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Analysis and Evaluation of Climate Risk Management Systems Using Gray Relational Analysis

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ABSTRACT

Climate change is further disrupting businesses through increasing climate risks such as flooding and severe winds, resulting in higher costs and lower revenues. In response, FM Global launched the Climate Risk Report, which addresses these climate risks and helps businesses improve their resilience while building long-term confidence. The report is aimed at executives, including CEOs, CFOs and risk managers, to help them make informed decisions about climate resilience investments.

Research significance: This research is important as it improves climate risk management and decision-making for businesses facing increasing climate challenges. Combining data from over 60,000 engineering visits, AI and predictive analytics, the Climate Risk Report provides an accurate and comprehensive climate risk assessment.

This methodology helps businesses categorize risks into actionable insights and build resilience through data-driven choices. By emphasizing data quality and using advanced technologies, this research deepens the understanding of climate-related losses, helping companies reduce billions worth of potential damages and increase overall climate resilience.

Methology: **Alternatives:** 1. AI-Powered Resilience System, 2. Climate Risk Prediction Model, 3. Data Quality Profiling Framework, 4. Integrated Climate Analytics Dashboard, 5. Predictive Hazard Mitigation Platform, 6. Actionable Climate Risk Mapper, and 7. Scalable Resilience Engineering Toolkit. Evaluation criteria include Scalability, Recognition, Complexity, Adoption Difficulty. Result: According to the results, Predictive Hazard Mitigation Platform ranked highest, while Data Quality Profiling Framework ranked lowest. Conclusion: AI for Predictive Hazard Mitigation Platform has the highest value for Climate Risk Report in education according to the Gray Relation Analysis (GRA) approach.

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Introduction

A significant challenge was ensuring that the data used to build the models was of high quality and consistent with the source systems. To address this, a rigorous, iterative process was implemented throughout the ETL process that focused on data profiling, validation, and cleansing, ensuring the accuracy of the data used. Solution and Responsibilities: As the Technology Lead, I worked closely with data scientists and engineering experts to ensure that AI models were integrated into the Hazura Cloud platform. We established a comprehensive data quality framework that included profiling, optimization, and the use of SSIS tools to maintain the integrity and accuracy of the data for reporting. The Climate Risk Report provides clients with critical insights to protect their properties from climate risks and has been recognized by various industry awards. It has significantly helped businesses by providing actionable climate risk recommendations, leading to billions of dollars in potential losses being reduced.

The coefficient of variation of the response variable was significantly high at 88.56%, indicating significant heterogeneity in the level of climate risk disclosure among Brazilian companies. This indicates considerable variation in the data, with some companies disclosing little or no information on climate risks, while others provided extensive details. The level of disclosure varies between companies, the study says. [1] In the field of climate risk management, general communications regarding climate change events can often be misunderstood, and warnings about the immediate threat posed by specific impacts can be misunderstood or not responded to properly.

For example, focus groups examining perceptions of surface flood warnings in the UK revealed that the public and professional emergency responders often struggle to accurately interpret flood probability information. [2] The scientific community has a lot to contribute to this, and they are increasingly recognizing the need to focus more on detail and determining what specific information is needed. This approach can help prepare effectively for climate risks. For example, if a stress test is performed and no operational risks are identified under various climate scenarios, the decision maker can assess climate risk and find minimal or no risks, fulfilling the review requirements without the extensive effort associated with a full GCM-led uncertainty analysis. [3] The time frame for implementing adaptation measures is an important factor to consider.

Users of climate risk information are increasingly focusing on the coming decades, due to concerns that climate change could prevent the United Nations Millennium Development Goals (MDGs) from being achieved, or that new investments may not be effective or lead to poor adaptation. This presents significant technical challenges, as global climate in the coming decades will largely be affected by natural variability arising from perturbations in ocean-atmosphere interactions (OA), changes in solar activity, and the number of aerosols released into the stratosphere by large volcanic eruptions. [4] Each year, with the support of hundreds of institutional investors, CDP requires businesses to report on their corporate climate-related risks, opportunities and performance. Each year, thousands of businesses voluntarily respond, sharing information about their emissions performance and categorizing operational climate risks and opportunities as regulatory, climate-related or a result of changing perceptions of their reputation.

Other risk disclosure platforms complement CDP's disclosure efforts. Investors use risk measurement scores as an additional tool when making investment choices, as the risk disclosure standard is aligned with the TCFD criteria. By marketing these measurement scores to investors, business climate risk management creates new revenue streams. For example, investment research firm Morningstar has developed a climate risk score that assigns a number to businesses according to their exposure to climate. [5] The prolonged duration of this system resulted in extensive rainfall over several days. At the same time, Harvey produced a moderate-altitude storm surge along the coast, which affected a wide area with high water levels and multiple tidal cycles over five days. This significantly inhibited inland freshwater drainage capacity. In terms of climate, exceptionally high sea surface temperatures intensified the tropical system, and the resulting sea level rise resulted in higher baseline sea levels than had been seen a century earlier. [6] The corporate investment community's concerted efforts have created incentives for businesses to disclose information related to climate change. The Carbon Disclosure Project (CDP), the largest international association of institutional investors, unites its members to call for corporate transparency on greenhouse gas emissions. Furthermore, disparities in climate change reporting are being addressed by the Climate Disclosure Standards Board (CDSB). [7] If climate change is perceived as a significant but uncertain challenge for businesses, companies are likely to implement climate risk measures that are consistent with their regular enterprise risk management processes.

However, if this approach is not adopted, climate change adaptation may be viewed as a separate, less important issue, causing companies to overlook climate risks in their corporate planning. As a result, businesses may be unprepared for the negative impacts of climate change, and their adaptation efforts may be delayed. [8] Climate risk management integrates information and data about climate-related events, trends, forecasts, and projections to enhance decision-making and minimize potential harm or losses. This process is multifaceted, requiring a comprehensive approach that addresses socio-economic and environmental factors. The successful use of climate information depends on three key elements: relevance, credibility and legitimacy. Relevance refers to how well the information aligns with the needs of decision-makers, existing practices and decision-making protocols, and its timely delivery. Credibility concerns the perceived accuracy and reliability of the information.

Legitimacy involves ensuring that the information is presented impartially, respects user values and beliefs, and gives fair consideration to differing opinions and interests. [9] To improve our understanding of risk management strategies in the context of climate change, we look at how businesses across industries view and respond to different climate risks. This article specifically highlights how businesses typically approach climate risks with a short-term perspective, focusing on mitigating immediate regulatory issues rather than eliminating them altogether. It also shows that businesses in climate-regulated high-emissions sectors are taking the most significant steps to reduce regulatory risks. These findings suggest that market incentives or physical threats alone may not be enough to drive meaningful business action on climate change, with important implications for politicians and corporate executives. Instead, legislation may be important in determining how businesses respond to the risks associated with climate change. [10] This demonstrates how businesses are responding to climate risks in the short term, prioritizing reducing immediate regulatory risks rather than eliminating them altogether.

It also demonstrates that companies operating in climate-regulated high-emissions industries are addressing regulatory risks in more substantial ways. These findings have significant implications for business executives and policymakers, suggesting that market incentives or tangible risks alone may not be enough to drive sufficient corporate climate change action. Rather, regulatory measures can play a significant role in guiding business responses to climate-related risks. [11] To address concerns about the lack of country-level control variables, we conduct several robustness tests. We use an instrumental variable technique to account for this, and we consistently find comparable results. Furthermore, we use country estimates to link firm characteristics to observations, and the results are consistent. In addition, our results hold up well when we consider variables such as whether a firm is an international firm or has climate risk insurance. We independently include CRI sub-indicators, test alternative measures of climate-related risk, and exclude U.S. firms from the model. [12] After providing a brief summary of the essential elements of dominant adaptive governance, we look at the importance of unbounded climate threats and their consequences. The importance of regional structures is illustrated using the concepts of knowledge communities and norm diffusion. Looking to the future, we highlight additional efforts to better address unbounded climate threats, exploring possible governance responses at different scales and levels, and incorporating multiple perspectives on international relations. [13] It is safe to say that the work of the IPCC has had a significant impact on the current conceptualization of climate vulnerability and risk.

Our aim in this study is not to redefine concepts or definitions, but rather to examine and evaluate how dynamics are incorporated into the design of existing assessments. It is crucial to assess the progress of the field in light of new techniques and methodologies. To do this, we provide a comprehensive analysis of sub-national assessments of climate risk and vulnerability, distinguishing between exposure and vulnerability dynamics based on three criteria. Our research question is: How are the dynamics of climate risk handled? [14] First, traditional macroeconomic and financial research techniques are inadequate to handle the unique features of climate risks, such as deep uncertainty, nonlinearity, and intra-activity. Rather than rebranding current models as "climate change" or "green," researchers need to address the fundamental issues raised by climate threats to make progress in this area. [15] Our survey looks at five key topics: how climate risks affect investment choices, how they affect risk management, how they affect stakeholder engagement, how they affect asset pricing, and how investor's view companies' exposure to climate risks.

When asked the first questions about the importance of climate risks, respondents found traditional financial risks to be the most important. These were followed by operational, governance, and social concerns. Environmental and climate threats came in fifth and sixth place, respectively. However, this low ranking does not mean that climate concerns are not important from a financial perspective. [16] Environmental processes and their interactions are just one of the many ways in which risk is transferred from one region to another. These processes include changes in shared resources such as fisheries or transboundary water flows, as well as air and water pollution that crosses jurisdictional boundaries. However, there are many direct and indirect mechanisms by which climate risks can permeate complex socio-ecological systems. [17] This kind of attentive listening helps to prevent overly prescriptive responses to difficult issues. For example, scientists might avoid it altogether if they were to justify uncertainty as a justification for inaction. If they knew that climate threats involve complex and unpredictable processes, the public might be reluctant to accept judgments based on incomplete knowledge. An analogy can be drawn to the past, when British consumers were assured that British beef was completely safe, despite unresolved evidence of the spread of bovine spongiform encephalopathy (BSE) to humans. [18] A new feature has recently emerged as a result of potential changes in rainfall patterns due to global warming, emphasizing the importance of determining whether rainfall records reflect these changes. It is wrong to assess the risks posed to farmers by climate change based on 50 to 60 years of records without first ensuring that no significant changes have occurred in the past few years. [19] Planning is aided by the Hunger and Climate Vulnerability Index, which provides a national assessment of food security and climate risks.

This methodology can be scaled to sub-national levels to accurately identify and assess environmental risks, monitor vulnerability trends, assess project performance, and/or explore potential climate change impacts by integrating climate projections and adaptation scenarios into the vulnerability index model. [20] In the first stage, we introduce the idea of adaptive boundaries and draw attention to the difficulties in making decisions when faced with climate risk. In the second stage, we explore how decision-makers can use insurance to address these issues and manage adaptive boundaries. In the third stage, we explore the shortcomings of insurance as a climate risk management tool and propose policies that can help vulnerable people and countries move from adaptive boundaries to a safe and manageable risk space. [21] Businesses can use a variety of corporate governance techniques, for example establishing a dedicated carbon management team, linking CEO compensation to carbon reduction targets, or defining carbon targets. From a resource-based perspective, businesses that are more aware of carbon risks ensure that their resources are used and coordinated efficiently to achieve the intended climate performance outcomes. One of the most important elements of managerial competence in carbon management is the ability to assess climate risks and opportunities. [22]

Materials and methods

[21] As far as we are aware, this is the first thorough prospective study carried out in real-world clinical settings to investigate the potential benefits of a 12-month lifestyle intervention on histological features associated with NASH. Until now, only a few studies have explored this area. examined the effects of lifestyle changes on NAFLD. Variations in study designs—such as differing methods of intervention, lack of standardized endpoints, diverse NAFLD phenotypes, and varying follow-up durations—along with relatively small patient samples in previous trials have resulted in inconclusive recommendations regarding weight loss strategies for treating NAFLD. [22] Strong protein-protein interactions with GRA6, mostly mediated by hydrophobic interactions, enable GRA4 to

associate with network barriers. GRA6 that has undergone phosphorylation exhibits a higher affinity for network membranes inside the vacuole. Furthermore, a multimeric complex that is consistently related to an intravacuolar network—possibly implicated in the transport process—is formed when cross-linked GRA4 and GRA6 bind particularly to GRA 2. of proteins or nutrients into the vacuole. [23] The field of information systems known as gray systems utilizes gray theory, a method adept at mathematically analyzing systems to tackle uncertainty and incomplete data. This approach is particularly effective for addressing problems involving discrete data and missing information. Gray Prediction, Gray The five primary components of the program are Relational Analysis (GRA), Gray Decision, Gray Programming, and Gray Control. theory. [24] We describe an expanded fuzzy GRA technique for MCDM issues, in which the criteria weights are unknown and the Triangular fuzzy integers with interval values are used to represent the criteria values. utilizing linguistic variables. Optimization models grounded in the basic ideas of classical GRA have been created to ascertain these weights. After that, interval-valued triangular fuzzy estimates are used in the computational stages of the expanded GRA method for MCDM to rank the alternatives and select the preferred option. [25] Gray relational analysis (GRA) is an essential method for examining gray data in uncertain systems. This study highlights that, due to variations in the shape and threshold of different sequences, A particular model that is sensitive to data normalization is the absolute GRA (AGRA) model. Hence, normalization should be conducted as an initial step before performing gray correlation analysis.[26] To determine the entropy weights of the criteria, intuitive fuzzy entropy is used. Due to its simplicity and readability, the GRA technique is often used for multi-criteria decision-making situations. Therefore, a new strategy that can improve the efficiency of personnel selection procedures is to combine the GRA technique with intuitive fuzzy sets. [27] Energy producers have been evaluated using various models and techniques. Gray relational analysis (GRA) is a paradigm for making decisions using multiple criteria and ambiguous situations. Gray numbers are used in this strategy to deal with ambiguity and insufficient information in the evaluations. Interval scales can be used to translate verbal concepts into numerical values, where Gray numbers represent the personal preferences of the decision maker. Using a new sustainability paradigm, we compare and evaluate several renewable and non-renewable energy sources in this research. GRA has been used in many investigations, however, it has some shortcomings. [28] Another method for developing a decision-making model that combines quantitative analysis with fuzzy data is the Gray System. The Gray System is used when information is only partially known. Its five components are Gray Method Prediction, Gray Method Decision Making, Gray Correlation Analysis (GRA), Gray Control, and Programming. GRA is a useful technique when dealing with complex problems involving relationships between multiple variables and discrete data sets under complex attribute conditions. The GRA model is often used to solve problems related to uncertainty, especially when working with discrete and incomplete data. [29] The goal of this study is to investigate the GRA approach combined with the CRITIC method to address probabilistic linguistic MAGDM problems with uncertain weights. The main uncertainties in this study are as follows: (1) the focus is on linguistic MAGDM problems; (2) the CRITIC method is used to objectively calculate attribute weights using the scoring function of PLTs; (3) the GRA method is extended to combine PLTSs with unknown weight information; and (4) a case study is included to select a platform for EVCS to demonstrate the proposed approach. [30]

Alternatives

AI-Powered Resilience System:

This system uses artificial intelligence to improve the ability of organizations to withstand and recover from climate-related challenges. It integrates AI algorithms to analyze vast datasets, predict climate impacts, strengthen resilience strategies, and provide real-time recommendations for better decision-making and resource allocation.

Climate Risk Prediction Model:

This model uses historical climate data, weather patterns, and predictive analytics to predict potential climate risks that a company or region may face in the future. It assesses risks such as floods, storms, and heat waves, helping businesses prepare for and mitigate these risks before they occur.

Data Quality Specification Framework:

This framework ensures the accuracy and consistency of climate-related data by providing a structured approach to assessing and improving data quality. It profiles and monitors datasets to identify anomalies, outliers, and gaps, ensuring that the data used for analysis and decision-making is reliable and accurate.

Unified Climate Analytics Dashboard:

An interactive and comprehensive tool that aggregates and visualizes climate-related data in real time. It integrates multiple data sources, such as climate risk, business resilience, and environmental conditions, enabling users to track key indicators, monitor performance, and make informed decisions on climate-related actions.

Predictive Risk Mitigation Platform:

This platform uses machine learning and predictive analytics to identify potential hazards, such as extreme weather events, and recommends mitigation measures to reduce their impact. By anticipating climate-related risks, this platform helps organizations proactively protect their assets and operations.

Actionable Climate Risk Mapper:

A visual tool that maps climate risks at a granular level, such as location, building, or asset type. It provides actionable insights by highlighting areas most vulnerable to climate events, enabling stakeholders to take targeted steps to reduce exposure and implement climate resilience measures.

Scalable Resilience Engineering Toolkit:

A set of tools and methodologies designed to support the design, testing, and implementation of scalable resilience strategies. From infrastructure design to resource management, this toolkit helps organizations implement engineering solutions that can withstand the impacts of climate change, ensuring long-term sustainability.

Benefit Parameters

Scalability: The ability to manage billions of data points and a wide range of scenarios.

Recognition: Industry accolades, media features, and professional accolades.

Non-Benefit Parameters

Complexity: Difficulties in data integration, ETL processes, and quality assurance.

Adoption Challenges: Obstacles that prevent users from effectively implementing solutions.

Analysis and dissection

Table 1. Climate Risk Report

	DATA SET			
	Scalability	Recognition	Complexity	Adoption Difficulty
1. AI-Powered Resilience System	8	8	6	6
2. Climate Risk Prediction Model	8	7	5	5
3. Data Quality Profiling Framework	7	7	8	7
4. Integrated Climate Analytics Dashboard	8	8	6	6
5. Predictive Hazard Mitigation Platform	9	8	7	6
6. Actionable Climate Risk Mapper	8	7	6	6
7. Scalable Resilience Engineering Toolkit	9	8	7	7

This table outlines a climate risk report that rates different datasets based on four key criteria: scalability, recognition, complexity, and difficulty of adoption. Each dataset is scored on a scale of 1 to 10, with higher scores indicating better performance or greater challenges, depending on the metric. Both the AI-powered resilience system and the integrated climate analytics dashboard are rated highly for scalability (8) and recognition (8). They demonstrate moderate complexity and difficulty of adoption (6 each), suggesting a balance between advanced capabilities and usability. The climate risk prediction model scores slightly lower in recognition (7) and shows low complexity and difficulty of adoption (5 each), making it accessible while still being useful.

Similarly, the actionable climate risk mapper reflects this trend, with moderate scores across all metrics, ensuring usability without sacrificing performance. The Data Quality Specification Framework stands out for its high complexity (8) but slightly lower scalability and acceptance (7 each). This may indicate its technical depth and potential mainstream use. Finally, the Predictive Risk Reduction Platform and the Scalable Resilience Engineering Toolkit achieve high scalability (9) and acceptance (8) with relatively high complexity (7) and adoption difficulty (6–7). These systems can be very robust, but may require significant effort to implement.

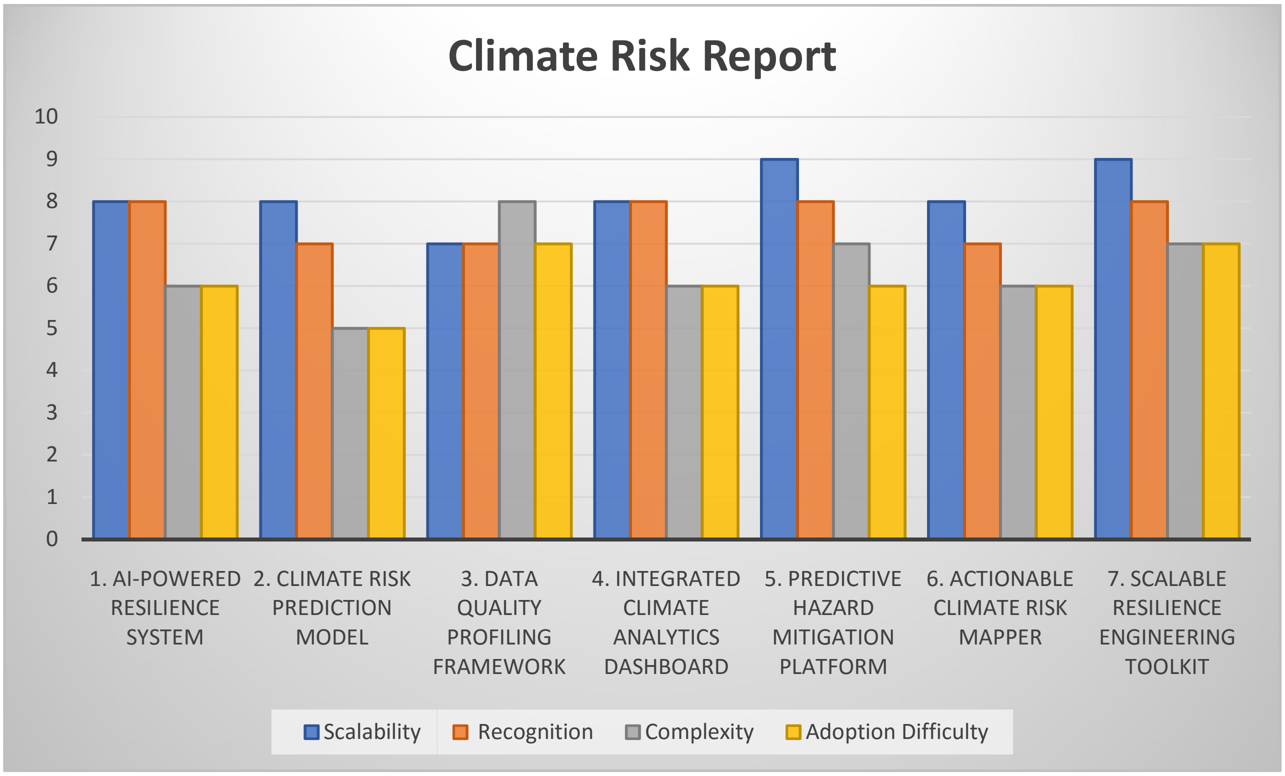

Figure 1. Climate Risk Report

The Climate Risk Report Map provides a visual analysis of seven climate risk-related datasets rated on four key metrics: scalability, recognition, complexity, and difficulty of adoption. Each dataset is rated on a scale of 1 to 10, with distinct colors representing the criteria – blue for scalability, orange for recognition, gray for complexity, and yellow for difficulty of adoption. The Forecast Risk Reduction Platform and the Scalable Resilience Engineering Toolkit achieve the highest scalability scores (9), indicating their strong potential for large-scale application. Similarly, the AI-powered Resilience System and the Integrated Climate Analytics Dashboard perform well in several categories (score 8), reflecting their strong structure and widespread recognition.

The Data Quality Specification Framework stands out due to its high complexity, emphasizing its technical sophistication but also signaling potential implementation difficulties. On the other hand, the climate risk prediction model and the actionable climate risk mapper maintain balanced, moderate scores across all parameters, making them more accessible and easier to integrate into existing systems.

Table 2. Normalized Data

	Normalized Data			
	Scalability	Recognition	Complexity	Adoption Difficulty
1. AI-Powered Resilience System	0.5000	1.0000	0.6667	0.5000
2. Climate Risk Prediction Model	0.5000	0.0000	1.0000	1.0000
3. Data Quality Profiling Framework	0.0000	0.0000	0.0000	0.0000
4. Integrated Climate Analytics Dashboard	0.5000	1.0000	0.6667	0.5000
5. Predictive Hazard Mitigation Platform	1.0000	1.0000	0.3333	0.5000
6. Actionable Climate Risk Mapper	0.5000	0.0000	0.6667	0.5000
7. Scalable Resilience Engineering Toolkit	1.0000	1.0000	0.3333	0.0000

The normalized data table provides a scaled assessment of seven climate risk-related datasets based on four key factors: scalability, recognition, complexity, and adoption difficulty. Values range from 0 to 1, where 1 represents the highest score in a given category and 0 represents the lowest, allowing for clear comparisons of performance across datasets. The Predictive Risk Reduction Platform and the Scalable Resilience Engineering Toolkit receive the highest scores in scalability (1.0000) and recognition (1.0000), reflecting their strong adaptability and broad acceptance. However, their complexity scores (0.3333) indicate that while they are efficient, they are not as technically complex as some other solutions. Interestingly, the Scalable Resilience Engineering Toolkit has an adoption difficulty score of 0.0000, making it one of the easiest to implement. In contrast, the climate risk prediction model stands out with the highest complexity (1.0000) and adoption difficulty (1.0000), indicating that integration requires considerable effort despite its capabilities. Meanwhile, the data quality specification framework scores 0.0000 on all metrics, indicating that it is the least scalable, least recognized, and least complex of the datasets.

Table 3. Deviation sequence

	Deviation sequence			
	Scalability	Recognition	Complexity	Adoption Difficulty
1. AI-Powered Resilience System	0.5000	0.0000	0.3333	0.5000
2. Climate Risk Prediction Model	0.5000	1.0000	0.0000	0.0000
3. Data Quality Profiling Framework	1.0000	1.0000	1.0000	1.0000
4. Integrated Climate Analytics Dashboard	0.5000	0.0000	0.3333	0.5000
5. Predictive Hazard Mitigation Platform	0.0000	0.0000	0.6667	0.5000
6. Actionable Climate Risk Mapper	0.5000	1.0000	0.3333	0.5000
7. Scalable Resilience Engineering Toolkit	0.0000	0.0000	0.6667	1.0000

The deviation rank table highlights the variation in four primary assessment criteria – scalability, recognition, complexity and adoption difficulty – across seven climate risk-related datasets. Values range from 0 to 1, where 0 represents the least deviation and 1 represents the greatest deviation from a reference point. This table helps to identify datasets with the most variation in performance on these factors. The data quality specification framework shows the most significant deviation across all categories (1.0000), indicating significant differences in scalability, recognition, complexity and adoption difficulty compared to other datasets. This suggests that this may be an outlier or may show inconsistent performance. In contrast, the Predictive Risk Reduction Platform and the Scalable Resilience Engineering Toolkit show the least deviation in scalability (0.0000), meaning they closely align with the reference standard in this area. However, both show a moderate deviation in complexity (0.6667), reflecting some variation in technical sophistication. In addition, the scalable resilience engineering toolkit has a high deviation in adoption difficulty (1.0000), indicating that its implementation ease differs significantly from other datasets.

Table 4. Grey relation coefficient

	Grey relation coefficient			
	Scalability	Recognition	Complexity	Adoption Difficulty
1. AI-Powered Resilience System	0.5000	1.0000	0.6000	0.5000
2. Climate Risk Prediction Model	0.5000	0.3333	1.0000	1.0000
3. Data Quality Profiling Framework	0.3333	0.3333	0.3333	0.3333
4. Integrated Climate Analytics Dashboard	0.5000	1.0000	0.6000	0.5000
5. Predictive Hazard Mitigation Platform	1.0000	1.0000	0.4286	0.5000
6. Actionable Climate Risk Mapper	0.5000	0.3333	0.6000	0.5000
7. Scalable Resilience Engineering Toolkit	1.0000	1.0000	0.4286	0.3333

The Gray Relation Coefficient Index assesses the relationships between seven climate risk-related datasets based on four essential factors: scalability, recognition, complexity, and adoption difficulty. Scores range from 0 to 1, with higher values indicating stronger similarity to the best reference, allowing for the identification of more useful and balanced datasets. Both the Predictive Risk Reduction Platform and the Scalable Resilience Engineering Toolkit receive very high ratings in scalability (1.0000) and recognition (1.0000), reflecting their strong adaptability and broad acceptance. However, their complexity scores (0.4286) are lower than the other datasets, suggesting that they may be less technically sophisticated. In addition, the Scalable Resilience Engineering Toolkit has a relatively low adoption difficulty score (0.3333), making it one of the easiest to implement. On the other hand, the climate risk prediction model stands out with the highest complexity (1.0000) and adoption difficulty (1.0000), indicating that although technically advanced, integration may be very challenging. In contrast, the data quality specification framework maintains a consistent score of 0.3333 across all metrics, indicating that it has low relevance compared to other datasets.

Table 5. GRG

	GRG
1. AI-Powered Resilience System	0.6500
2. Climate Risk Prediction Model	0.7083
3. Data Quality Profiling Framework	0.3333
4. Integrated Climate Analytics Dashboard	0.6500
5. Predictive Hazard Mitigation Platform	0.7321
6. Actionable Climate Risk Mapper	0.4833
7. Scalable Resilience Engineering Toolkit	0.6905

Table 5 outlines the various systems and platforms related to climate risk and resilience, each accompanied by a score reflecting its perceived effectiveness or importance in global risk management (GRG). These scores can indicate how much impact each system has in strengthening resilience to climate-related challenges. The "Predictive Risk Reduction Platform" ranks highest with a score of 0.7321, highlighting its importance as a key tool for predicting and managing climate risks. The "Climate Risk Prediction Model" with a score of 0.7083, underscoring its importance in predicting climate risks. Both platforms are important in proactive risk management strategies. Systems such as the "AI-powered Resilience System" (0.6500) and the "Integrated Climate Analytics Dashboard" (0.6500) also play a key role in improving climate resilience through technological solutions and data integration. Additionally, the "Scalable Resilience Engineering Toolkit" (0.6905) emphasizes the importance of providing flexible engineering solutions to improve resilience at various scales. At the lower end of the scale, the "Actionable Climate Risk Mapper" (0.4833) and the "Data Quality Specification Framework" (0.3333) are still valuable, but may be considered less essential in directly driving resilience efforts compared to the higher-rated systems.

Table 6. Rank

	Rank
1. AI-Powered Resilience System	4
2. Climate Risk Prediction Model	2
3. Data Quality Profiling Framework	7
4. Integrated Climate Analytics Dashboard	4
5. Predictive Hazard Mitigation Platform	1
6. Actionable Climate Risk Mapper	6
7. Scalable Resilience Engineering Toolkit	3

Table 6 provides a ranking of various systems and platforms related to climate risk and resilience, with each system assigned a rank based on its importance or priority. A lower ranking number indicates a higher perceived importance. At the top of the list is the "Predictive Risk Mitigation Platform" at number 1, highlighting its key role in identifying and managing climate-related risks. It is considered the most important tool in this category. The "Climate Risk Prediction Model" and the "Scalable Resilience Engineering Toolkit" are ranked 2 and 3 respectively, reflecting their importance in predicting climate risks and providing adaptive solutions for resilience. The "AI-powered resilience system" and the "Integrated Climate Analytics Dashboard" both rank 4, indicating that they are considered equally important in improving climate resilience through the use of technology and integrated analytics. At the lower end, the "Actionable Climate Risk Mapper" ranks 6th, indicating that it has somewhat lower priority in terms of immediate impact. The "Data Quality Specification Framework" ranks 7th, placing it as the least important system relative to the others in improving climate resilience efforts.

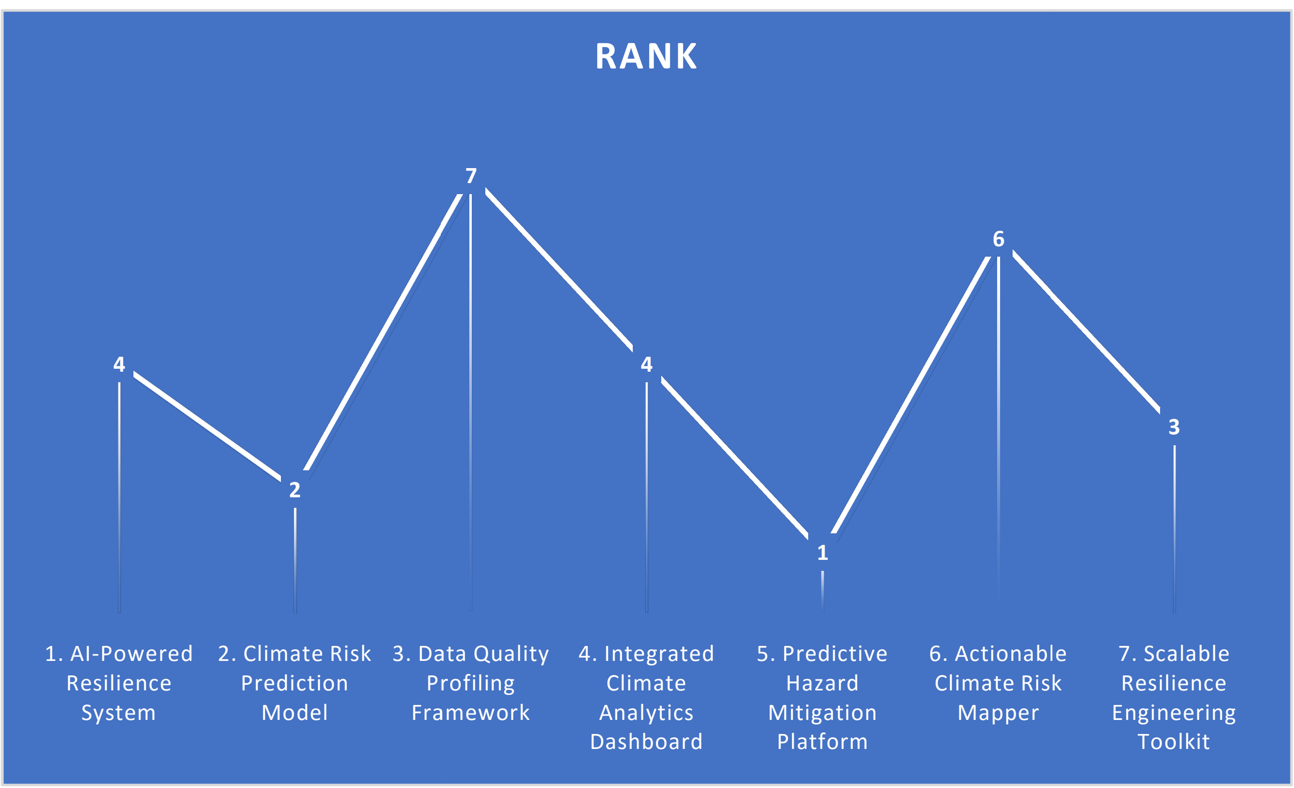

Figure 2. Rank

Figure 2 provides a visual overview of the rankings for various climate resilience and risk management systems, illustrating the relative priority of each system based on its assigned rank. Predictive Risk Reduction Platform" ranks first, emphasizing its important role in addressing and mitigating climate-related risks, making it a very important tool in climate resilience efforts. Next is "Climate Risk Prediction Model" in second place, highlighting its importance in predicting climate-related risks. Scalable Resilience Engineering Toolkit" ranks third, reflecting its importance in providing adaptive engineering solutions for resilience in various contexts. "AI-Powered Resilience System," "Integrated Climate Analytics Dashboard," and "Actionable Climate Risk Mapper" all share fourth place, suggesting their equal contribution to improving climate resilience through technology and data integration. At the bottom of the list, "Data Quality Specification Framework" is ranked seventh, indicating that it is considered less essential in directly improving climate resilience efforts. The ranking distribution shows a clear focus on risk reduction and climate risk prediction, with other tools playing a supporting role in comparison

Conclusion

Climate risk disclosure is remarkably inconsistent among Brazilian companies, as they provide varying levels of information on climate-related risks. Some companies provide extensive disclosures, while others provide very little or no information, which is relevant given the important role of transparent communication in addressing climate risks. This variation underscores the need for a more standardized approach to climate risk reporting, as insufficient disclosure can leave companies vulnerable to climate-related disruptions. The study highlights the challenges in effectively communicating climate risks, where generic warnings are often misunderstood. It emphasizes the importance of providing comprehensive, contextual information that is accessible and clear to both the public and experts. For example, the complexity of flood risk perceptions, as seen in UK focus groups, highlights the need to communicate climate information in a way that ensures appropriate responses to climate threats.

Long-term climate projections and stress tests are critical for risk management, as they allow businesses and policymakers to assess future climate impacts. However, the uncertainties surrounding climate change, particularly due to natural variability, make it necessary for businesses to adopt flexible and adaptive strategies to manage climate risks over time. Integrating climate projections into vulnerability models, such as the Hunger and Climate Vulnerability Index, can provide a broader understanding of climate risks and food security at both national and local levels. Furthermore, the study highlights the important role of regulation in encouraging corporate action on climate risks. Market forces alone will not be sufficient to enable businesses to effectively manage climate risks. Regulatory measures and corporate governance measures, such as setting carbon reduction targets and linking CEO compensation to climate performance, can encourage companies to focus on long-term sustainability and invest in climate resilience.

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