



Note: The figure reports the annual number of articles assigned to each research pattern based on their dominant topic, defined as the topic with the highest posterior probability in the document-topic distribution. Dominant-topic assignment does not imply that an article is exclusively associated with a single topic.

STUDY 2 – EMERGING TRENDS IN CLIMATE RISK RESEARCH (2020–2024)

To identify recent research trajectories in the climate risk literature, a second topic modelling analysis was conducted focusing on studies published between 2020 and 2024. This temporal restriction allows the identification of emerging thematic directions that reflect the evolving priorities and methodological developments within the field.

Like the previous analysis, the LDA algorithm was applied to the corpus of abstracts. A grid search procedure was implemented to determine the most appropriate model configuration by systematically varying the number of topics, the number of passes, and the hyperparameters α and β.

Model performance was evaluated using the same two complementary metrics: the Coherence Score (Cs), which captures the semantic interpretability and internal consistency of topics, and the Perplexity Score (Ps), which measures the predictive performance of the model (Röder et al., 2015; Gupta et al., 2022; Kretinin & Nguyen, 2022; Rüdiger et al., 2022).

The model selection exercise identified the four-topic solution, trained with 110 passes, $\alpha = 0.4$, and $\beta = 0.3$, as the optimal configuration. Within the feasible region delimited by perplexity-based boundary screening, this specification achieved the highest semantic coherence, indicating clearly defined thematic structures (Cs = 0.505; Ps = 4.19e−3 + 1). Consistent with the methodology described in Section 3, coherence served as the primary selection criterion, and the final four-topic solution was confirmed through the structured qualitative validation procedure.

Figure 3 presents the average coherence and perplexity scores across the tested topic numbers, illustrating the trade-off between interpretability and predictive fit. Models with fewer topics tend to merge conceptually distinct themes, whereas models with a higher number of topics generate more fragmented and unstable topic distributions. The four-topic solution therefore offers the most balanced representation of emerging thematic developments in climate risk research[4].

Figure 3: Average Coherence and Perplexity Scores by Number of Topics (2020–2024 Subcorpus, Four-Trend Model)

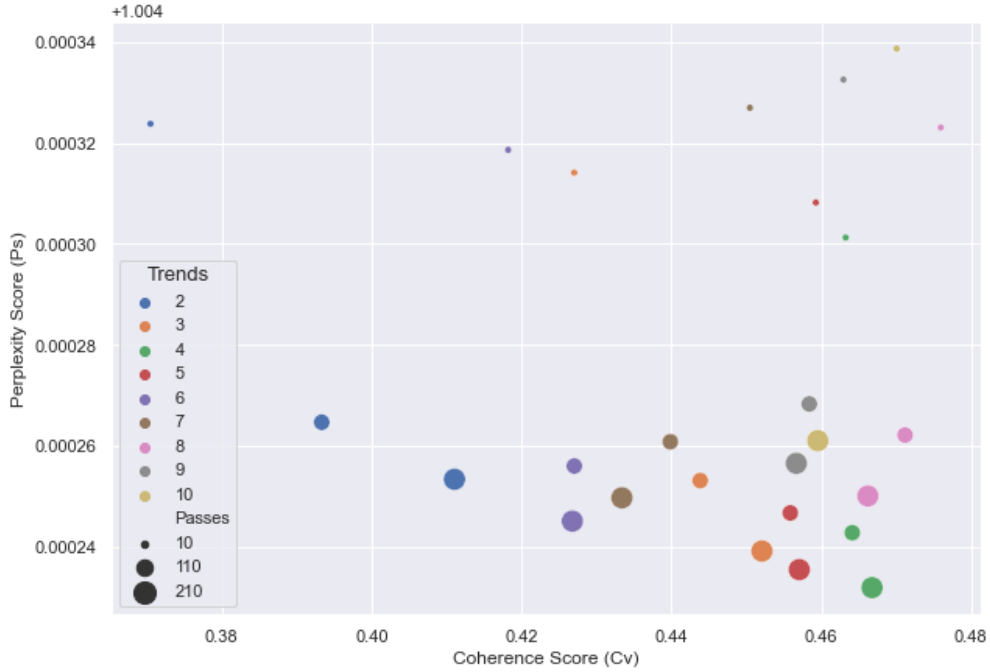


Table 2 presents the term-topic matrix for the four-term model.

[4] Detailed trajectories of coherence and perplexity across the full set of tested models are reported in the Appendix D (Figure D.1.2).

Table 2: Four-Trend Model Term-Topic Matrix.

Trend	Terms expressed as lemmas									
1	Climate	Change	Adaptation	Risk	Vulnerability	Urban	Management	Policy	Assessment	Community
	0.043	0.019	0.012	0.010	0.009	0.007	0.006	0.006	0.005	0.005
2	Climate	Country	Effect	Change	Financial	Market	Company	Risk	Energy	Impact
	0.041	0.010	0.010	0.010	0.010	0.010	0.010	0.009	0.008	0.008
3	Climate	Temperature	Extreme	Scenario	Change	Region	Precipitation	Index	Using	Simulation
	0.032	0.014	0.014	0.013	0.012	0.010	0.008	0.008	0.007	0.007
4	Farmer	Yield	Agricultural	System	Production	Household	Agriculture	Diversification	Using	Strategy
	8	0.016	0.015	0.012	0.010	0.010	0.008	0.008	0.007	0.006

Note: terms are organized in decreasing order of probability within each topic.

The topic modeling analysis revealed four emerging thematic trends representing the evolving directions in climate risk research between 2020 and 2024. Interpreted through the dominant lemmas associated with each topic, these trends reflect a shift in scholarly attention from traditional conceptual frameworks towards more integrated, operational and impact-oriented approaches.

5.1 Trend 1: Urban Climate Adaptation

Top Terms: Climate, Change, Adaptation, Risk, Vulnerability, Urban, Management, Policy, Assessment, Community

This trend goes beyond physical risk analysis to examine how cities govern climate adaptation through policies, institutions, and participatory processes. The prominence of the terms "urban," "policy," and "community" reflects the growing recognition that cities are exposure hotspots and key arenas for equitable adaptation (IPCC, 2022).

Empirical evidence confirms that urban populations face intensifying climate impacts, including heat exposure and health burdens. Vulnerable groups are disproportionately affected (Romanello et al., 2023; van Daalen et al., 2024). Effective adaptation requires multi-level governance and coordinated frameworks; however, implementation gaps

persist between policy design and execution, especially in the Global South (Nocentini, 2024; Liss et al., 2025).

Participatory, justice-based approaches are becoming increasingly essential. Inclusive planning that incorporates local knowledge and addresses power asymmetries strengthens both legitimacy and effectiveness (Lao et al., 2025; Parsons et al., 2025). Thus, cities emerge not only as sites of risk, but also as laboratories for adaptive innovation.

5.2 Trend 2: Climate Risk and Financial Stability

Top Terms: Climate, Country, Effect, Change, Financial, Market, Company, Risk, Energy, Impact

This trend reflects the increasing incorporation of climate risk into financial markets and corporate strategy. The co-occurrence of the terms "financial," "market," "company," and "risk" reflects a paradigm shift in which climate change is now recognized as a systemic financial concern (NGFS, 2022).

Research demonstrates the bidirectional relationship between financial stability and climate policy. Financial resilience enhances the effectiveness of climate policy mitigation, while climate policies reshape firm-level investment behavior and market dynamics (Bartram et al., 2022; Sun et al., 2022). At the asset level, climate risks are increasingly influencing returns and volatility, especially in energy markets and carbon-intensive sectors (Bauer et al., 2023; Bouri et al., 2023).

Cross-country analysis reveals divergent regulatory approaches. Many financial institutions still lack adequate models to quantify climate exposures (ECB, 2021). Robust corporate governance structures are critical for superior climate risk management

(Khatib, 2024). This trend connects micro-level corporate resilience to macro-prudential regulation (Battiston et al., 2017).

5.3 Trend 3: Extreme Climate Events and Climate Modeling

Top Terms: Climate, Temperature, Extreme, Scenario, Change, Region, Precipitation, Index, Using, Simulation.

This methodological approach uses scenarios, indices, and simulations to project climate extremes and their impacts. Research increasingly emphasizes the interaction of concurrent hazards—compound events, such as simultaneous heat waves and droughts, produce cascading effects that are underestimated by single-hazard frameworks (Zscheischler et al., 2018; Kornhuber et al., 2023; Thompson et al., 2023).

Scenario modelling has become central to climate science and risk governance. Frameworks developed by the IPCC (2021) and the NGFS (2022) allow policymakers and financial supervisors to assess vulnerabilities under different emissions scenarios. These scenarios translate into measurable outcomes: climate-adjusted sovereign ratings indicate that warming could reduce creditworthiness as early as 2030 (Klusak et al., 2023).

Regional and sectoral applications extend these insights, providing temperature-related mortality projections, Arctic sea ice shift projections, and ecological adaptation strategy recommendations (García-León et al., 2024; Sumata et al., 2023; Xu & Prescott, 2024). This trend bridges the gap between climate modelling, policy analysis, and risk management.

5.4 Trend 4: Agriculture, Food Security, and Household Resilience

Top Terms: Farmer, Yield, Agricultural, System, Production, Household, Agriculture, Diversification, Using, Strategy

This trend focuses on agricultural systems and household vulnerability to climate variability. The prominence of terms such as "farmer," "yield," and "household" reflects direct concerns about productivity, livelihoods, and food security.

Recent research expands beyond yield analysis to include household resilience and adaptation strategies. Diversification of crops, livelihoods, and risk management mechanisms emerges as a key response (Surminski, 2013; Donatti et al., 2024). Soil carbon dynamics and ecosystem services also play crucial roles in maintaining productivity (Beillouin et al., 2023). Vulnerability is intertwined with social and institutional inequalities as rural households navigate complex adaptation pathways (Boas et al., 2022).

Figure 4 shows the annual number of articles assigned to each emerging research trend based on their dominant topic, defined as the topic with the highest posterior probability in the document-topic distribution. The four-topic model was estimated using articles published between 2020 and 2024.

Figure 4: Annual distribution of the four emerging research trends, 2020-2024

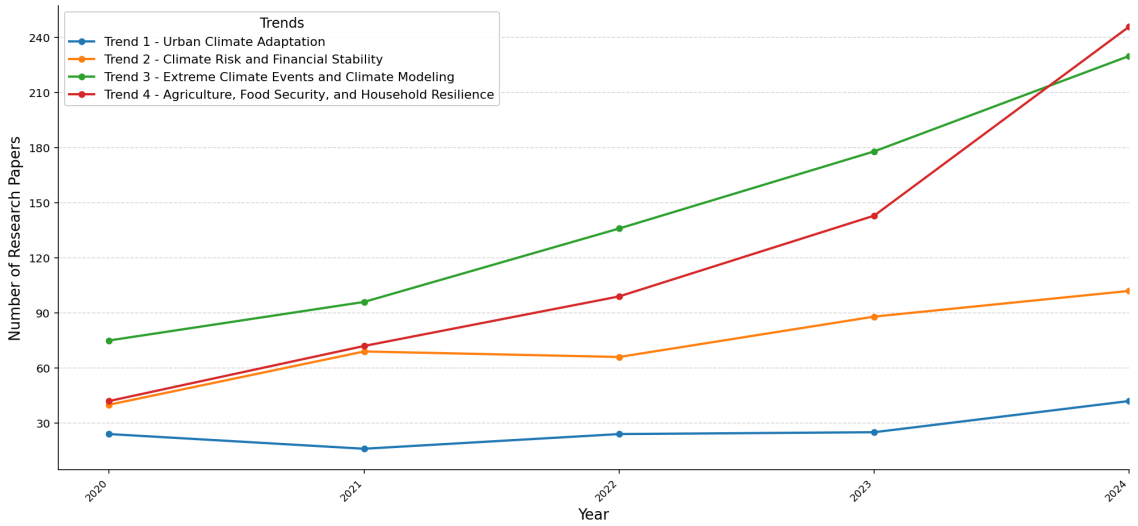


Figure 4 reveals sustained growth across the four emerging research trends between 2020 and 2024, with Climate Risk and Financial Stability showing the strongest acceleration and becoming the most prominent trend in 2024.

5.5 Strategic Blind Spots and Future Actions

5.5.1 Underestimating Compound and Cascading Risks

This bibliometric analysis reveals a field in transition: climate risk research is conceptually mature but remains fragmented by disciplinary silos and methodological asymmetries. Considerable progress has been made in investigating the financial, environmental, and macroeconomic aspects of climate-related risks. However, a significant gap remains between academic advances and practical application. The result is literature that is thematically rich but often lacks the systemic coherence necessary for guiding real-world decision-making. Below, we translate the key research gaps identified in our analysis into strategic blind spots for businesses and policymakers and outline a forward-looking agenda for action.

One particularly pressing vulnerability is the tendency to underestimate the risks of compound climate events and cascading failures. Studies by Zscheischler et al. (2018)

and Kornhuber et al. (2023) reveal that simultaneous, interconnected events, such as droughts paired with heat waves and floods following wildfires, amplify impacts across interdependent systems, including agriculture, infrastructure, and global supply chains. .

Despite their significance, compound risks are dramatically underrepresented in corporate risk models, which typically assume independent events and linear propagation effects. For example, a manufacturer that relies on a single logistics corridor may model flood and earthquake risks separately. This approach misses the possibility that a climate-induced event in one region could trigger cascading failures across suppliers, transport networks, and energy grids continents away.

Future research must prioritize integrating multi-hazard interactions and nonlinear stress transmissions into climate-economic simulations. For practitioners, this means shifting from siloed risk assessments to dynamic scenario planning. This new approach explores how interconnected failures could propagate through operations, supply chains, and customer bases. In turn, regulators should consider whether current stress-testing frameworks adequately capture these systemic interdependencies.

5.5.2 Dichotomy Between Physical and Transition Risks

While analytically useful, the conceptual separation between physical and transition risk frameworks oversimplifies real-world dynamics. Few studies have examined how these two domains interact and co-evolve. For instance, aggressive climate mitigation policies could unintentionally amplify short-term physical vulnerabilities, especially in regions or sectors that are already structurally fragile (Bartram et al., 2022). If not managed properly, a rapid shift away from fossil fuels could destabilize communities whose economies depend on carbon-intensive industries, thereby impairing their ability to adapt to physical climate impacts. This false dichotomy creates blind spots for managers. A company may

have sophisticated models for its carbon footprint (transition risk) and asset exposure to floods (physical risk) yet lack an integrated framework to understand their interaction. For example, a climate policy that raises carbon prices could increase operating costs and reduce the financial resilience of suppliers in vulnerable regions, thereby amplifying overall business risk.

There is an urgent need for integrative modelling efforts that capture the co-evolution of policy frameworks, corporate behaviour, and climate impacts across jurisdictions and time horizons. For decision-makers, this means developing integrated risk governance structures that bridge the functions of sustainability, finance, and operations—breaking down the internal silos that mirror the academic fragmentation we have documented.

5.5.3 Gap Between Risk Awareness and Investor Action

A critical disconnect persists between risk awareness and actual investor behaviour. Bauer et al. (2023) found that financial analysts and capital markets consistently underestimate the negative financial impacts of physical hazards, especially heat exposure. This systematic mispricing indicates an ongoing delay in integrating climate signals into valuation models, despite growing evidence of their significance.

This gap creates vulnerabilities and opportunities. Companies that proactively address climate risks may be undervalued by markets operating under outdated assumptions. Conversely, firms exposed to unmodeled physical risks face the prospect of sudden repricing when investor awareness catches up with reality, which could have severe consequences for the cost of capital and shareholder value.

Closing this gap requires coordinated action across multiple fronts, including improved transparency and standardization in climate risk disclosure; the development of forward-

looking climate finance indicators that regulators and rating agencies can rely on; and sustained investor education on how physical climate risks affect financial performance. For corporate leaders, the message is clear: Treat climate risk management as a strategy to protect value, not just a compliance exercise.

5.5.4 The Corporate Resilience Black Box

At the firm level, research is beginning to shed light on corporate adaptation and resilience mechanisms. Studies by Naseer et al. (2024) and Ren et al. (2022), suggest that financial flexibility and environmental, social and governance (ESG) performance can partially mitigate the effects of climate-related shocks. However, current approaches often isolate these moderating factors and neglect the combined influence of governance quality, geographic exposure, supply chain structure and sectoral interdependencies on resilience outcomes.

Organizations should understand resilience as an emergent property of complex systems, not as a checklist of isolated attributes. For example, a firm with strong governance but concentrated supplier networks in climate-vulnerable regions remains exposed. Similarly, a firm with diversified operations but weak board oversight may lack the strategic capacity to adapt.

A priority for future research is developing multidimensional resilience indices that integrate financial, operational, and environmental factors at the company and sector levels. For practitioners, this means shifting from mere compliance exercises to thoroughly stress-testing business models under compound climate scenarios. It involves examining not only whether individual assets are protected but also whether the organization can adapt and thrive under conditions of deep uncertainty.

5.5.5 Data and the Knowledge Gap

Data limitations remain a critical constraint. As noted by Dlamini et al. (2023) and Wiltshire (2024), existing climate and crop models often lack the spatial and temporal granularity needed to capture localised and non-linear effects, particularly in regions where data are scarce. These limitations are particularly evident in developing countries, where observation networks and modelling infrastructures are limited. Nevertheless, recent advances in remote sensing, high-frequency data collection and machine learning offer promising opportunities to improve model accuracy and enable scenario testing under complex risk conditions.

Adding to this issue, climate risk research continues to disproportionately focus on high-income countries with well-established capital markets. This bias limits the generalizability of findings and overlooks the acute vulnerability of lower-income regions. Boas et al. (2022) highlight the unequal exposure of communities in the Global South, where adaptive capacity is often limited by institutional fragility and financial instability.

For multinational corporations, this data gap translates directly into strategic uncertainty when operating or sourcing from emerging markets. For global policymakers, it undermines the evidence base for equitable climate action. Future research should prioritize comparative, cross-regional analyses that incorporate local knowledge systems and strengthen resilience in the most vulnerable areas.

5.5.6 Frontier Issues: Bringing the Margins to the Centre

Several emerging issues remain on the fringes of mainstream climate risk discourse, particularly in financial and economic analyses. Climate-induced migration, biodiversity

loss, and climate justice are gaining visibility (Boas et al., 2022), yet they are rarely integrated into quantitative risk models or regulatory frameworks. However, these dimensions are fundamental to understanding the full scope of systemic risk.

For businesses, climate migration will reshape labour markets, consumer bases, and operational stability. Biodiversity loss threatens supply chains in ways that current models do not capture. Concerns about climate justice increasingly influence regulatory expectations and social license to operate. Incorporating these dimensions into climate finance research would enable a more comprehensive approach.

5.5.7 From Fragmentation to Integration

Taken together, these blind spots reveal a common theme: the fragmentation documented in the literature is reflected in organizational and policy silos that hinder effective action. The way forward lies in integration — across physical and transition risk frameworks, research disciplines and geographical boundaries. For researchers, this means adopting more collaborative and interdisciplinary approaches. For business leaders, this means bringing climate risk into the heart of strategic decision-making, rather than keeping it on the periphery of sustainability reporting. For policymakers, it means creating regulatory frameworks that recognise complexity, incentivize resilience and promote equity.

5.6 Limitations and Future Research

5.6.1 Language and Database Coverage

Although including non-English publications would have added only 24 articles – less than one percent of the 2,715 analysed - language-related selection bias cannot be entirely ruled out. This small number may reflect the coverage and indexing practices of the Web of Science Core Collection rather than an absence of relevant research in other languages.

Studies published in regional journals, indexed in other databases or disseminated through institutional reports and gray literature may therefore remain outside the analytical corpus. Future research could combine multiple bibliographic databases and include regional and non-English sources to determine if broader coverage reveals different geographical or thematic perspectives.

5.6.2 Search-Term Sensitivity and Corpus Boundaries

The sensitivity analysis showed that the composition of the corpus depends on the terminology used in the search strategy. Expanding the search to include related terms retrieved approximately 9.4 times as many records as the initial search based on “climate risk”, primarily because “environmental risk” encompasses hazards and concerns that are not necessarily related to climate change. Other terms, such as “climate vulnerability”, “transition risk” and “climate finance”, represent overlapping, yet conceptually distinct research domains. Retaining “climate risk” therefore prioritised conceptual specificity and the interpretability of the topic models, though it may have excluded relevant studies framed through alternative terminology. The complete results of the search-strategy sensitivity analysis are presented in Appendix C (Table C.1.1).

Future research could compare topic models estimated using broader or complementary search strategies to determine whether changes in corpus boundaries produce different thematic structures.

5. CONCLUSION: NAVIGATING THE CLIMATE RISK LANDSCAPE

This study aimed to map the intellectual landscape of climate risk research, not as an end in itself, but rather as foundation for more effective guidance. Using bibliometric analyses and LDA topic modelling, we identified six consolidated research patterns constituting the core domains of climate risk scholarship and four emerging trends signaling the field's

future trajectory. The result is a structured roadmap that reveals the achievements and fault lines of this rapidly evolving, interdisciplinary field.

Three major insights emerged from our analysis. First, climate risk research has undergone a fundamental transformation. Early scholarship, which was primarily rooted in physical climate models and adaptation theories, has given way to a more expansive field that integrates empirical financial analysis, market-based risk assessments, and corporate strategy. This convergence of climate science, economics, and finance reflects the growing recognition that climate risk is a systemic force that is reshaping economies, markets, and organizations, not merely an environmental concern.

Second, the field is simultaneously consolidating and diversifying. Our six consolidated patterns, ranging from climate adaptation and community resilience to climate finance and energy transition, represent the established pillars upon which current knowledge rests. However, the four emerging trends we identify—urban climate adaptation, financial stability and corporate exposure, extreme event modeling, and agricultural resilience—indicate that the field is continuously expanding into new areas and responding to real-world challenges with methodological innovation and interdisciplinary reach.

Third, despite significant progress, fragmentation persists. The physical-transition risk dichotomy, underrepresentation of compound and cascading risks, and the gap between risk awareness and investor behavior point to systemic blind spots that constrain academic understanding and practical action.

Our findings have clear implications for a range of audiences. For researchers, the blind spots identified — compound risks, physical-transition interactions and organizational resilience — represent key areas for future research, requiring the interdisciplinary approaches that our analysis shows are becoming increasingly prevalent. For business

leaders, the message is clear: climate risk is a core strategic consideration, not an afterthought in the realm of compliance. Companies that incorporate climate scenarios into their capital allocation, supply chain design and governance processes will be better placed to navigate uncertainty and seize emerging opportunities. For policymakers, integrated risk governance, which can address compound, cross-border challenges relating to the environment, finance and social welfare, is a necessity, not a luxury.

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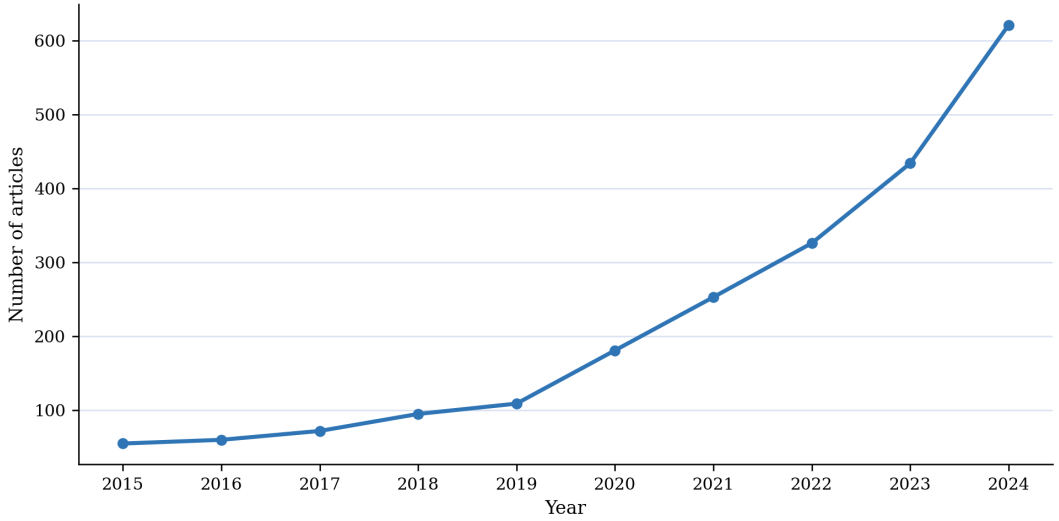
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Appendix A

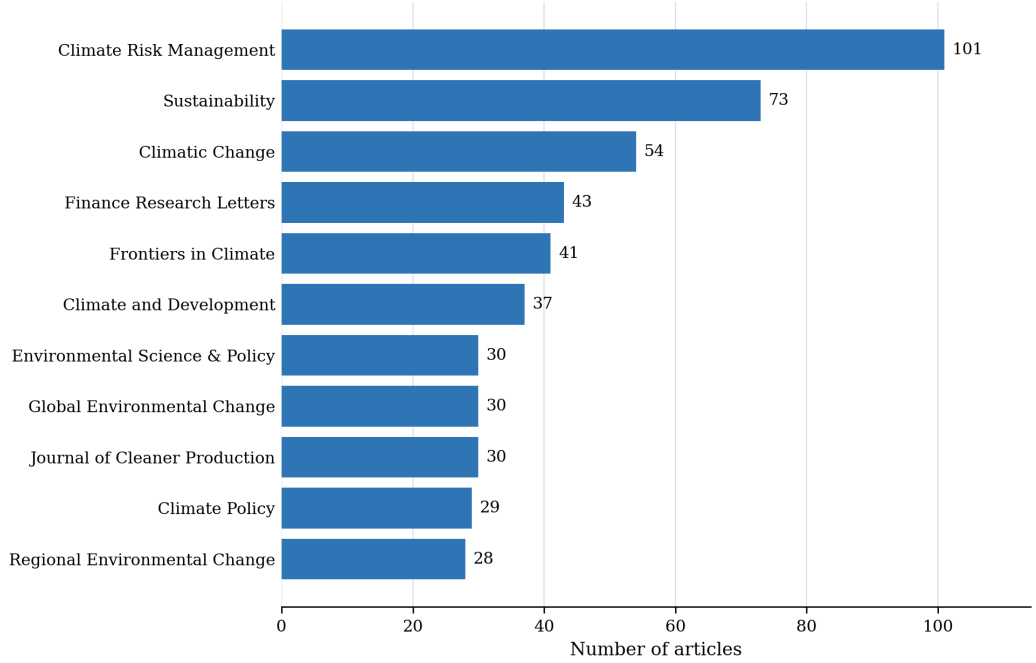
Descriptive Overview of the Dataset

Figure A.1.1: Annual number of climate risk articles published between 2015 and 2024.



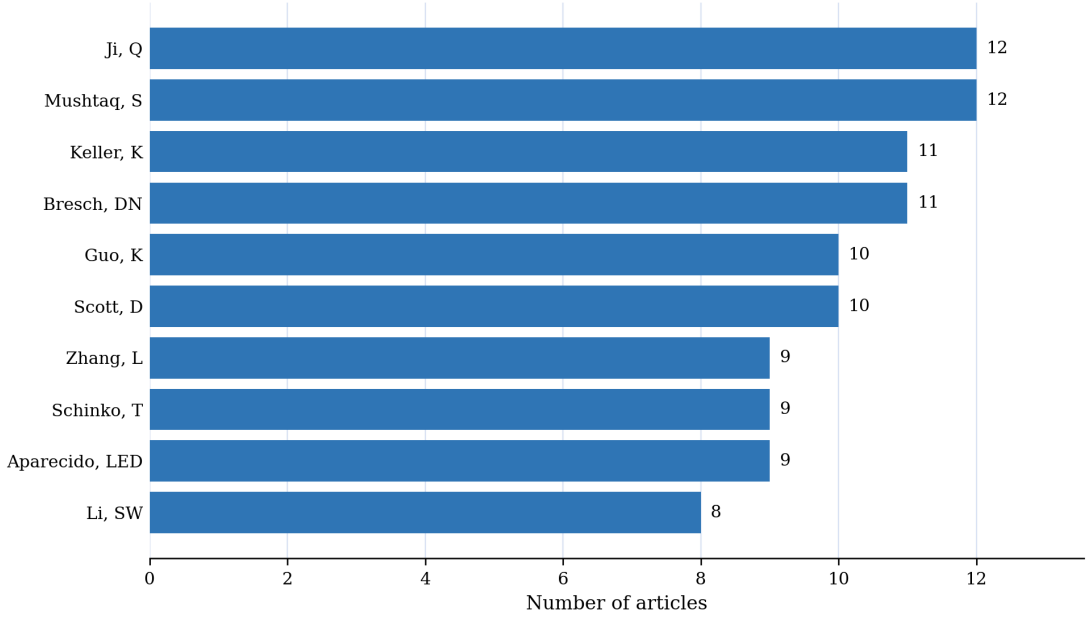
Note: The figure focuses on the most recent ten complete publication years. Publications from 2025 were excluded because that year was incomplete at the original data-collection cut-off.

Figure A.1.2. Leading journals by number of articles in the dataset



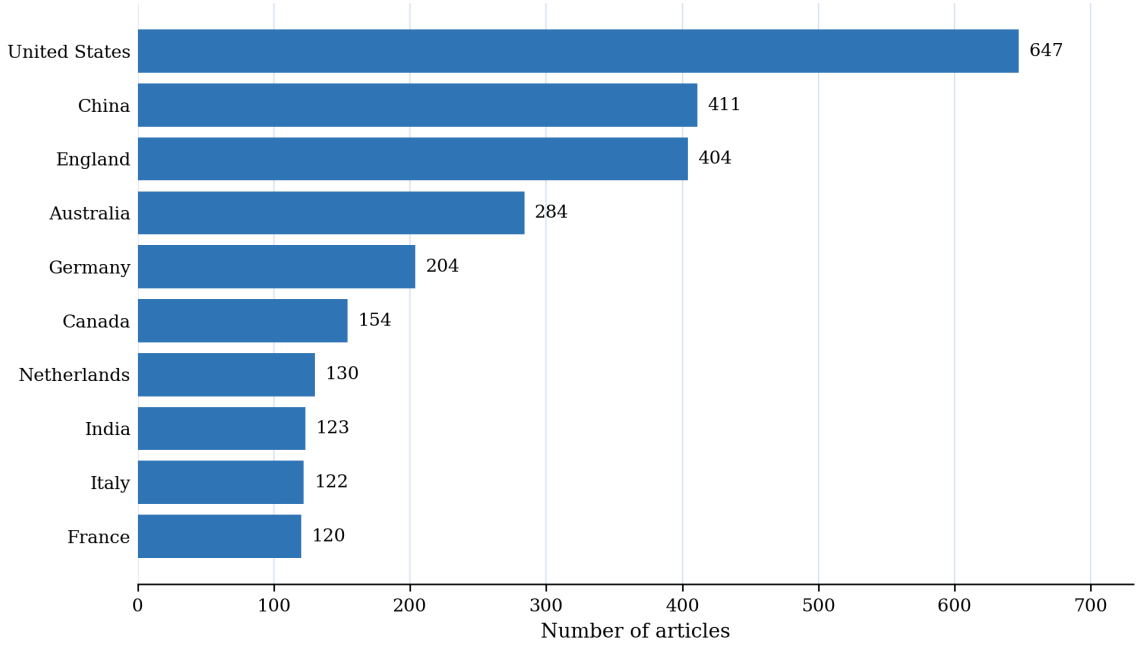
Note: Counts refer to English-language journal articles indexed in the Web of Science Core Collection and published up to 2024.

Figure A.1.3. Most productive authors in the descriptive dataset



Note: Author names are reported as indexed in Web of Science. The figure measures publication productivity rather than citation impact or network influence.

Figure A.1.4. Leading countries by number of articles with at least one author affiliation in the country.



Note: Countries were identified from author affiliations. Internationally co-authored articles were assigned to every country represented; country counts are therefore not mutually exclusive. The Web of Science designation “England” is retained to preserve the database classification.

Appendix B

Latent Dirichlet Analysis Protocol

Prior to applying the LDA algorithm, a structured preprocessing protocol was implemented to ensure the integrity and analytical suitability of the textual data. This process involved removing numerical characters and punctuation, converting all text to lowercase, lemmatizing, eliminating stop words, tokenizing, and identifying relevant n-grams. To extract semantically meaningful bigrams and trigrams, Pointwise Mutual Information (PMI) scores were calculated and subsequently ranked separately. through manual evaluation, a threshold score of 5 was determined, allowing for the retention of only those n-grams exhibiting strong contextual significance and consistent co-occurrence patterns (Georgieva-Trifonova, 2021).

A grid search procedure was conducted to optimize the parameters of the LDA model, with the aim of enhancing model performance by simultaneously maximizing the Coherence Score (Cs) and minimizing the Perplexity Score (Ps) (Kretinin & Nguyen, 2022). The Coherence Score (Cs) assesses the semantic clarity and internal consistency of the generated topics, with higher values indicating greater interpretability and thematic coherence (Röder et al., 2015; Syed & Spruit, 2017; Gupta et al., 2022). Conversely, the Perplexity Score (Ps) reflects the model's predictive capability, where lower values suggest greater confidence in the topic distributions and stronger generalization capacity (Kretinin & Nguyen, 2022; Rüdiger et al., 2022).

The grid search encompassed systematic variations in key LDA parameters, including the number of passes (P = 10, P = 110, and P = 210), the number of topics (K from 2 to 10), and the values of the hyperparameters alpha ($\alpha = 0.1$; $\alpha = 0.2$; $\alpha = 0.3$; $\alpha = 0.4$, and $\alpha = 0.5$) and beta ($\beta = 0.1$; $\beta = 0.2$; $\beta = 0.3$; $\beta = 0.4$, and $\beta = 0.5$). The number of passes denotes the total iterations over the entire corpus during the training phase, whereas the number of

topics corresponds to the latent thematic structures identified by the algorithm (Goyal & Kashyap, 2022). The hyperparameters alpha and beta regulate the sparsity of topics within documents and the sparsity of words within topics, respectively (Goyal & Kashyap, 2022). Specifically, a higher alpha value promotes the inclusion of a greater number of topics per document, while a higher beta value leads to the representation of each topic by a broader range of words (Goyal & Kashyap, 2022).

Appendix C

Search Strategy and Sensitivity Analysis

Table C.1.1: Search-term sensitivity analysis

Cumulative search specification	Records retrieved	Records added at each stage	Increase relative to the initial corpus
"climate risk" - initial analytical corpus	2,715	-	-
Previous term OR "climate vulnerability"	3,473	758	27.9%
Previous terms OR "climate adaptation risk"	3,474	1	28.0%
Previous terms OR "environmental risk"	**24,665**	**21,191**	**808.5%**
Previous terms OR "transition risk"	24,875	210	816.2%
Previous terms OR "climate finance"	25,620	745	843.6%

Note: Search terms were added cumulatively in the order presented. All searches were conducted in the Web of Science Core Collection using the same search field and eligibility criteria as those applied to the initial analytical corpus. "Records added at each stage" indicates the incremental contribution of each term when added to the preceding cumulative specification. The percentage increase was calculated relative to the initial corpus of 2,715 articles. This search-term sensitivity analysis evaluates changes in the number of records retrieved under alternative search specifications; it does not assess the stability of the LDA topic structure.

Table: C.1.2*:* Definition and use of the main analytical terms

Term	Definition	Use in this study
Topic	A probability distribution over words generated statistically by the LDA model, with each document represented as a mixture of topics (Blei et al., 2003).	Refers exclusively to the direct statistical output of the LDA models.
Research pattern	The substantive interpretation assigned to an LDA-derived topic based on its highest-probability terms and highest-loading abstracts.	Refers to the six topics identified and interpreted from the complete corpus of 2,715 *climate risk* articles published up to 2024.
Emerging research trend	The substantive interpretation of an LDA-derived topic identified within a recent, temporally restricted corpus.	Refers to the four topics identified and interpreted from the subset of 1,843 articles published between 2020 and 2024. "Emerging" indicates the recent temporal scope of the analysis and does not imply a statistically estimated publication growth rate.

Table C.1.3: Topic prevalence and representative articles in the six-topic model

Topic	Research pattern	Prevalence	Representative articles - topic proportion
1	Climate Adaptation and Community Resilience	1,297 - 47.77%	Nadimpalli et al. (2024), Reenvisioning inclusive futures: Applying narrative foresight to deconstruct the problem of urban flooding in the slums of Bengaluru, India - 98.72%; Ziervogel et al. (2022), Supporting transformative climate adaptation: Community-level capacity building and knowledge co-creation in South Africa - 98.43%; Bell et al. (2015), Developing rural community health risk assessments for climate change: A Tasmanian pilot study - 98.37%
2	Climate Risk and Insurance Mechanisms	13 - 0.5%	Adam and Abdulai (2024), Heterogeneous impact of crop diversification on farm net returns and risk exposure: Empirical evidence from Ghana - 81.06%; Vause (2023), State of Nature: Risk, Responsibility, and the Moral Economies of Agricultural Insurance in Nineteenth-Century France - 58.65%; Johnson (2021), Paying ex gratia: Parametric insurance after calculative devices fail - 58.21%
3	Climate Finance and Green Investment	614 - 22.6%	Bose et al. (2024), Do foreign institutional investors influence corporate climate change disclosure quality? International evidence - 98.00%; Gan et al. (2024), Climate transition risk, environmental news coverage, and stock price crash risk - 97.21%; Fang (2024), Can climate risk exposure compel companies to undergo a green transformation? - 97.19%
4	Climate Extremes and Scenario Modelling	556 - 20.5%	Zeng et al. (2023), Typical synoptic patterns responsible for summer regional hourly extreme precipitation events over the Middle and Lower Yangtze River Basin, China - 98.66%; Hrinkevich et al. (2016), Climate risk modelling of balsam woolly adelgid damage severity in subalpine fir stands of western North America - 98.25%; Demory et al. (2020), European daily precipitation according to EURO-CORDEX regional climate models and high-resolution global climate models from HighResMIP - 98.16%
5	Climate Impacts and Agricultural Resilience	223 - 8.2%	Pires et al. (2024), Forage performance in silage production under water deficit conditions - 95.96%; Balwinder-Singh et al. (2019), Taking the climate risk out of transplanted and direct seeded rice: Insights from dynamic simulation in Eastern India - 93.51%; Anbazhagan et al. (2022), Dual-Purpose Sorghum: A targeted sustainable crop-livestock intervention for the smallholder subsistence farming communities of Adilabad, India - 90.47%
6	Climate Mitigation and Energy Transition	12 - 0.44%	Fallon et al. (2022), Understanding climate risk in future energy systems: An energy-climate data hackathon - 58.25%; Xu and Ramanathan (2017), Well below 2 °C: Mitigation strategies for avoiding dangerous to catastrophic climate changes - 51.50%; McKinley et al. (2011), A synthesis of current knowledge on forests and carbon storage in the United States - 46.79%
	Total	**2,715 - 100%**	

Note: Prevalence corresponds to the number and percentage of articles for which the respective topic had the highest posterior probability. Representative articles are the three articles with the highest topic proportions within each topic. Topic proportions were obtained from the document-topic distribution generated by the LDA model. Topic labels were assigned through the joint examination of the highest-probability terms, the highest-loading abstracts and their conceptual coherence. Dominant-topic assignment does not imply that an article is exclusively associated with one topic.

Table C.1.4: Topic prevalence and representative articles in the four-topic model, 2020-2024

Topic	Emerging research trend	Prevalence	Representative articles - topic proportion
1	Urban Climate Adaptation	723 - 39.2%	Ziervogel et al. (2022), *Supporting transformative climate adaptation: Community-level capacity building and knowledge co-creation in South Africa* - 99.26%; Schneider et al. (2020), *A rising tide of adaptation action: Comparing two coastal regions of Aotearoa-New Zealand* - 99.24%; Dakey et al. (2022), *A community-based approach to mainstream human-nature interactions into coastal risk governance: A case of Katrenikona, India* - 99.13%
2	Climate Risk and Financial Stability	620 - 33.6%	Bose et al. (2024), *Do foreign institutional investors influence corporate climate change disclosure quality? International evidence* - 99.05%; Yildiz and Temiz (2024), *Climate change exposure, environmental performance, and the cost of capital in the energy sector: Fossil fuel versus renewable energy firms* - 98.78%; Zhang et al. (2024), *From financialisation to sustainability: The impact of climate risks on shadow banking activities in non-financial firms in China* - 98.72%
3	Extreme Climate Events and Climate Modelling	368 - 20%	Zeng et al. (2023), *Typical synoptic patterns responsible for summer regional hourly extreme precipitation events over the Middle and Lower Yangtze River Basin, China* - 99.37%; Zhang et al. (2024), *Assessing climate extremes in dynamical downscaling simulations driven by a novel bias-corrected CMIP6 data* - 99.35%; de Lima et al. (2022), *Agroclimatic zoning for the incidence of brown eye spot on coffee under climate change scenarios* - 99.33%
4	Agriculture, Food Security, and Household Resilience	132 - 7.2%	Adam and Abdulai (2024), *Heterogeneous impact of crop diversification on farm net returns and risk exposure: Empirical evidence from Ghana* - 99.51%; Baudracco et al. (2022), *Strategies to double milk production per farm in Argentina: Investment, economics and risk analysis* - 83.95%; Makate et al. (2023), *Rainfall shocks and inequality have heterogeneous effects on farmers' seed purchase decisions in East Africa* - 82.64%
	Total	**1.843 - 100%**	

Note: Prevalence corresponds to the number and percentage of articles for which the respective topic had the highest posterior probability. Representative articles are the three articles with the highest topic proportions within each topic. Topic proportions are derived from the document-topic distribution generated by the LDA model. The four-topic model was estimated using articles published between 2020 and 2024. Topic labels are interpretative and were assigned through the joint examination of the highest-probability terms, the highest-loading abstracts and their conceptual coherence.

Appendix D

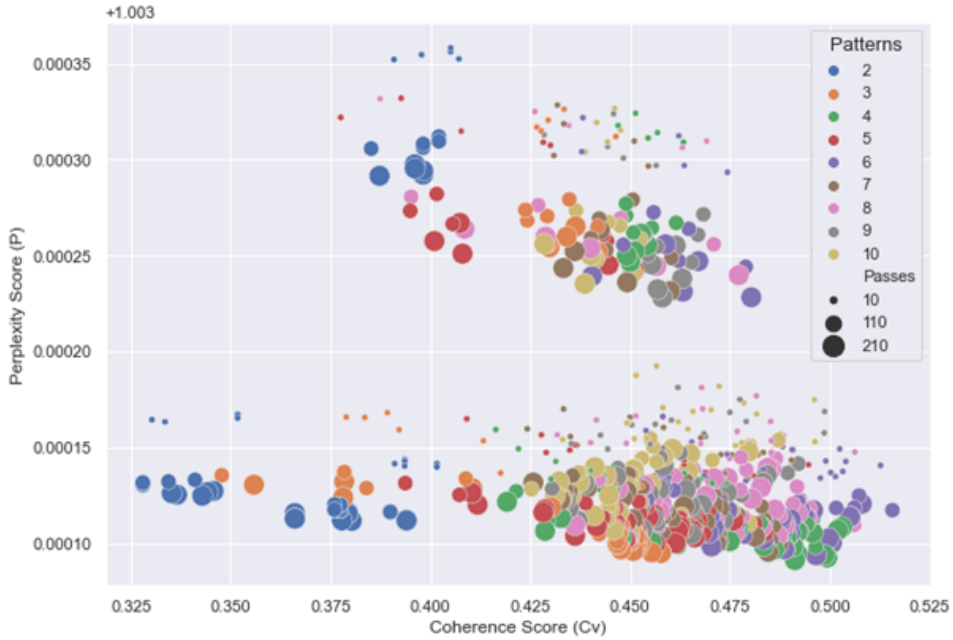
LDA Model Selection for Patterns and Trends

A grid search procedure was implemented to identify the optimal LDA configuration. In total, 675 models were estimated by varying the number of topics (K = 2–10), the number of passes (P = 10, 110, 210), and the hyperparameters α and β (ranging from 0.1 to 0.5).

Two complementary metrics were used to evaluate model performance: the Coherence Score (Cs), which measures the semantic consistency and interpretability of topics, and the Perplexity Score (Ps), which evaluates the model's predictive capacity. Higher coherence values indicate more interpretable topics, whereas lower perplexity values suggest stronger generalisation ability (Gupta et al., 2022; Röder et al., 2015; Kretinin & Nguyen, 2022; Rüdiger et al., 2022).

Figure D.1.1 presents the trajectories of coherence and perplexity across all tested topic numbers. This visualization provides transparency regarding the robustness of the model selection process and the exploration of the search space.

Figure D.1.1: Coherence and Perplexity Scores by Number of Topics (Full Corpus, Six-Pattern Model)



A grid search procedure was conducted to determine the optimal LDA configuration for identifying emerging trends in the climate risk literature. Multiple model specifications were estimated by varying the number of topics, the number of passes, and the hyperparameters α and β.

Model performance was evaluated using the Coherence Score (Cs), which captures topic interpretability, and the Perplexity Score (Ps), which measures predictive performance.

Figure D.1.2 illustrates the trajectories of coherence and perplexity across the tested topic numbers. This figure provides transparency regarding the robustness of the model selection process and the exploration of the search space.

Figure D.1.2: Coherence and Perplexity Scores by Number of Topics (2020–2024 Subcorpus, Four-Trend Model)

