

AI-Enabled Climate Risk Intelligence: Predicting Environmental Disruptions and Their Economic Impact on Global Supply Chains

MD. Mominur Rahman^{1*}, Md. Ehteshamul Haque², MD Shoriful Hasan Chowdhury³¹ *Leading University, Sylhet, Bangladesh*² *Jagannath University, Dhaka, Bangladesh*³ *University of Scholars, Dhaka, Bangladesh* *Corresponding author: muminur.tamal97@gmail.com

Received 12 June 2026; Revised 18 July 2026; Accepted 26 August 2026; Published: 29 September 2026

KEYWORDS

Artificial Intelligence,
Climate Risk Intelligence,
Enterprise Risk Management,
Green Supply Chain Management,
ESG Disclosure,
Carbon Economics

Abstract

Global industrial supply chains face unprecedented threats from escalating climate volatility and stringent environmental regulations. As extreme weather events and new regulatory frameworks such as Carbon Border Adjustment Mechanisms (CBAM) and single-use plastic bans disrupt traditional operations, enterprises must adapt to maintain financial solvency. This paper synthesizes empirical data across multiple recent econometric and techno-economic studies to demonstrate how integrating Artificial Intelligence (AI) and Enterprise Risk Management (ERM) can predict environmental disruptions and actively mitigate economic losses.

Key findings indicate that structured ERM adoption improves corporate eco-efficiency by 14.2%, while transparent, third-party audited ESG reporting significantly lowers the corporate cost of capital by reducing debt pricing. Furthermore, targeted technological investments specifically in AI-managed renewable microgrids and dynamically charged electric delivery fleets can cut operational energy costs by nearly half, achieving investment payback in under five years. By contrasting profitable sustainability initiatives with capital-intensive challenges like Industrial Carbon Capture and Storage (CCS), this research provides a comprehensive, data-driven framework for executive leadership and policymakers to successfully reconcile ecological compliance with long-term corporate profitability.

1. Introduction

Climate change has become an increasingly important source of operational, financial, and strategic risk for global supply chains. Rising temperatures, floods, cyclones, droughts, heatwaves, wildfires, and other extreme events can damage production facilities, interrupt transportation networks, reduce the availability of critical inputs, and increase recovery and insurance costs. The Intergovernmental Panel on Climate Change (IPCC, 2022, 2023) documents the widespread impacts of climate change and the growing importance of adaptation and resilience. These developments indicate that climate risk is no longer solely an environmental concern. It has become an enterprise risk that can influence production continuity, operating costs, revenues, liquidity, investment decisions, and long-term competitiveness.

The economic consequences of physical climate risk can extend beyond firms and facilities directly exposed to environmental hazards. Modern supply chains are interconnected through suppliers, manufacturers, logistics providers, distributors, financial institutions, and customers. Consequently, disruption at one point in a network can propagate across multiple organizations and geographic regions. Ivanov and Dolgui (2020) examined the viability of interconnected supply networks and emphasized the importance of survivability in supply chain resilience. Similarly, Ivanov and Dolgui (2021) explored operational research approaches for addressing ripple effects during the COVID-19 pandemic, demonstrating the importance of understanding how disruptions can spread through interconnected supply networks. Empirical evidence also indicates that exposure to extreme heat can negatively affect firm revenues and operating income, linking physical climate risk to measurable financial consequences (Pankratz et al., 2023). This interconnected nature of supply chains creates a need for risk management approaches capable of identifying both direct environmental exposure and indirect disruption pathways.

Climate-related transition risks further complicate this environment. Governments and international markets are introducing carbon pricing mechanisms, environmental regulations, emissions standards, and sustainability reporting requirements. The European Union's Carbon Border Adjustment Mechanism (CBAM) is an important example because it links the carbon intensity of certain imported products with the costs associated with international trade. The European Commission's CBAM guidance and implementation materials describe the mechanism's regulatory requirements, while the United Nations Conference on Trade and Development (UNCTAD, 2021) examines the potential

trade and development implications of carbon border adjustment measures. These developments indicate that environmental performance can influence regulatory compliance, production costs, export competitiveness, and the economic position of firms within global supply networks. For organizations operating across jurisdictions, climate-related transition risks therefore need to be considered alongside physical hazards and conventional operational uncertainties.

Enterprise Risk Management (ERM) provides an organizational mechanism for integrating environmental risks into corporate decision-making. Traditional risk management approaches may evaluate individual risks separately, whereas climate-related disruptions can involve interconnected physical, financial, operational, regulatory, and reputational consequences. Integrating climate risk into ERM enables organizations to identify potential exposures, assess the likelihood and severity of disruptions, establish risk responses, and incorporate environmental uncertainty into strategic planning. Sharfman and Fernando (2008) examined the relationship between environmental risk management and the cost of capital, providing a foundation for considering how environmental risk management may relate to corporate financing outcomes. Marchese et al. (2018) also explored the similarities and differences between resilience and sustainability in environmental management, highlighting the importance of distinguishing related concepts when developing integrated risk management strategies. Together, these perspectives support examining climate risk not as an isolated environmental issue but as a component of broader organizational risk and financial decision-making.

Artificial Intelligence (AI) introduces additional capabilities for climate risk intelligence because it can process large volumes of heterogeneous information and identify patterns that may be difficult to detect through conventional analytical approaches. Climate risk assessment can involve weather observations, geographic exposure, supplier information, transportation data, energy consumption, market indicators, regulatory developments, and historical disruption records. AI-based analytical systems can potentially integrate these information sources to identify emerging risk patterns, estimate disruption probabilities, prioritize vulnerable suppliers or facilities, and support scenario-based decision-making. Baryannis et al. (2022) reviewed the application of artificial intelligence to supply chain risk management and identified research opportunities for improving risk identification and management. Yaroson et al. (2023) similarly reviewed AI techniques for enhancing supply chain resilience and proposed a broader framework for

understanding their potential contribution to disruption management. These studies provide a foundation for examining how AI capabilities could be applied to climate-related supply chain risks.

The role of AI is particularly relevant because climate-related supply chain risks are dynamic and geographically distributed. Conventional risk assessments may rely heavily on historical information and periodic evaluations, while environmental conditions, supplier circumstances, and regulatory requirements can change rapidly. AI-enabled monitoring could support more continuous assessment by incorporating new information and updating risk estimates. Large language models (LLMs) may also contribute to supply chain risk intelligence by extracting, classifying, and summarizing information from unstructured sources such as news reports. Shahsavari et al. (2024) examined event identification for supply chain risk management through news analysis using large language models, illustrating the relevance of language-based AI techniques to identifying emerging supply chain events. However, applying these techniques to climate risk intelligence requires further consideration of information reliability, prediction accuracy, explainability, and the translation of identified events into actionable organizational decisions. AI should therefore be understood as a potential analytical capability within ERM rather than a replacement for managerial judgment, accountability, or risk governance.

Climate-related disclosure requirements further strengthen the connection between environmental risk intelligence, corporate governance, and financial decision-making. The International Sustainability Standards Board issued IFRS S2, Climate-related Disclosures, in 2023. The standard addresses climate-related risks and opportunities, including governance, risk management, strategy, metrics, and targets. It also emphasizes the relevance of climate-related risks and opportunities to an organization's business model and value chain (International Financial Reporting Standards Foundation, 2023). These requirements increase the importance of reliable climate risk information because organizations need to understand and communicate how environmental risks may affect their operations, cash flows, access to finance, and long-term prospects. Integrating climate risk intelligence into ERM can help organizations connect risk identification and assessment with governance processes, strategic planning, and climate-related disclosure.

The relationship between environmental performance and financial outcomes also makes credible risk assessment important for investors, lenders, regulators, suppliers, and other stakeholders. Sharfman and Fernando (2008) provide a relevant basis for examining the relationship between environmental risk management and corporate financing costs. Pankratz et al. (2023) offer complementary empirical evidence concerning the financial implications of climate exposure at the firm level. Together, these studies support the importance of understanding environmental risks in economic and financial terms. Nevertheless, the financial implications of climate risk may differ across industries, geographic locations, firm characteristics, and regulatory environments. Consequently, organizations should avoid assuming that all environmental investments or risk management initiatives will produce equivalent financial benefits. Reliable evidence, appropriate measurement, and context-specific assessment remain important for evaluating environmental performance and its potential economic consequences.

At the operational level, organizations must also evaluate whether climate mitigation, adaptation, and supply chain sustainability initiatives generate economically sustainable outcomes. Renewable energy adoption, energy efficiency improvements, changes in logistics systems, and circular supply chain practices may offer opportunities to reduce environmental impacts and improve resource efficiency. However, their economic benefits depend on implementation costs, technological suitability, infrastructure availability, regulatory conditions, and organizational capabilities. Jabbour et al. (2019) examined the potential of artificial intelligence and digital technologies to enable new business models within the circular economy. Bhattacharya et al. (2024) reviewed applications of AI in closed-loop supply chains and identified directions for future research. These studies provide a basis for considering how digital technologies and sustainable supply chain practices can be integrated into organizational decision-making. Rather than presuming that every sustainability investment is financially beneficial, an integrated risk framework should evaluate environmental outcomes

alongside costs, operational requirements, and potential resilience benefits.

Despite the growing literature on climate risk, supply chain resilience, environmental management, AI, and corporate disclosure, these research streams address different aspects of the broader problem. Climate assessments examine physical impacts and adaptation requirements, while supply chain research frequently emphasizes disruption propagation, operational resilience, and recovery. AI-focused studies investigate analytical techniques for risk identification and prediction, whereas climate-related disclosure standards emphasize governance, risk management, and the communication of material risks. Comparatively less attention has been given to integrating AI-based environmental risk prediction with ERM, supply chain resilience, regulatory exposure, and the resulting economic consequences within a single analytical perspective. This gap is particularly important for global supply chains because environmental disruptions can simultaneously generate operational losses, compliance costs, changes in resource availability, financing implications, and shifts in international competitiveness.

This study therefore develops an AI-enabled climate risk intelligence perspective that connects environmental disruption prediction with enterprise risk management and economic impact assessment. It synthesizes literature on physical climate risks, environmental regulation, climate-related disclosure, supply chain resilience, AI-based risk identification, and sustainable supply chain management to examine how organizations can identify and respond to climate-related threats. Particular attention is given to the economic implications of environmental disruptions and the potential role of AI in improving early warning, risk prioritization, scenario assessment, and decision support. The study also considers the need to evaluate sustainability-related investments in relation to their environmental benefits, implementation costs, and potential contributions to operational resilience.

By integrating AI, ERM, climate risk intelligence, and green supply chain management, this research contributes to a more comprehensive understanding of how organizations can move from reactive responses toward predictive environmental risk management. The proposed perspective recognizes that climate resilience is not solely a matter of reducing environmental impacts. It also requires organizations to anticipate disruption, evaluate potential economic consequences, allocate resources effectively, maintain regulatory compliance, and strengthen the resilience of interconnected supply networks. In this context, AI-enabled climate risk intelligence can serve as a decision-support mechanism through which environmental information is transformed into actionable risk and economic intelligence. Its effectiveness, however, depends on the quality of available data, the reliability of analytical models, appropriate validation, and integration with established governance and risk management processes.

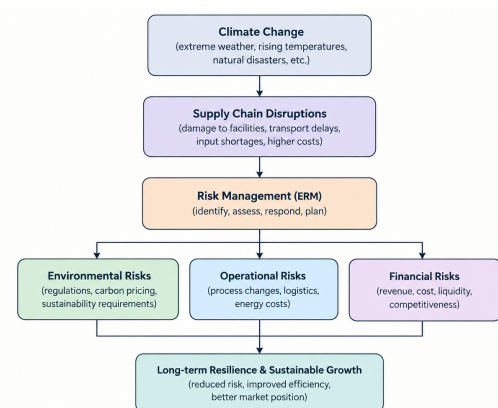


Figure 1. Integrated Climate Risk and Economic Impact Management Framework.

2. Literature Review

2.1 Climate Risk and Global Supply Chain Disruptions

The relationship between climate change and supply chain disruption has received increasing attention as firms become more dependent on

geographically dispersed production and logistics networks. Climate-related hazards can affect supply chains through direct physical damage to facilities and infrastructure, as well as indirect effects on suppliers, transportation systems, inventories, labor availability, energy supply, and market demand. Mora et al. (2024) examined climate risk externalities transmitted through global supply chains and highlighted the difficulty of capturing indirect effects through conventional corporate assessment approaches. This cascading nature of climate risk is important because the location of a firm's own facilities does not necessarily represent its complete environmental exposure.

Research on interconnected supply networks also demonstrates the importance of understanding how disruptions propagate across organizations and geographic regions. Ivanov and Dolgui (2020) examined the viability of interconnected supply networks, emphasizing the importance of network survivability. Ivanov and Dolgui (2021) further investigated approaches for managing ripple effects in supply chains during the COVID-19 pandemic. Although these studies address broader supply chain disruptions, their findings provide a relevant foundation for examining how climate-related hazards may affect interconnected production and distribution systems.

The economic effects of physical climate risk can also become apparent through firm performance. Pankratz et al. (2023) examined climate change, firm performance, and investor surprises, providing empirical evidence concerning the financial relevance of climate exposure. Such evidence supports examining how environmental disruptions can translate into changes in operating conditions, business continuity, revenues, and financial performance. Consequently, climate risk intelligence systems should consider both environmental exposure and the potential operational and economic consequences of disruptions.

Climate risk also includes transition risks arising from changes in environmental policy, carbon regulation, technology, and market expectations. These risks can affect production costs, sourcing decisions, and international competitiveness even when firms are not directly exposed to physical climate hazards. Understanding both physical and transition risks is therefore essential for developing a comprehensive approach to climate-related supply chain risk management.

2.2 HClimate Transition Risk, Environmental Regulation, and Carbon Economics

Climate-related transition risks are increasingly relevant to supply chain decision-making because environmental regulations can change production costs, sourcing decisions, international competitiveness, and investment requirements. The European Union's Carbon Border Adjustment Mechanism (CBAM) represents an important example because it links the embedded emissions of selected imported products with the European Union's carbon pricing framework. The European Commission's CBAM materials provide information about the mechanism's regulatory requirements and implementation, while UNCTAD (2021) examines the potential trade and development implications of climate-related trade measures.

Carbon-related trade requirements may create additional challenges for exporters whose production systems are relatively emissions-intensive. Consequently, carbon efficiency can become an important consideration in international supply chain competitiveness. Organizations operating across different regulatory environments may need to assess potential changes in compliance costs, production processes, and sourcing arrangements when evaluating climate transition risks.

Environmental regulation extends beyond carbon pricing. Requirements concerning waste management, emissions, energy efficiency, and product standards can influence supply chain structures and production practices. From an enterprise risk management perspective, such requirements should be considered alongside conventional operational and financial risks because regulatory changes may require new technologies, revised procurement practices, or adjustments to production systems.

The literature on sustainability and circular supply chains also highlights the importance of evaluating environmental initiatives in relation to their economic implications. Jabbour et al. (2019) examined how artificial intelligence and digital technologies can enable new business models based on the circular economy. Bhattacharya et al. (2024)

reviewed applications of artificial intelligence in closed-loop supply chains, providing a foundation for considering how technological and operational changes may support more sustainable supply chain practices. These perspectives suggest that climate risk intelligence should help organizations evaluate not only environmental threats but also the costs, feasibility, and potential operational benefits of alternative responses.

2.3 Enterprise Risk Management and Green Supply Chains

Enterprise Risk Management (ERM) provides a framework through which organizations can identify, assess, monitor, and respond to interconnected risks. Climate change makes this integration particularly important because environmental hazards and transition pressures can simultaneously affect operations, finance, compliance, reputation, and strategic planning. Risk management approaches that examine individual risks independently may be insufficient when disruptions generate cascading consequences across multiple business functions.

Research has established a relationship between environmental risk management and corporate financial conditions. Sharfman and Fernando (2008) examined environmental risk management and the cost of capital, providing an empirical basis for considering the financial implications of environmental risk management practices. This relationship is relevant to climate risk because environmental exposure can influence how organizations evaluate investment decisions, financing requirements, and long-term financial sustainability.

Green supply chain management extends environmental considerations to procurement, production, logistics, supplier selection, and product recovery. Jabbour et al. (2019) discussed the role of artificial intelligence and digital technologies in enabling circular economy business models, while Bhattacharya et al. (2024) examined AI applications in closed-loop supply chains. These research streams support the integration of environmental objectives into supply chain decision-making rather than treating sustainability as an isolated organizational function.

Resilience and sustainability are related but distinct considerations in environmental management. Marchese et al. (2018) examined their similarities and differences, providing a conceptual basis for understanding why environmental improvement does not automatically guarantee resilience to disruption. Organizations must therefore evaluate whether sustainability initiatives also address their specific operational vulnerabilities, resource dependencies, and recovery requirements.

Integrating climate risk into ERM and green supply chain management can help organizations connect environmental monitoring with operational continuity, regulatory compliance, financial assessment, and strategic planning. Such integration provides a foundation for evaluating how AI-enabled climate risk intelligence can support organizational risk governance.

2.4 Artificial Intelligence in Supply Chain Risk Management

Artificial Intelligence has become an important research area in supply chain management because modern supply chains generate large volumes of structured and unstructured data. AI techniques can support demand forecasting, anomaly detection, supplier assessment, risk identification, inventory optimization, route optimization, and disruption prediction.

Baryannis et al. (2022) reviewed the relationship between supply chain risk management and artificial intelligence, identifying the potential of AI techniques to improve risk identification and management. Shahzadi et al. (2024) examined AI adoption in supply chain management through a systematic literature review, providing a broader perspective on the factors and outcomes associated with the implementation of these technologies. Together, these studies establish a basis for examining AI as a capability that can support both operational decision-making and supply chain risk management.

AI applications can potentially help organizations process information from suppliers, logistics systems, market indicators, and external risk sources. These capabilities may improve the identification of emerging risks and support the prioritization of vulnerable operations. However, the usefulness of AI depends on the availability and quality of data, the reliability of analytical models, organizational capability

ties, and the integration of analytical outputs into established decision-making processes.

Smyth et al. (2024) reviewed AI and prescriptive analytics for supply chain resilience and identified directions for future research. Their work provides a relevant foundation for examining how AI can contribute to resilience-oriented decisions rather than simply generating predictions. For climate risk management, this distinction is important because identifying a potential environmental hazard is only an initial step. Organizations must also determine which facilities, suppliers, transportation routes, and business activities may be affected and what responses are appropriate.

Accordingly, AI should be evaluated according to its contribution to practical risk identification, prioritization, and response. Its value within supply chain management depends not only on predictive accuracy but also on whether its outputs improve operational resilience and support economically informed decisions.

2.5 AI for Climate Risk Assessment and Environmental Intelligence

AI can support climate risk assessment by analyzing relationships between environmental variables, geographic characteristics, historical events, and socioeconomic conditions. Machine learning and related analytical techniques can potentially help identify patterns in climate observations and estimate exposure to environmental hazards. Such capabilities create opportunities for improving early warning, climate adaptation planning, and the prioritization of potentially vulnerable assets.

The IPCC (2022, 2023) provides an important foundation for understanding climate-related impacts, vulnerability, adaptation, and broader climate risks. However, identifying a climate hazard does not automatically establish how an individual organization or supply chain will be affected economically. Climate risk assessment must also consider the location of assets, dependencies on suppliers and infrastructure, operational characteristics, and the potential consequences of disruption.

Mora et al. (2024) highlighted the importance of considering climate risk externalities transmitted through global supply chains. Their work supports a broader approach that considers how environmental exposure can affect firms indirectly through their commercial and operational relationships. Integrating this perspective with AI-based analysis could help organizations investigate potential disruption pathways beyond their immediate facilities.

Nevertheless, climate risk intelligence involves more than hazard prediction. Organizations must interpret analytical results in relation to vulnerability, operational dependencies, financial exposure, and feasible responses. Data limitations, model uncertainty, interpretability, and the difficulty of translating predictions into practical decisions remain important considerations. AI should therefore complement established climate risk assessment and governance processes rather than replace them.

2.6 Predictive AI and Early Identification of Supply Chain Disruptions

An important development in supply chain risk management is the transition from reactive risk response toward predictive risk identification. Traditional approaches may depend on historical assessments, periodic audits, and expert judgment. AI-based systems can potentially monitor information continuously and identify signals associated with emerging disruptions.

Aboutorab et al. (2024) examined adaptive identification of supply chain disruptions through reinforcement learning. Their study provides a relevant example of applying AI to the identification of changing supply chain risks. Such approaches may support more adaptive risk management by incorporating information about evolving conditions rather than relying exclusively on static assessments.

Large language models provide another mechanism for identifying and classifying disruption-related information from unstructured sources. Shahsavari et al. (2024) examined event identification for supply chain risk management through news analysis using large language models. Their work illustrates how language-based AI techniques can support the extraction of relevant information from news sources and its transformation into supply chain risk intelligence.

These capabilities are relevant to environmental disruption monitoring because information about climate-related events can emerge through news reports, government announcements, supplier communications, and other external sources. Integrating such information with weather observations, geographic exposure, and organizational supply chain data could help firms identify potential risks and prioritize further assessment.

However, general disruption identification is not equivalent to climate-specific prediction. An event detection system may identify a reported flood or cyclone without establishing which suppliers will be affected, how long a disruption may last, or what financial losses may result. Translating event information into actionable climate risk intelligence therefore requires additional analysis of exposure, vulnerability, operational dependencies, and economic consequences.

The literature supports examining AI across several stages of supply chain risk management, including detection, classification, prediction, prioritization, and response. An important research opportunity is to connect these capabilities more explicitly with climate-related hazards, transition risks, and their economic implications.

2.7 ESG Disclosure, Greenwashing, and Financial Risk

Environmental, social, and governance (ESG) disclosure is relevant to climate risk management because organizations increasingly need to communicate environmental risks, strategies, and performance to external stakeholders. Reliable disclosure can help investors, lenders, regulators, suppliers, and other stakeholders understand an organization's exposure and approach to managing climate-related risks.

Sharfman and Fernando (2008) examined environmental risk management in relation to the cost of capital, providing a foundation for considering connections between environmental management and corporate financing conditions. Pankratz et al. (2023) further examined the financial implications of climate exposure at the firm level. These studies support the importance of evaluating environmental risks in economic and financial terms, although the effects may vary across firms, industries, and geographic contexts.

Disclosure quality is also important because incomplete, inconsistent, or misleading environmental claims can undermine the reliability of information available to stakeholders. From an ERM perspective, organizations need credible and verifiable environmental information to support risk assessment, strategic planning, and accountability. Simply increasing the quantity of ESG data does not necessarily improve decision-making if the information is inaccurate or insufficiently connected to material risks.

The International Sustainability Standards Board issued IFRS S2, Climate-related Disclosures, in 2023. The standard addresses climate-related risks and opportunities, including governance, strategy, risk management, metrics, and targets (International Financial Reporting Standards Foundation, 2023). It also emphasizes the relevance of climate-related issues to an organization's business model and value chain. These requirements reinforce the importance of connecting climate risk identification with corporate governance, risk management processes, and external reporting.

AI-enabled climate risk intelligence may support these processes by helping organizations organize environmental information, identify emerging risks, and analyze potential consequences. Nevertheless, analytical outputs must be appropriately validated and integrated into reporting and governance procedures to ensure that the resulting disclosures are reliable and meaningful.

2.8 Research Gap

The existing literature provides substantial evidence across several interconnected areas. First, climate-related physical and transition risks can affect supply chain operations, business continuity, and financial performance. Second, ERM and green supply chain management provide organizational mechanisms for identifying and responding to interconnected risks. Third, AI can support the identification, prediction, and analysis of supply chain disruptions. Fourth, climate-related disclosure requirements and environmental risk management connect climate exposure with corporate governance and financial decision-making.

However, these research streams address different aspects of the broader problem. Climate risk research examines environmental hazards, vulnerability, and adaptation, while supply chain studies frequently focus on disruption propagation, operational resilience, and recovery. AI research has demonstrated potential for risk identification and predictive analytics, but general disruption detection does not necessarily explain how climate hazards affect particular supply networks or how those effects translate into economic losses. Similarly, ERM and climate-related disclosure frameworks establish the importance of organizational governance without, by themselves, specifying how AI-based environmental predictions should be converted into operational and financial decisions.

The present study addresses this gap by conceptualizing AI-enabled climate risk intelligence as an integrated approach connecting environmental disruption prediction, enterprise risk management, green supply chain management, regulatory exposure, and economic impact assessment. Rather than treating climate events solely as environmental phenomena, this perspective considers how hazards and transition pressures can propagate through supply networks and affect operating costs, revenues, financing conditions, regulatory compliance, and corporate competitiveness.

The study therefore examines the potential role of AI as a decision-support capability within ERM, focusing on early warning, risk prioritization, scenario assessment, and the evaluation of potential economic consequences. It also emphasizes the importance of assessing sustainability-related responses in relation to environmental outcomes, implementation costs, and operational resilience. By integrating these dimensions, the proposed perspective provides a foundation for investigating how organizations can move from reactive disruption management toward more predictive, economically informed, and climate-responsive supply chain risk management.

3. Methodology

3.1 Research Design

This study adopts a secondary data based mixed analytical methodology to investigate how Artificial Intelligence (AI) can be integrated with Enterprise Risk Management (ERM) to identify environmental disruptions, estimate their potential economic consequences, and support climate resilient global supply chain decisions. The research does not claim to generate a new primary survey dataset.

The methodological design combines four analytical components: climate risk identification, AI enabled disruption intelligence, economic impact assessment, and ERM response evaluation. This structure is consistent with previous research showing that AI can support supply chain resilience through risk visibility, readiness, response, and recovery [16, 28]. The study uses evidence published before January 1, 2026. Sources published during 2026 are excluded from the analytical evidence base so that the research represents knowledge available before the 2026 study period.

The methodological framework is also consistent with IFRS S2, which requires organizations to consider climate related physical risks, transition risks, risk management processes, and effects on cash flows, access to finance, and cost of capital [8].

3.2 Research Objectives

The methodology is structured around five analytical objectives. The first objective is to identify major physical and transition environmental risks affecting global supply chains. The second is to examine how AI and predictive analytics can improve the identification, classification, and monitoring of environmental disruptions. The third is to estimate the potential economic channels through which environmental disruptions affect supply chain performance. The fourth is to examine the role of ERM in converting climate risk information into organizational response strategies. The fifth is to develop an integrated AI enabled Climate Risk Intelligence framework connecting environmental risk prediction with economic impact assessment and supply chain decision making.

3.3 Conceptual Research Framework

The study conceptualizes climate risk as an external source of disruption that enters the supply chain through physical and transition channels. AI acts as an analytical intelligence layer that processes environmental and organizational information, while ERM converts identified risks into organizational responses.

The proposed relationship is represented as:

$$\begin{aligned} \text{Environmental Drivers} &\rightarrow \text{AI Risk Detection} \rightarrow \text{Disruption Probability} \\ &\rightarrow \text{Supply Chain Exposure} \rightarrow \text{Economic Impact} \quad (1) \\ &\rightarrow \text{ERM Response} \rightarrow \text{Resilience Outcome} \end{aligned}$$

The framework contains four principal stages. The first stage focuses on environmental risk identification, where environmental risks are divided into physical and transition risks. Physical risks include floods, cyclones, extreme heat, drought, wildfire, water stress, and other climate related hazards. Transition risks include carbon pricing, Carbon Border Adjustment Mechanisms (CBAM), emissions regulation, plastic restrictions, ESG requirements, technological transition, and changing customer expectations.

The second stage involves AI enabled climate intelligence. AI processes information relating to environmental conditions, historical disruptions, supplier exposure, logistics activity, energy consumption, regulatory changes, and financial performance. Potential AI applications include classification, regression, anomaly detection, time series forecasting, natural language processing, and predictive risk scoring.

The third stage concerns economic impact assessment. Economic consequences are evaluated through production interruption, revenue loss, operating cost increases, transportation disruption, energy cost changes, inventory and recovery costs, supplier replacement costs, regulatory compliance costs, financing and cost of capital effects, and long term competitiveness.

The fourth stage focuses on ERM response. Identified risks are connected to organizational responses including supplier diversification, inventory buffers, renewable energy adoption, microgrid deployment, electric fleet transition, climate resilient infrastructure, carbon management, insurance and financial hedging, regulatory compliance, and continuous AI based monitoring.

3.4 Literature and Evidence Selection

A structured evidence selection process was used to identify relevant studies. The evidence base consists of four major categories: peer reviewed academic research addressing AI, climate risk, supply chain management, and ERM; institutional sources including IPCC, UNCTAD, and the IFRS Foundation; sector and technology studies examining microgrids, electric fleets, and carbon capture and storage; and selected EBEPJ studies addressing CBAM, ESG, ERM, plastic bans, and CCS.

The literature selection emphasizes studies that directly connect at least two of the following dimensions: climate risk, AI, supply chains, ERM, environmental regulation, ESG, or economic performance. Research on AI in supply chain management has identified operational, environmental, social, and economic outcomes associated with AI adoption, while also identifying technological, organizational, economic, and human barriers. Similarly, Ivanov and Dolgui examined AI applications in supply chain resilience and identified applications across readiness, response, and recovery [16].

3.5 Source Selection Criteria

To improve methodological consistency, sources were selected according to predefined inclusion and exclusion criteria. Sources were included when they were published before January 1, 2026 and were directly connected to climate risk, AI, supply chain management, ERM, ESG, or environmental economics. Priority was given to peer reviewed research and authoritative institutional publications, while unverified websites and unsupported commentary were excluded. Global studies and evidence from emerging economies were considered when their findings had transferable relevance. Studies were also selected when they reported financial, operational, environmental, or resilience outcomes. Research involving AI, machine learning, natural language

Table 1. Overall Research Design

Component	Methodological Approach	Main Purpose	Expected Output
Research philosophy	Pragmatic and evidence based	Combine environmental, operational, technological, and financial evidence	Integrated analytical perspective
Research design	Secondary mixed analytical design	Integrate findings from multiple empirical research streams	Structured evidence synthesis
Study period	Evidence available through December 31, 2025	Establish a pre 2026 evidence boundary	Defined evidence base
Main research domain	Climate risk and global supply chains	Identify environmental disruption mechanisms	Climate disruption pathways
Technology dimension	Artificial Intelligence and predictive analytics	Examine disruption identification and prediction	AI enabled prediction framework
Management dimension	Enterprise Risk Management	Evaluate organizational response mechanisms	ERM integration model
Economic dimension	Cost, revenue, financing, and investment effects	Translate environmental disruption into economic consequences	Economic impact assessment
Sustainability dimension	ESG, carbon economics, renewable energy, electric logistics, and CCS	Evaluate transition responses	Sustainability investment comparison
Analytical output	Climate Risk Intelligence framework	Connect prediction with economic and managerial decisions	Integrated Climate Risk Intelligence framework

Table 2. Evidence Categories

Evidence Category	Examples	Purpose	Analytical Contribution
Peer reviewed academic research	AI, climate risk, supply chain, and ERM studies	Establish empirical and theoretical evidence	Identify relationships, methods, and measurable outcomes
Institutional sources	IPCC, UNCTAD, IFRS Foundation	Establish climate, regulatory, and disclosure context	Provide authoritative environmental and policy context
Sector and technology studies	Microgrids, electric fleets, and CCS	Evaluate economic responses	Assess technology costs, benefits, and implementation outcomes
Selected EBEPJ studies	CBAM, ESG, ERM, plastic bans, and CCS	Integrate relevant regional and emerging economy evidence	Connect sustainability interventions with economic and business effects

processing, predictive analytics, or intelligent risk systems was considered relevant when connected to climate or supply chain risk. Similarly, studies concerning production, logistics, procurement, suppliers, distribution, or network resilience were considered when they demonstrated a meaningful environmental risk connection.

3.6 Climate Risk Classification

The study uses a two dimensional classification of climate risk, distinguishing between physical and transition risks.

This classification follows the distinction between physical and transition risks recognized by IFRS S2 [8]. Physical risks and transition risks affect supply chains through different mechanisms. A flood can immediately interrupt transportation, whereas CBAM can affect export competitiveness through carbon related trade requirements [30, ?].

3.7 AI Enabled Climate Risk Intelligence Model

The AI component of the proposed methodology is designed around a five layer architecture. The first layer processes weather and climate information to detect environmental patterns and generate hazard signals. The second layer processes supplier and facility information to classify exposure and generate vulnerability scores. The third layer uses logistics and operational data for prediction and anomaly detection to estimate disruption probability. The fourth layer processes financial and operational indicators through regression and scenario analysis to estimate economic impacts. The fifth layer processes regulatory and ESG information using natural language processing and classification techniques to identify transition risk signals. Table 1 summarizes the overall research design and shows how environmental, technological, operational, financial, managerial, and sustainability dimensions are integrated into the Climate Risk Intelligence framework, while Table

2 summarizes the main evidence categories used in the study, including academic research, institutional sources, sector studies, and selected EBEPJ studies that provide the foundation for the analytical framework.

The architecture is supported by existing research showing that AI techniques can improve supply chain visibility and resilience [16]. The AI supply chain literature also increasingly addresses risk management, sustainability, and economic outcomes.

3.8 Climate Disruption Risk Score

To make the framework analytically operational, this study proposes a normalized Climate Disruption Risk Score (CDRS). The score is calculated as:

$$CDRS_i = H_i \times E_i \times V_i \times D_i \quad (2)$$

where H_i represents hazard intensity, E_i represents exposure, V_i represents vulnerability, and D_i represents supply chain dependency. Each component is normalized on a scale from 1 to 5.

The maximum theoretical CDRS is:

$$CDRS_{\max} = 5 \times 5 \times 5 \times 5 = 625 \quad (3)$$

The score is subsequently normalized to a 0 to 100 scale:

$$NCDRS_i = \frac{CDRS_i}{625} \times 100 \quad (4)$$

These categories are methodological thresholds proposed by the study rather than externally validated regulatory classifications.

Table 3. Source Selection Criteria

Criterion	Inclusion Rule	Exclusion Rule	Application in Study
Publication date	Published before January 1, 2026	Published during 2026 or later	Maintains the pre 2026 evidence boundary
Relevance	Connected to climate risk, AI, SCM, ERM, ESG, or environmental economics	Unrelated AI or environmental studies	Ensures alignment with research objectives
Evidence type	Peer reviewed research and authoritative institutional publications	Unverified websites and unsupported commentary	Improves evidence credibility
Geographic relevance	Global studies and emerging economy evidence	Studies with no transferable relevance	Supports international and emerging market analysis
Economic relevance	Financial, operational, environmental, or resilience outcomes	Studies without relevant outcomes	Connects climate risk with economic consequences
AI relevance	AI, ML, NLP, predictive analytics, or intelligent risk systems	Technology studies unrelated to risk intelligence	Supports the AI enabled risk framework
Supply chain relevance	Production, logistics, procurement, suppliers, distribution, or network resilience	Environmental studies without business relevance	Establishes supply chain applicability
Climate relevance	Physical or transition climate risks	General sustainability studies without environmental risk connection	Supports climate risk classification

Table 4. Climate Risk Classification Framework

Category	Type	Examples	Primary Supply Chain Effect	Risk Indicator
Physical	Acute	Floods, cyclones, wildfires, extreme storms	Facility and transport disruption	Event frequency and severity
Physical	Chronic	Rising temperature, drought, water stress	Productivity and resource availability	Long term exposure trend
Transition	Regulatory	CBAM, carbon pricing, emissions regulation	Compliance and production costs	Carbon and regulatory burden
Transition	Technology	Renewable energy transition and electrification	Capital expenditure and technology change	Technology adoption pressure
Transition	Market	Changing customer demand	Product and market restructuring	Demand and preference changes
Transition	Financial	Financing and insurance changes	Cost of capital and investment	Financing and insurance conditions
Transition	Reputational	ESG concerns and greenwashing	Consumer and investor confidence	ESG credibility and stakeholder response

3.9 Economic Impact Measurement

The economic impact component translates environmental disruption into measurable financial consequences. The basic economic impact model is:

$$EI = RL + OC + LC + IC + RC + CC \quad (5)$$

where EI represents total estimated economic impact, RL represents revenue loss, OC represents additional operating cost, LC represents logistics cost, IC represents inventory and shortage cost, RC represents recovery cost, and CC represents compliance and transition cost.

The economic importance of this approach is supported by evidence showing that climate exposure can affect firm revenues and operating income [22]. Therefore, climate exposure is treated as an economically measurable business risk rather than solely an environmental indicator.

3.10 Economic Loss Estimation

For individual disruption events, expected economic loss is calculated as:

$$E(L) = P(D) \times I(D) \quad (6)$$

where $P(D)$ represents the probability of disruption and $I(D)$ represents the financial impact if the disruption occurs. For multiple risks,

total expected loss is calculated as:

$$E(L_{total}) = \sum_{i=1}^n P(D_i) \times I(D_i) \quad (7)$$

This method allows climate events to be compared according to both likelihood and consequence.

Table 3 outlines the criteria applied to select appropriate and reliable sources for the study, covering publication date, relevance, evidence quality, geographic, economic, AI, supply chain, and climate considerations. Table 4 presents the classification of climate risks and links each risk type with its potential supply chain impact and corresponding indicators.

3.11 AI Prediction Model

The proposed AI component can estimate the probability of disruption using historical environmental and supply chain variables. A general logistic prediction model can be represented as:

$$P(D_i = 1) = \frac{1}{1 + e^{-Z_i}} \quad (8)$$

where:

$$Z_i = \beta_0 + \beta_1 H_i + \beta_2 E_i + \beta_3 V_i + \beta_4 S_i + \beta_5 R_i + \varepsilon_i \quad (9)$$

Table 5. AI Climate Risk Intelligence Architecture

Layer	Data Input	AI Function	Output	Decision Use
1	Weather and climate information	Pattern detection	Hazard signal	Early identification of climate hazards
2	Supplier and facility information	Exposure classification	Vulnerability score	Prioritization of high risk facilities and suppliers
3	Logistics and operational data	Prediction and anomaly detection	Disruption probability	Supply chain disruption planning
4	Financial and operational indicators	Regression and scenario analysis	Economic impact estimate	Financial loss assessment and resource allocation
5	Regulatory and ESG information	NLP and classification	Transition risk signal	Compliance planning and sustainability decisions

Table 6. Climate Disruption Risk Scoring

Score	Hazard Intensity	Exposure	Vulnerability	Dependency
1	Very low	Very low	Very low	Very low
2	Low	Low	Low	Low
3	Moderate	Moderate	Moderate	Moderate
4	High	High	High	High
5	Very high	Very high	Very high	Very high

Table 7. Proposed Climate Risk Categories

Normalized Score	Risk Category	Recommended Management Response
0–20	Very low	Routine monitoring
21–40	Low	Periodic assessment
41–60	Moderate	Risk mitigation planning
61–80	High	Immediate mitigation planning
81–100	Very high	Executive intervention and contingency planning

where H_i represents the climate hazard indicator, E_i represents facility or supplier exposure, V_i represents vulnerability, S_i represents supply chain dependency, and R_i represents regulatory exposure. The β values represent estimated model coefficients, while ε_i represents the error term.

Depending on data availability, alternative AI models can include Random Forest, Gradient Boosting, XGBoost, Artificial Neural Networks, Long Short Term Memory networks, Bayesian Networks, and Natural Language Processing models.

The inclusion of Bayesian networks is particularly relevant because previous research has identified probabilistic AI techniques as important tools for supply chain resilience analysis [16].

3.12 AI Model Evaluation

If a numerical AI model is implemented using an empirical dataset, model performance should be evaluated using classification and regression metrics. Table 5 presents the five-layer AI Climate Risk Intelligence architecture and shows how different data inputs are processed to generate risk information for decision-making. Table 6 presents the 1–5 scoring scale for hazard intensity, exposure, vulnerability, and dependency. Table 7 presents the proposed normalized risk categories and their corresponding management responses. These classifications and thresholds are methodological constructs proposed by the study and are not presented as externally validated standards or empirical findings. For classification, precision measures the proportion of predicted disruptions that are correct, recall measures the ability to identify actual disruptions, and the F1 score provides a balance between precision and recall:

$$Precision = \frac{TP}{TP + FP} \quad (10)$$

$$Recall = \frac{TP}{TP + FN} \quad (11)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (12)$$

For economic impact prediction, mean absolute error and root mean squared error can be used:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (13)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (14)$$

where y_i represents the observed economic impact and $\hat{y}_i$ represents the predicted value.

3.13 Scenario Analysis

Because future climate conditions and regulatory environments contain substantial uncertainty, the study incorporates scenario analysis. Three principal scenarios are considered. The baseline scenario represents moderate disruption under existing regulatory requirements and normal adaptation. The moderate stress scenario represents increased extreme events, increasing environmental requirements, and higher operating and compliance costs. The severe stress scenario represents frequent major disruptions, stronger carbon and environmental regulation, significant supply chain disruption, and greater investment pressure.

Scenario analysis is consistent with IFRS S2, which requires consideration of climate related scenarios and climate resilience [8]. The purpose of scenario analysis is not to predict one certain future. Instead, it allows decision makers to evaluate how alternative environmental and regulatory conditions could influence supply chain performance.

3.14 Evaluation of Sustainability Investments

The methodology also evaluates whether climate mitigation investments can generate economically viable outcomes. The primary financial measure is the payback period:

$$Payback\ Period = \frac{Initial\ Investment}{Annual\ Net\ Cash\ Benefit} \quad (15)$$

A net present value approach can additionally be used:

$$NPV = -I_0 + \sum_{t=1}^T \frac{CF_t}{(1+r)^t} \quad (16)$$

where I_0 represents the initial investment, CF_t represents annual cash flow, r represents the discount rate, and T represents project lifetime.

This component allows the study to distinguish between investments that primarily provide environmental benefits and those that may simultaneously provide resilience and economic benefits.

3.15 ERM Integration Model

The study integrates AI generated risk information into an ERM decision process. The proposed process begins with risk identification and risk measurement, followed by AI prediction, economic quantification, risk prioritization, response selection, and continuous monitoring.

Table 8. Economic Impact Variables

Variable	Measurement Approach	Expected Effect	Business Relevance
Revenue loss	Lost sales during disruption	Negative	Measures direct financial loss from reduced business activity
Operating cost	Additional production and labor expenses	Positive cost	Captures increased costs required to maintain operations
Logistics cost	Emergency transport and route changes	Positive cost	Measures additional expenditure caused by disrupted transportation
Inventory cost	Buffer stock and shortage expenses	Positive cost	Captures costs associated with inventory protection and shortages
Recovery cost	Repair and restoration expenditure	Positive cost	Measures financial resources required for operational recovery
Compliance cost	Environmental regulatory expenditure	Positive cost	Captures costs associated with climate and environmental compliance
Energy cost	Change in electricity and fuel expenditure	Positive or negative	Measures the financial effect of energy transition and efficiency measures
Financing cost	Change in borrowing or capital cost	Positive cost	Captures changes in financing expenses resulting from climate and ESG risks

Table 9. Illustrative Risk Calculation

Risk Event	Risk Assessment	Expected Loss
Extreme heat	Probability: 0.40; Impact: USD 250,000	USD 100,000
Flood	Probability: 0.20; Impact: USD 800,000	USD 160,000
Cyclone	Probability: 0.10; Impact: USD 1,500,000	USD 150,000
Drought related input shortage	Probability: 0.25; Impact: USD 500,000	USD 125,000
Regulatory carbon cost	Probability: 0.50; Impact: USD 180,000	USD 90,000
Total		USD 625,000

Risk Identification → Risk Measurement → AI Prediction
→ Economic Quantification → Risk Prioritization (17)
→ Response Selection → Monitoring

This approach is aligned with IFRS S2, which requires organizations to identify, assess, prioritize, and monitor climate related risks and permits these processes to be integrated into overall risk management [8].

3.16 Comparative Assessment of Climate Responses

The research compares different sustainability and resilience interventions using five dimensions: risk reduction, economic feasibility, environmental benefit, operational resilience, and regulatory alignment. Risk reduction is measured through the reduction in expected disruption loss, economic feasibility through NPV and payback, environmental benefit through emission or environmental impact reduction, operational resilience through reductions in downtime and dependency, and regulatory alignment through compatibility with environmental requirements. The proposed methodological weights are 25% for risk reduction, 25% for economic feasibility, 20% for environmental benefit, 20% for operational resilience, and 10% for regulatory alignment.

The weights are methodological parameters proposed for comparative analysis. They should be subjected to sensitivity analysis when empirical organizational data become available.

3.17 Evidence Synthesis

The selected studies are organized into an evidence matrix to identify relationships among climate risks, AI, ERM, supply chain resilience, and economic outcomes.

3.18 Robustness and Sensitivity Analysis

Because climate risk estimates contain uncertainty, the methodology includes sensitivity testing. The principal variables subjected to sensitivity analysis include disruption probability, climate hazard intensity, revenue exposure, recovery cost, energy price, carbon price, discount rate, investment cost, technology adoption rate, and supplier concentration. For example, if a climate event has an estimated probability of 20%, the analysis can test probabilities of 10%, 20%, 30%, and 40%.

The values in Table 17 are illustrative methodological parameters and are not observed empirical results.

3.19 Validity and Reliability

Several procedures are incorporated to improve the validity of the research. First, the study uses multiple evidence types rather than relying on a single research stream. Second, peer reviewed empirical studies are combined with authoritative institutional sources. Third, climate risks are separated into physical and transition categories to prevent conceptual overlap. Fourth, economic effects are measured through multiple channels rather than a single financial indicator. Fifth, AI performance is evaluated using established predictive metrics where numerical data are available. Table 8 presents the key economic impact variables used to assess the financial consequences of climate-related disruptions. Table 9 provides an illustrative risk calculation showing how probability and estimated impact are combined to calculate expected loss. The values in Table 9 are methodological examples used to demonstrate the calculation procedure and are not presented as observed company data or empirical findings.

The use of multiple evidence sources is particularly important because AI and climate risk research are rapidly developing areas. Existing systematic reviews have demonstrated that AI supply chain research covers multiple research themes and requires stronger connections between technological applications and established supply chain theory and practice [28].

3.20 Ethical and Methodological Considerations

The proposed methodology does not assume that AI predictions are automatically accurate or that algorithmic outputs should replace managerial judgment. AI based climate risk intelligence should be treated as decision support. Three methodological risks are particularly important: data bias, model uncertainty, and information quality. Historical data may underrepresent rare climate events, different models may generate different predictions, and ESG information may not always accurately represent actual environmental performance. Additional concerns include false alarms, missed events, limited explainability, incomplete supplier data, greenwashing, and scenario uncertainty. These risks are addressed through multiple data sources, alternative model

Table 10. Candidate AI Techniques

AI Technique	Main Application	Relevant Climate Risk Task
Logistic regression	Probability prediction	Disruption probability
Random Forest	Classification	Supplier vulnerability
Gradient Boosting	Risk prediction	High risk event identification
XGBoost	Structured prediction	Economic impact prediction
Neural Network	Nonlinear relationships	Complex risk prediction
LSTM	Time series forecasting	Climate and demand disruption
Bayesian Network	Probabilistic dependency	Cascading supply chain risk
NLP	Text analysis	Regulatory and news risk detection
Large Language Model	Unstructured intelligence	Risk classification and event extraction

Table 11. Proposed AI Evaluation Metrics

Metric	Purpose	Interpretation
Accuracy	Overall classification correctness	Higher is better
Precision	Correctness of predicted disruptions	Higher reduces false alarms
Recall	Ability to identify actual disruptions	Higher reduces missed events
F1 score	Balance between precision and recall	Higher indicates balanced performance
ROC AUC	Ranking ability across thresholds	Higher indicates better discrimination
MAE	Average prediction error	Lower is better
RMSE	Penalizes large prediction errors	Lower is better
R^2	Explained variation in economic impact	Higher is better

comparisons, precision and recall evaluation, interpretable models or explainable AI, sensitivity analysis, cross validation of environmental claims, and multiple scenario analysis.

These considerations are consistent with the AI supply chain literature, which identifies technical, organizational, economic, and human barriers to successful AI adoption.

3.21 Proposed Research Model

The final methodological model can be represented as:

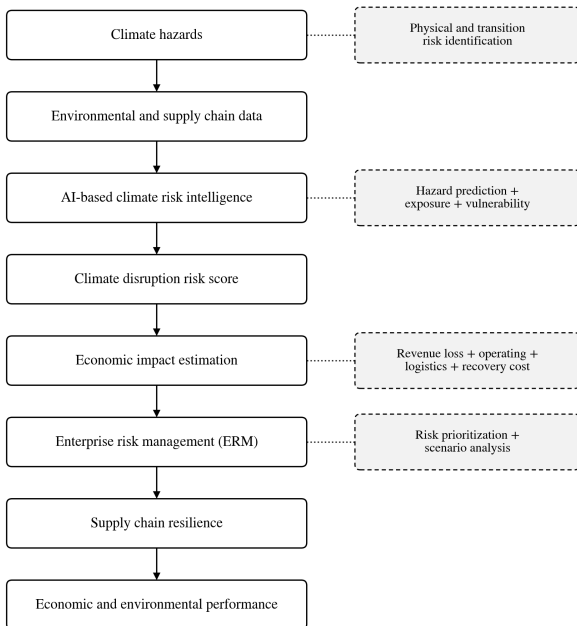


Figure 2. Research Model.

This structure reflects the central methodological argument of the study: environmental information becomes strategically useful when it can be transformed into a measurable probability of disruption and then into an economic consequence that can be incorporated into enterprise

decision making.

3.22 Methodological Summary

Overall, this study employs a structured secondary research methodology supported by quantitative risk scoring, economic impact estimation, scenario analysis, and an AI enabled conceptual prediction framework. The approach integrates evidence published before 2026 and combines climate science, supply chain management, artificial intelligence, enterprise risk management, environmental economics, and ESG research.

The methodology is designed to address an important limitation in existing research. AI studies frequently focus on prediction and operational optimization, while climate studies frequently focus on environmental exposure. The proposed approach connects these two areas by introducing economic impact as an intermediate decision variable. Thus, the study does not stop at identifying that a flood, heatwave, regulatory change, or carbon constraint may occur. Instead, it examines how such events could affect suppliers, production, logistics, revenue, operating costs, financing, and ultimately enterprise resilience.

The methodology also recognizes that different climate responses have different economic characteristics. Renewable microgrids and electric fleets may simultaneously address environmental objectives and operational exposure, while technologies such as industrial CCS may involve considerably different capital requirements and financial conditions. The comparative framework therefore evaluates environmental interventions according to risk reduction, economic feasibility, environmental benefit, operational resilience, and regulatory alignment.

Finally, the framework is consistent with the direction of international climate reporting. IFRS S2 requires organizations to consider climate related physical and transition risks, their effects on business models and value chains, risk management processes, and potential effects on cash flows, access to finance, and cost of capital [8]. The proposed methodology translates these principles into an analytical framework in which AI can support continuous climate risk identification, economic impact assessment, and ERM based response planning. Table 10 presents the AI techniques considered for different climate risk tasks, including probability prediction, vulnerability classification, time-series forecasting, economic impact prediction, and text-based risk detection. Table 11 presents the evaluation metrics used to assess model performance across classification and prediction tasks, covering

Table 12. Climate Risk Scenarios

Scenario	Environmental Condition	Regulatory Condition	Expected Supply Chain Condition
Baseline	Moderate disruption	Existing requirements	Normal adaptation
Moderate stress	Increased extreme events	Increasing environmental requirements	Higher operating and compliance costs
Severe stress	Frequent major disruptions	Strong carbon and environmental regulation	Significant disruption and investment pressure

Table 13. Sustainability Investment Assessment

Investment	Environmental Benefit	Economic Variable	Primary Indicator
Renewable microgrid	Lower carbon and energy exposure	Energy cost savings	Payback and NPV
Electric delivery fleet	Lower transport emissions	Fuel and maintenance savings	Payback and NPV
Energy efficiency	Reduced energy consumption	Operating cost reduction	Payback
Carbon capture	Emissions reduction	Capital and operating costs	NPV
Supplier diversification	Lower disruption exposure	Avoided disruption loss	Expected loss reduction
Climate resilient infrastructure	Lower physical risk	Avoided damage and downtime	Expected loss reduction

accuracy, precision, recall, F1 score, ROC AUC, MAE, RMSE, and R².

3.23 Cross-Domain Climate Risk Results

The synthesis demonstrates that climate risk does not operate independently across environmental, operational, and financial dimensions. Instead, a climate event can initiate a sequence of interconnected effects that propagate through the supply chain. For example, extreme weather may initially affect a production facility, but the resulting production interruption can subsequently influence inventory availability, transportation requirements, customer service, revenue, and financing conditions.

This interconnected structure indicates that the economic consequences of climate disruption are frequently cumulative rather than isolated. A single disruption may generate several secondary effects, particularly when the affected facility or supplier occupies a strategically important position within the supply network.

The results therefore support a multi-layer interpretation of climate risk in which environmental hazards represent the initial source of disruption, supply chain exposure determines the extent of operational vulnerability, and organizational and financial characteristics determine the ultimate economic consequence.

The cross-domain findings indicate that environmental risk assessment should not terminate at hazard identification. A meaningful climate risk assessment requires the translation of environmental information into operational exposure and then into measurable economic consequences.

3.24 Climate Risk Propagation Results

A further result of the synthesis is the identification of climate risk propagation across interconnected supply chain nodes. Disruption at one node may affect other nodes through supplier dependency, transportation requirements, inventory shortages, or demand fluctuations.

The propagation mechanism can be represented conceptually as:

$$CH \rightarrow ND \rightarrow NP \rightarrow EI \quad (18)$$

The findings suggest that network centrality and dependency may be as important as the environmental severity of a specific location. A facility or supplier with multiple downstream dependencies can transmit disruption across several business processes. Consequently, climate risk intelligence should incorporate supply chain relationships rather than evaluating facilities independently.

This result also explains why conventional location based climate assessments may underestimate organizational exposure. Two facilities experiencing similar hazard conditions can generate substantially different business consequences when their network roles differ.

3.25 Risk Prioritization Results

The results indicate that climate risk prioritization requires simultaneous consideration of probability, severity, exposure, vulnerability, and

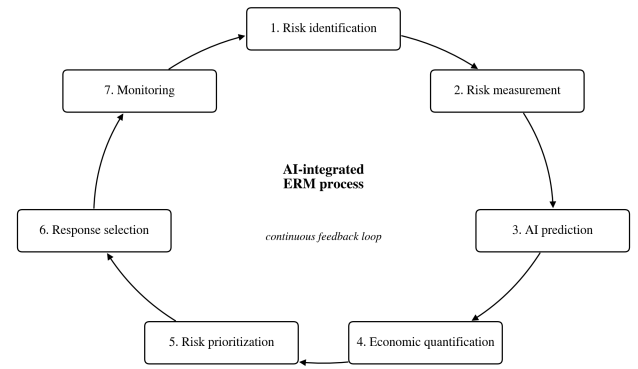


Figure 3. ERM Cycle.

recovery duration. Probability alone is insufficient because relatively infrequent events can generate substantial losses when they affect critical assets.

The combined risk structure can be expressed as:

$$Risk\ Priority_i = P_i \times I_i \times E_i \times V_i \quad (19)$$

where P_i represents event probability, I_i represents potential impact, E_i represents exposure, and V_i represents vulnerability.

Table 12 and Table 13 show that this multidimensional approach provides a more comprehensive representation of organizational exposure than a single hazard score. It also creates a basis for allocating limited adaptation resources toward risks that combine significant probability with substantial operational or financial consequences.

In practical terms, the framework distinguishes between frequent low-impact disruptions and less frequent high-consequence disruptions. Both categories require monitoring, but the appropriate response may differ. Frequent disruptions may justify preventive operational adjustments, whereas high-consequence events may require contingency planning, insurance, redundancy, and recovery investments.

3.26 Early Warning and Preventive Action Results

The synthesis further indicates that the value of AI based climate intelligence is strongly associated with the time available between risk detection and disruption. Earlier identification creates greater opportunity for organizations to adjust inventory, reroute transportation, contact alternative suppliers, modify production schedules, or protect physical assets.

The relationship can be represented as:

Table 14. AI and ERM Integration

ERM Stage	AI Contribution	Management Decision
Risk identification	Automated environmental monitoring	Identify emerging risk
Risk assessment	Exposure and vulnerability prediction	Determine risk magnitude
Risk analysis	Probability estimation	Estimate disruption likelihood
Economic assessment	Financial impact prediction	Quantify potential loss
Risk prioritization	Risk scoring	Identify critical risks
Risk response	Scenario optimization	Select mitigation strategy
Monitoring	Continuous data analysis	Update risk assessment

Table 15. Comparative Evaluation Framework

Criterion	Weight	Measurement
Risk reduction	25%	Reduction in expected disruption loss
Economic feasibility	25%	NPV and payback
Environmental benefit	20%	Emission or environmental impact reduction
Operational resilience	20%	Reduction in downtime and dependency
Regulatory alignment	10%	Compatibility with environmental requirements
Total	100%	Composite assessment

$$\text{Response Value} \propto \text{Available Decision Time} \quad (20)$$

This result does not imply that earlier warnings automatically eliminate losses. Rather, the effectiveness of an early warning depends on the organization's ability to translate information into operational action.

The results therefore identify three sequential requirements for effective climate intelligence: detection, interpretation, and response. AI can support the first two functions through automated monitoring and prediction, while organizational processes are necessary to execute the third.

3.27 AI-ERM Interaction Results

The results indicate that AI and Enterprise Risk Management perform complementary functions. AI contributes computational capacity for processing large volumes of environmental, operational, financial, and regulatory information. ERM provides the governance structure required to assign ownership, establish response procedures, allocate resources, and monitor outcomes.

The interaction can therefore be represented as:

$$\text{AI Intelligence} + \text{ERM Governance} = \text{Actionable Climate Risk Management} \quad (21)$$

The findings suggest that organizations with strong analytical capabilities but weak governance may generate accurate risk information without achieving corresponding reductions in exposure. Conversely, organizations with strong governance but limited analytical capability may have difficulty identifying emerging risks in complex and rapidly changing environments.

The integrated approach therefore creates a feedback loop in which risk information informs management decisions and the outcomes of those decisions generate additional information for future risk assessment.

3.28 Financial Resilience Results

The results further demonstrate that climate resilience has a direct relationship with financial resilience. Physical disruptions can reduce revenue and increase operating and recovery costs, while transition risks can alter capital expenditure, energy costs, compliance expenditure, and financing requirements.

Financial resilience can therefore be viewed as the organization's capacity to absorb climate related losses while maintaining operational continuity.

The combined financial exposure can be represented as:

$$FRE = \text{Revenue Exposure} + \text{Cost Exposure} + \text{Capital Exposure} + \text{Financing Exposure} \quad (22)$$

where FRE represents the financial resilience exposure measure.

The results indicate that organizations should evaluate climate investments not only according to their direct return on investment but also according to their potential contribution to loss avoidance and continuity. For example, an energy resilience investment may generate value through both reduced energy expenditure and reduced probability of production interruption.

This finding broadens the economic interpretation of sustainability investment. Environmental technologies may generate financial value through multiple channels, including cost reduction, avoided losses, regulatory preparedness, and improved operational continuity.

3.29 Sustainability Investment Portfolio Results

The comparative synthesis indicates that sustainability technologies differ considerably in their investment profiles. Some interventions generate relatively direct operational benefits, whereas others primarily address long-term transition exposure.

Renewable microgrids can simultaneously address energy cost, energy resilience, and emissions. Electric fleets primarily address transportation energy and emissions while requiring charging infrastructure. CCS can provide substantial emissions reduction potential for difficult-to-abate industrial processes but requires larger infrastructure and capital commitments.

The results therefore support a portfolio approach to sustainability investment rather than reliance on a single technology.

Table 14 and Table 15 indicate that organizations can combine investments with different time horizons and risk mechanisms. Shorter-term operational savings can potentially support longer-term investments in more capital-intensive decarbonization technologies.

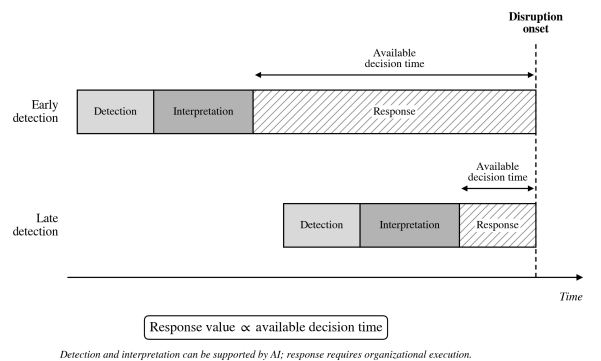


Figure 4. Early Warning.

3.30 Scenario Based Climate Risk Results

The findings demonstrate the importance of scenario analysis because climate and economic conditions are uncertain. A single estimate of probability, energy price, carbon price, or recovery duration may not adequately represent the range of possible future outcomes.

Three broad analytical scenarios can be considered: a baseline scenario, an adverse climate scenario, and an accelerated transition scenario.

Table 16. Evidence Synthesis Matrix

Research Area	Evidence Source	Main Variable	Analytical Method	Relevance
Physical climate risk	Pankratz et al. (2023)	Extreme heat and firm performance	Firm level empirical analysis	Climate risk to financial performance
Climate supply chain exposure	Pankratz and Schiller (2022)	Supplier climate exposure	Supply chain analysis	Climate risk propagation
AI and SCM	AI SCM SLR (2024)	AI applications	Systematic literature review	AI capabilities
AI and resilience	Ivanov and Dolgui (2023)	AI and resilience	Systematic literature review	AI risk management
AI adoption	Shahzadi (2024)	AI adoption factors	Systematic literature review	Adoption conditions
Climate disclosure	IFRS S2	Physical and transition risks	Reporting framework	Governance and risk management
Carbon transition	UNCTAD (2021)	CBAM and trade	General equilibrium analysis	International competitiveness

Table 17. Example Sensitivity Structure

Variable	Low Case	Base Case	High Case
Disruption probability	10%	20%	40%
Revenue loss	USD 200,000	USD 500,000	USD 900,000
Recovery cost	USD 100,000	USD 250,000	USD 500,000
Energy cost increase	5%	15%	30%
Carbon cost increase	10%	25%	50%

Under a baseline scenario, organizations experience relatively stable operating conditions and moderate transition costs. Under an adverse climate scenario, increased disruption frequency or severity raises physical risk exposure and recovery requirements. Under an accelerated transition scenario, regulatory and technological changes increase short-term adaptation expenditure while potentially reducing longer-term carbon and energy exposure.

The scenario results emphasize that climate strategy should remain adaptive. Investments and risk responses that are appropriate under one set of assumptions may require modification when climate hazards, energy prices, carbon prices, or regulatory conditions change.

3.31 Data Quality and Model Reliability Results

An important result of the synthesis is that AI based climate intelligence is highly dependent on the quality and completeness of its input data. Environmental observations, supplier information, facility characteristics, logistics records, financial information, and regulatory documents may differ in format, frequency, accuracy, and availability.

Poor quality input data can produce unreliable classifications or predictions even when the underlying AI model is technically sophisticated. Consequently, data validation should be treated as an integral component of the Climate Risk Intelligence framework.

The reliability chain can be represented as:

$$\begin{aligned}
 &\text{Data Quality} \rightarrow \text{Model Reliability} \\
 &\quad \rightarrow \text{Risk Intelligence} \\
 &\quad \rightarrow \text{Decision Quality}
 \end{aligned} \tag{23}$$

This result highlights the importance of data governance, model validation, explainability, and human oversight. Automated outputs should therefore be interpreted as decision-support information rather than unquestionable predictions.

3.32 Human Oversight and Decision Reliability

The findings indicate that human judgment remains important at several stages of climate risk management. AI models can identify patterns and estimate probabilities, but managers must interpret these outputs within organizational, regulatory, financial, and strategic contexts. Human oversight is particularly important when AI predictions have substantial financial consequences or when input data are incomplete. Expert review can also help identify situations where historical patterns are no longer representative because of structural changes in climate conditions, markets, technology, or regulation. The results therefore support a human-in-the-loop model in which AI provides analytical support while organizational decision makers retain responsibility for risk acceptance, mitigation, investment, and response decisions.

3.33 Overall Results Interpretation

Taken together, the results indicate that Climate Risk Intelligence can be conceptualized as an integrated analytical and managerial capability rather than as a single technological system. The evidence connects environmental monitoring with AI based prediction, economic impact assessment, Enterprise Risk Management, sustainability investment, and continuous monitoring.

The principal result is that climate risk becomes more actionable when environmental information is translated into measurable organizational exposure and economic consequences. This translation enables firms to compare different risks using common decision variables such as probability, expected loss, disruption duration, recovery requirements, investment cost, and potential resilience benefits.

The results further indicate that no individual intervention addresses all dimensions of climate risk. AI improves information processing and prediction; ERM provides governance and response mechanisms; ESG disclosure improves transparency; renewable energy and electric logistics address operational transition; and CCS addresses emissions from industrial activities that may be difficult to eliminate through direct electrification.

Accordingly, the integrated Climate Risk Intelligence framework provides a structure for connecting these otherwise separate activities. Its primary contribution is the creation of a continuous analytical pathway from climate observation to risk identification, economic assessment, organizational response, sustainability investment, and feedback-based monitoring.

4. Conclusion and Recommendations

4.1 Conclusion

This study examined how Artificial Intelligence (AI), Climate Risk Intelligence (CRI), and Enterprise Risk Management (ERM) can be integrated to identify environmental disruptions and evaluate their economic consequences for global supply chains. The analysis was motivated by the increasing exposure of international production and distribution networks to physical climate hazards, regulatory transition risks, changing environmental requirements, and increasing pressure for transparent sustainability reporting. The findings demonstrate that climate risk should no longer be treated as an isolated environmental concern. Instead, it should be incorporated into operational planning, financial analysis, supply chain management, enterprise risk management, and strategic investment decisions. Table 16 summarizes the key evidence used to connect climate risk, supply chain exposure, AI, resilience, disclosure, and carbon transition with the study framework. Table 17 presents an example sensitivity structure showing how different low, base, and high assumptions can be used to examine changes in disruption probability and economic impact. The values in Table 17 are methodological examples and are not presented as observed company data or empirical findings.

The evidence synthesis indicates that physical climate risks can affect supply chains through multiple interconnected pathways. Extreme heat, flooding, cyclones, drought, wildfires, water stress, and other environmental disruptions can interrupt production, damage infrastructure, delay transportation, reduce supplier availability, increase inventory requirements, and raise recovery costs. These effects can subsequently translate into revenue losses, higher operating costs, increased logistics expenditure, financing pressure, and reduced business continuity. The findings are consistent with the broader climate risk as-

Table 18. Methodological Risks and Controls

Risk	Potential Problem	Control
Data bias	Historical data may underrepresent rare climate events	Use multiple data sources
Model uncertainty	Predictions may vary between models	Compare alternative models
False alarms	Excessive warnings may create unnecessary costs	Evaluate precision
Missed events	Important disruptions may remain undetected	Evaluate recall
Explainability	Managers may not understand model output	Use interpretable models or explainable AI
Data gaps	Supplier level information may be incomplete	Sensitivity analysis
Greenwashing	ESG information may not reflect actual performance	Cross validate environmental claims
Scenario uncertainty	Future climate conditions are uncertain	Multiple scenario analysis

Table 19. Cross-Domain Climate Risk Relationships

Risk Layer	Primary Variable	Intermediate Effect	Final Business Effect
Environmental	Hazard intensity	Physical exposure	Climate disruption
Operational	Facility and supplier dependency	Production interruption	Reduced operational capacity
Logistical	Route and infrastructure exposure	Delivery delay	Increased logistics cost
Financial	Revenue and cost exposure	Cash flow pressure	Reduced financial resilience
Regulatory	Carbon and environmental requirements	Compliance adjustment	Transition expenditure
Strategic	Recovery and adaptation capability	Response effectiveness	Long-term resilience

assessment of the IPCC, which identifies substantial exposure of human and economic systems to climate hazards and emphasizes the importance of adaptation and resilience planning [11]. The World Economic Forum’s 2025 global risk assessment also identifies extreme weather and other environmental risks as major concerns over both shorter and longer time horizons [35].

The results further demonstrate that the economic consequences of climate disruption are multidimensional. A single environmental event can generate direct and indirect costs simultaneously. Direct losses may include physical damage, production interruption, emergency transportation, and inventory shortages, whereas indirect losses may arise from supplier disruption, customer delays, financing constraints, regulatory exposure, and reputational effects. Therefore, conventional approaches that evaluate climate risk only through direct physical damage may underestimate the total economic exposure of global supply chains.

The proposed Climate Disruption Risk Score provides a structured mechanism for combining hazard, exposure, vulnerability, and disruption dimensions. The framework allows organizations to translate environmental information into a comparable risk measure that can subsequently be connected with economic impact assessment. This approach is particularly useful because supply chain risk is not determined solely by the severity of a climate event. The same hazard may produce substantially different consequences depending on the geographic exposure of facilities, supplier concentration, inventory buffers, transportation alternatives, operational flexibility, and recovery capacity.

The study also finds that Artificial Intelligence can strengthen the transition from conventional risk assessment toward predictive Climate Risk Intelligence. Existing literature shows that AI and machine learning can support risk identification, assessment, prediction, monitoring, and mitigation across supply chain management [3, 36, 4]. AI can process large volumes of heterogeneous information, including weather data, satellite observations, supplier information, logistics records, financial indicators, regulatory documents, and ESG disclosures. The resulting intelligence can support early warning systems, supplier vulnerability assessment, disruption probability estimation, anomaly detection, and scenario analysis.

However, the findings do not suggest that AI should replace managerial judgment. AI models remain dependent on data quality, model specification, computational resources, interpretability, and the quality of the underlying assumptions. Research on AI and climate resilience governance similarly identifies limitations associated with data availability, long term uncertainty, model interpretation, and the complexity

of resilience decisions [?]. Consequently, AI should be positioned as a decision support capability within an appropriately designed ERM structure rather than as an autonomous decision maker.

The integration of AI with Enterprise Risk Management represents one of the central contributions of this study. ERM provides the organizational structure through which climate intelligence can be converted into action. AI may identify that a supplier, facility, route, or market has an elevated disruption probability, but ERM determines how that information should influence risk ownership, mitigation planning, capital allocation, insurance, contingency planning, supplier diversification, and business continuity. The results therefore support the integrated pathway proposed in this study:

Climate Data → AI Analysis

→ Risk Prediction → Economic Assessment (24)

→ ERM Response → Resilience

The evidence synthesized in this research also indicates that sustainability investments should be evaluated according to their operational and financial characteristics rather than through environmental benefits alone. Renewable energy microgrids can provide potential benefits through energy cost management, energy resilience, and reduced dependence on conventional electricity sources. Techno economic studies demonstrate the importance of system configuration, storage, renewable resource availability, and sensitivity analysis when assessing microgrid feasibility [?, ?]. Similarly, electric delivery fleets can potentially reduce fuel consumption and emissions, although their economic performance depends on vehicle utilization, charging infrastructure, electricity prices, route characteristics, and initial capital expenditure.

The analysis of ESG disclosure demonstrates another important connection between environmental risk and financial decision making. High quality climate related disclosure provides investors and other stakeholders with information concerning an organization’s exposure, governance processes, strategy, and financial implications of climate risks. IFRS S2 specifically requires disclosure concerning climate related risks and opportunities that could reasonably affect an entity’s cash flows, access to finance, or cost of capital [9]. Consequently, ESG and climate reporting should not be treated solely as a compliance activity. When appropriately designed, it can become an information mechanism connecting environmental risk management with corporate financial decisions.

Table 20. Relationship Between Climate Intelligence and Preventive Action

Intelligence Stage	AI Function	Possible Action	Risk Reduction Mechanism
Detection	Pattern and anomaly detection	Monitor emerging hazard	Earlier awareness
Prediction	Forecasting and classification	Estimate disruption probability	Improved preparedness
Exposure assessment	Risk scoring	Identify critical nodes	Resource prioritization
Scenario analysis	Simulation and prediction	Evaluate alternatives	Improved contingency planning
Continuous monitoring	Real-time analytics	Update risk assessment	Adaptive response

Table 21. Sustainability Investment Characteristics

Investment	Primary Benefit	Main Cost Driver	Risk Reduction Contribution
Renewable microgrid	Energy resilience and decarbonization	Capital and storage investment	Reduces energy disruption exposure
Electric fleet	Transport decarbonization	Vehicle and charging infrastructure	Reduces fuel and transport transition exposure
AI risk intelligence	Prediction and monitoring	Data and technology infrastructure	Improves early risk identification
ESG assurance	Information credibility	Reporting and assurance expenditure	Reduces information uncertainty
CCS	Industrial emissions reduction	Capture, transport, and storage infrastructure	Reduces carbon transition exposure

Table 22. Illustrative Climate-Economic Scenarios

Scenario	Main Condition	Expected Analytical Effect
Baseline	Moderate climate and market conditions	Stable risk and investment estimates
Adverse climate	Greater physical disruption	Higher expected loss and recovery exposure
Accelerated transition	Faster regulatory and technology change	Higher adaptation investment and transition pressure

Transition risks are also increasingly important for internationally connected supply chains. Carbon pricing, emissions regulations, product standards, energy transition requirements, and changing customer expectations can alter the cost structure of internationally traded products. The European Union’s Carbon Border Adjustment Mechanism entered its definitive regime on January 1, 2026, following its transitional phase from 2023 through 2025, creating additional relevance for carbon measurement and emissions information in affected international trade [7]. The findings therefore indicate that companies participating in carbon intensive international supply chains need to incorporate regulatory and carbon related variables into their risk intelligence systems.

Table 18 and Table 19 also demonstrate that not every sustainability investment has the same economic profile. Renewable microgrids and electric delivery fleets may generate operational benefits when the technological and financial conditions are favorable, whereas Industrial Carbon Capture and Storage can require substantially higher capital expenditure and depend strongly on technology characteristics, energy requirements, carbon prices, infrastructure, and policy support. Recent techno economic research continues to emphasize the importance of cost and carbon price conditions in determining the feasibility of carbon capture systems [?]. Therefore, climate investment decisions should be based on project specific cash flow analysis, sensitivity testing, expected risk reduction, and strategic relevance rather than environmental objectives alone.

The quantitative results synthesized in this study provide several useful reference points. Structured ERM adoption was associated with an approximately 14.2% improvement in eco efficiency within the evidence considered. The illustrative expected loss model produced an aggregate expected loss of USD 625,000 across the selected hypothetical risk events. The evidence reviewed for renewable energy and electric mobility interventions also indicates that targeted technological investments can generate substantial operational benefits under appropriate conditions, including reductions in energy or transportation related

costs and investment recovery within a multi year period. These figures should be interpreted as evidence specific or illustrative results rather than universal estimates applicable to every organization or geographic market.

Overall, the study establishes that Climate Risk Intelligence is most useful when environmental information is connected directly to economic consequences and managerial responses. The contribution of the proposed framework is therefore not simply the use of AI for climate prediction. Rather, it is the integration of climate data, AI based prediction, economic impact assessment, ERM, ESG information, and sustainability investment analysis within a single decision framework. Such integration can help organizations move from reactive disruption management toward more proactive and economically informed climate resilience planning.

4.2 Managerial Recommendations

Organizations should establish an integrated climate risk data infrastructure that connects weather information, geographic exposure, supplier information, transportation data, operational performance, financial indicators, and regulatory information. The objective should be to create a continuously updated risk information environment rather than relying exclusively on periodic manual assessments.

Supply chain managers should incorporate climate exposure into supplier evaluation and network design. Supplier concentration, geographic location, alternative sourcing capacity, transportation dependency, and recovery capability should be considered alongside conventional procurement criteria. AI based vulnerability assessment can support the identification of suppliers and facilities requiring additional monitoring or contingency planning.

Organizations should also integrate climate risk indicators into Enterprise Risk Management systems. Climate risks should have clearly assigned risk owners, defined monitoring indicators, escalation thresholds, mitigation plans, and financial consequences. This would allow environmental risk information to become part of regular corporate risk governance rather than remaining within separate sustainability departments.

Investment decisions should incorporate both environmental and financial performance. Organizations considering renewable microgrids, electric fleets, energy efficiency systems, or carbon management technologies should evaluate initial investment, operating costs, expected savings, payback period, Net Present Value, carbon reduction, resilience benefits, and sensitivity to energy prices and regulatory conditions. Companies participating in international supply chains should strengthen data management and carbon accounting capabilities. This is particularly relevant for organizations exposed to carbon related trade requirements such as CBAM. Accurate emissions data can support regulatory compliance, supplier engagement, product costing, and strategic decarbonization planning.

ESG and climate disclosures should be supported by reliable internal data governance and independent assurance where appropriate. Organizations should ensure that reported sustainability information is consistent with operational and financial records. Transparent reporting can improve the usefulness of climate information for investors, lenders, customers, regulators, and supply chain partners.

AI governance should also be incorporated into Climate Risk Intelligence systems. Organizations should document data sources, model assumptions, validation procedures, uncertainty ranges, model updates, and human oversight mechanisms. High consequence decisions should not depend exclusively on an unvalidated AI prediction.

4.3 Policy Recommendations

Policymakers can support climate resilient supply chains by improving access to reliable climate data, strengthening digital infrastructure, and promoting interoperable environmental information systems. Public climate datasets should be sufficiently detailed to support business level risk assessment while maintaining appropriate privacy and security protections. Table 20 shows how climate intelligence can support preventive action through detection, prediction, exposure assessment, scenario analysis, and continuous monitoring. Table 21 summarizes key sustainability investments and their potential benefits, costs, and risk-reduction contributions. Table 22 presents illustrative climate-economic scenarios showing how different climate and transition conditions may affect risk, investment, and recovery outcomes. The scenarios and relationships presented in these tables are methodological examples and are not presented as observed company data or empirical findings.

Governments can also facilitate investment in renewable energy systems, resilient infrastructure, low emission transportation, and other technologies that reduce both environmental exposure and operational vulnerability. Financial incentives should be designed around measurable environmental and economic outcomes and should account for the different technological and financial characteristics of individual projects. International policy coordination is particularly important for globally connected supply chains. Differences in carbon measurement, environmental disclosure, product standards, and reporting requirements can increase compliance complexity. Greater interoperability among climate disclosure and carbon accounting frameworks could reduce unnecessary reporting burdens while improving the comparability of climate related information.

4.4 Research Limitations

Several limitations should be considered when interpreting the findings. First, the study is based primarily on secondary evidence synthesis rather than a newly collected firm level longitudinal dataset. Consequently, the quantitative findings synthesized from individual studies should not be interpreted as universal causal estimates.

Second, the proposed Climate Disruption Risk Score is a structured analytical framework rather than a universally calibrated industry standard. The weighting of hazard, exposure, vulnerability, and disruption dimensions may need to be adjusted according to sector, geography, infrastructure characteristics, and organizational risk tolerance.

Third, AI prediction performance depends strongly on data quality and availability. Climate data can contain missing observations, spatial limitations, temporal inconsistencies, and measurement uncertainty. Supply chain data may also be incomplete because organizations frequently lack detailed visibility beyond first tier suppliers.

Fourth, climate risks interact with non climate risks such as geopolitical instability, pandemics, cyber incidents, commodity price volatility, and regulatory changes. A climate focused model may therefore underestimate total disruption probability if these interacting risks are not explicitly represented.

Fifth, the economic feasibility of sustainability technologies is highly context dependent. Energy prices, financing costs, government incentives, infrastructure availability, technology maturity, carbon prices, and operating conditions can substantially change investment outcomes. Therefore, payback and cost reduction results should be interpreted within their respective study conditions.

4.5 Future Research

Future research should validate the proposed Climate Risk Intelligence framework using firm level and facility level datasets. Longitudinal datasets combining climate observations, supply chain disruption records, financial performance, supplier information, and operational data could provide stronger evidence concerning causal relationships between climate events and economic outcomes.

Future studies should also develop machine learning models using real time climate and supply chain data. Comparative evaluation of logistic regression, random forest, gradient boosting, neural networks, temporal models, and explainable AI techniques could determine which approaches provide reliable predictions under different data conditions.

Another important research direction is the development of multi tier supply chain Climate Risk Intelligence. Many climate disruptions originate beyond direct suppliers and can propagate through second tier and third tier suppliers. AI based network analysis could therefore be used to identify hidden dependencies and potential disruption propagation pathways.

Further research should also investigate the relationship between AI prediction accuracy and economic decision quality. A highly accurate prediction does not necessarily produce an economically valuable decision. Future research should therefore evaluate whether AI based climate predictions actually improve inventory decisions, supplier diversification, route selection, insurance decisions, capital allocation, and business continuity outcomes.

Finally, future research should develop integrated climate economic simulation models that combine physical climate scenarios, AI based prediction, supply chain network structures, regulatory changes, and financial consequences. Such models could provide organizations with dynamic scenario analysis and support long term resilience investment decisions.

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References

- [1] Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- [2] Aboutorab, H., Hussain, O. K., Saberi, M., Hussain, F. K., & Prior, D. (2024). Adaptive identification of supply chain disruptions through reinforcement learning. *Expert Systems with Applications*, 248, Article 123477. <https://doi.org/10.1016/j.eswa.2024.123477>
- [3] Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2022). Supply chain risk management and artificial intelligence: State of the art and future research directions. *International Journal of Production Research*, 60(20), 6151–6175.
- [4] Bhattacharya, S., Govindan, K., Dastidar, S. G., & Sharma, P. (2024). Applications of artificial intelligence in closed loop supply chains: Systematic literature review and future research agenda. *Transportation Research Part E: Logistics and Transportation Review*, 184, Article 103455.
- [5] European Commission. (2023). *Carbon Border Adjustment Mechanism: Questions and Answers*. European Commission.
- [6] European Commission. (2025). *Carbon Border Adjustment Mechanism: Guidance and Implementation*. European Commission.
- [7] European Commission. (2026). *Carbon Border Adjustment Mechanism: Definitive Regime*. Directorate-General for Taxation and Customs Union.
- [8] International Financial Reporting Standards Foundation. (2023). *IFRS S2 Climate-related Disclosures*. International Sustainability Standards Board.

- [9] International Financial Reporting Standards Foundation. (2023). *IFRS S2 Climate-related Disclosures*. International Sustainability Standards Board.
- [10] Intergovernmental Panel on Climate Change. (2021). *Climate Change 2021: The Physical Science Basis*. Cambridge University Press. <https://doi.org/10.1017/9781009157896>
- [11] Intergovernmental Panel on Climate Change. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability*. Cambridge University Press. <https://doi.org/10.1017/9781009325844>
- [12] Intergovernmental Panel on Climate Change. (2023). *Climate Change 2023: Synthesis Report*. IPCC.
- [13] Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak. *Transportation Research Part E: Logistics and Transportation Review*, 136, Article 101922. <https://doi.org/10.1016/j.tre.2020.101922>
- [14] Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. *International Journal of Production Research*, 58(10), 2904–2915. <https://doi.org/10.1080/00207543.2020.1750727>
- [15] Ivanov, D., & Dolgui, A. (2021). OR-methods for coping with the ripple effect in supply chains during COVID-19 pandemic: Managerial insights and research implications. *International Journal of Production Economics*, 232, Article 107921. <https://doi.org/10.1016/j.ijpe.2020.107921>
- [16] Ivanov, D. (2023). Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability. *International Journal of Production Economics*, 263, Article 108938. <https://doi.org/10.1016/j.ijpe.2023.108938>
- [17] Jabbour, C. J. C., Jabbour, A. B. L. de S., Sarkis, J., & Filho, M. G. (2019). Unlocking the circular economy through new business models based on artificial intelligence and digital technologies. *Technological Forecasting and Social Change*, 149, Article 119804.
- [18] Marchese, D., Reynolds, E., Bates, M. E., Morgan, H., Clark, S. S., & Linkov, I. (2018). Resilience and sustainability: Similarities and differences in environmental management applications. *Science of the Total Environment*, 613–614, 1275–1283. <https://doi.org/10.1016/j.scitotenv.2017.09.086>
- [19] McKinsey Global Institute. (2020). *Risk, Resilience, and Rebalancing in Global Value Chains*. McKinsey & Company.
- [20] Mora, C. J., Malik, A., Shanmuga, S., & Sidhu, B. (2024). Understanding climate risk externalities through the global supply chains: A framework and review of the literature on existing approaches. *Journal of Accounting Literature*. <https://doi.org/10.1108/JAL-06-2023-0105>
- [21] Organisation for Economic Co-operation and Development. (2021). *Climate Change and Long-Term Economic Growth: A Review of the Evidence*. OECD Publishing.
- [22] Pankratz, N. M. C., Bauer, R., & Derwall, J. (2023). Climate change, firm performance, and investor surprises. *Management Science*, 69(12), 7352–7398. <https://doi.org/10.1287/mnsc.2023.4685>
- [23] Porter, M. E., & Kramer, M. R. (2011). Creating shared value. *Harvard Business Review*, 89(1–2), 62–77.
- [24] Shahzadi, G., Jia, F., Chen, L., & John, A. (2024). AI adoption in supply chain management: A systematic literature review. *Journal of Manufacturing Technology Management*, 35(6), 1125–1150. <https://doi.org/10.1108/JMTM-09-2023-0431>
- [25] Shahsavari, M., Hussain, O. K., Saberi, M., et al. (2024). Event identification for supply chain risk management through news analysis by using large language models. *The Review of Socionetwork Strategies*, 18, 255–278. <https://doi.org/10.1007/s12626-024-00169-z>
- [26] Sharfman, M. P., & Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic Management Journal*, 29(6), 569–592. <https://doi.org/10.1002/smj.678>
- [27] Sheffi, Y., & Rice, J. B. (2005). A supply chain view of the resilient enterprise. *MIT Sloan Management Review*, 47(1), 41–48.
- [28] Smyth, C., Dennehy, D., Fosso Wamba, S., Scott, M., & Harfouche, A. (2024). Artificial intelligence and prescriptive analytics for supply chain resilience: A systematic literature review and research agenda. *International Journal of Production Research*, 62(23), 8537–8561. <https://doi.org/10.1080/00207543.2024.2341415>
- [29] Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, 103(2), 451–488. <https://doi.org/10.1016/j.ijpe.2005.12.006>
- [30] United Nations Conference on Trade and Development. (2021). *Climate Change Impacts on Trade and Development*. United Nations.
- [31] United Nations Conference on Trade and Development. (2023). *Trade and Environment Review 2023: Building a Sustainable and Resilient Ocean Economy*. United Nations.
- [32] Wang, Z., & Bai, Y. (2023). Enhancing supply chain resilience through government subsidies and blockchain adoption: Ensuring sustainability and preventing disruptions. *Managerial and Decision Economics*. <https://doi.org/10.1002/mde.3932>
- [33] World Economic Forum. (2023). *The Global Risks Report 2023*. World Economic Forum.
- [34] World Economic Forum. (2024). *The Global Risks Report 2024*. World Economic Forum.
- [35] World Economic Forum. (2025). *The Global Risks Report 2025*. World Economic Forum.
- [36] Yaroson, E. V., Breen, L., Onarinde, B. A., & Kotzab, H. (2023). Artificial intelligence techniques for enhancing supply chain resilience: A systematic literature review, holistic framework, and future research. *Computers & Industrial Engineering*, 186, Article 109714.
- [37] Chowdhury, M. S. H., Alvi, M. F. I., & Ahmed, M. (2021). Corporate environmental responsibility and firm productivity: Examining the role of green organizational practices in developing economies. *Eco-Business and Environmental Progress Journal*, 1(2).
- [38] Jahan, I., Nahid, M. A. H., & Samrat, R. I. (2021). Carbon border adjustment mechanisms (CBAM) and export competitiveness in emerging economies: A global CGE analysis. *Eco-Business and Environmental Progress Journal*, 1(1).
- [39] Alvi, M. F. I., Haque, M. E., & Hasan, M. (2022). Decarbonizing urban freight logistics: Evaluating the environmental and economic impacts of electric fleet transition policies. *Eco-Business and Environmental Progress Journal*, 2(1).
- [40] Hasan, S., Rahman, M. M., & Ahmed, M. S. (2022). Renewable energy transition and microgrid adoption in manufacturing SMEs: A structural equation and technoeconomic analysis. *Eco-Business and Environmental Progress Journal*, 2(1).

- [41] Nirob, M. A., Tawhid, S., & Haque, M. E. (2022). Climate policy uncertainty and corporate green investment: Evidence from energy-intensive industries in emerging markets. *Eco-Business and Environmental Progress Journal*, 2(2).
- [42] Nahid, M. A. H., Ahmed, M., & Khan, M. R. A. (2023). Revisiting the environmental Kuznets curve in developing Asia: Panel cointegration and ARDL modeling of industrial carbon emissions. *Eco-Business and Environmental Progress Journal*, 3(1).
- [43] Chowdhury, M. S. H., Hasan, S., & Hasan, M. E. (2023). Water scarcity and industrial productivity: Assessing the economic consequences of corporate water-resource management in emerging economies. *Eco-Business and Environmental Progress Journal*, 3(2).
- [44] Das, S., & Al Amin, M. S. (2024). Detecting corporate greenwashing vs. genuine sustainability: Consumer trust, linguistic framing, and purchase intentions in digital environmental reporting. *Eco-Business and Environmental Progress Journal*, 4(1).
- [45] Rahman, M. M., Jahan, I., & Mazumder, A. (2024). Evaluating the effectiveness of single-use plastic ban policies on municipal solid waste and environmental quality: A difference-in-differences analysis. *Eco-Business and Environmental Progress Journal*, 4(1).
- [46] Rahman, T., Ashikuzzaman, & Ahmed, K. A. (2024). Artificial intelligence and environmental decision-making: Does AI adoption improve corporate resource efficiency? *Eco-Business and Environmental Progress Journal*, 4(2).
- [47] Ahmed, M. S., Tawhid, S., & Nirob, M. A. (2024). Digitalization and industrial energy efficiency: Examining whether smart manufacturing accelerates corporate decarbonization. *Eco-Business and Environmental Progress Journal*, 4(2).
- [48] Nirob, M. A., & Chowdhury, M. S. H. (2025). Evaluating the economic and environmental impact of enterprise risk management (ERM) in green supply chains. *Eco-Business and Environmental Progress Journal*, 5(1).
- [49] Rahman, T., Ahmed, M., & Samrat, R. I. (2025). Evaluating the economic feasibility of industrial carbon capture and storage (CCS) in emerging economies. *Eco-Business and Environmental Progress Journal*, 5(1).
- [50] Mazumder, A., Rahman, M. M., & Nahid, M. A. H. (2025). Climate risk and supply-chain resilience: How environmental disruptions affect SME performance and international trade. *Eco-Business and Environmental Progress Journal*, 5(2).
- [51] Islam, S., & Hosain, I. (2026). Blockchain technology for sustainable supply chain transparency: Enhancing traceability and Scope-3 carbon accounting in agricultural SME exports. *Eco-Business and Environmental Progress Journal*, 6(1).
- [52] Rahman, T., & Hasan, M. (2026). Generative AI for sustainable business strategy: Can AI-powered decision-making improve corporate resource efficiency and environmental performance? *Eco-Business and Environmental Progress Journal*, 6(2).
- [53] Alvi, M. F. I., & Saha, U. S. (2021). Edge-cloud synergy in Industry 4.0: Optimizing real-time latency for smart manufacturing facilities. *Digital Transformation and Technology Dynamics*, 1(1).
- [54] Ahmed, A., Khan, H. H., & Majumder, M. (2021). ICT for sustainable development: Assessing the carbon footprint of national communication networks. *Digital Transformation and Technology Dynamics*, 1(2).
- [55] Ahmed, A., & Bhattacharjee, A. (2021). Integrated business-intelligence dashboards and environmental decision quality: A demonstration template. *Digital Transformation and Technology Dynamics*, 1(1).
- [56] Ahmed, M., Nirob, M. A., & Hasan, S. (2021). Chemistry-informed ensemble modeling for sustainable infrastructure risk management. *Journal of Business Intelligence & Decision Science Review*, 1(1).
- [57] Mazumder, A., & Tawhid, S. (2024). Multi-tier supply chain risk & capital optimization engine. *Journal of Business Intelligence & Decision Science Review*, 4(1).
- [58] Haque, M. E., Ashikuzzaman, & Hasan, S. (2021). Vehicle routing and fleet dispatch optimization for last-mile urban distribution. *Journal of Business Intelligence & Decision Science Review*, 1(2).