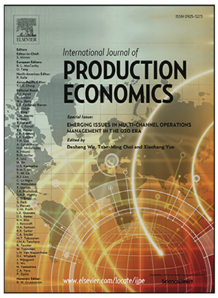

Identifying assets exposed to physical climate risk: A decision-support methodology

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Abstract

Climate events are increasingly affecting supply chains, leading to frequent and costly impacts. Managers lack a systematic approach to evaluate risks to individual facilities and employees. We propose a decision support methodology to help quantify the exposure of both to ten most common climate hazards. Using both historical and scenario-based climate data, the methodology distinguishes three dimensions for understanding climate risk: anomaly, extreme variability, and acceleration, applied to each peril from historical to projected data. This approach allows for the isolation of the components of climate change by peril, facilitating a better understanding of each component. Furthermore, it enables the development of adaptative responses tailored to each of the climate dimensions. A case study of a logistics group with more than 200 warehouses across 181 locations in eight European countries illustrates the approach, demonstrating its practicality and effectiveness. Our methodology offers firms, large and small, the opportunity to reinforce their resilience in the face of multiple physical risks. The metrics and scores presented in this paper can be extended to assess the growing issues of climate risks as they apply to occupational health and safety as well as natural resources management.

Keywords: Climate change, Climate risk, Supply chain, Decision support

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1. Introduction

Climate change is a reality. It is global and accelerating (IPCC, 2021). Climate change and global warming are causing more frequent and intense climatic anomalies, with increasing tangible effects on businesses and supply chains (Somarin et al., 2023). Physical climate risks, i.e., the physical consequences of climate change for people and businesses (Carney, 2015), are multiplying across the globe. Physical climate risks, also known simply as physical risks, can be event-driven (acute) or associated with longer-term shifts in climate patterns (chronic). They directly or indirectly affect organizations' premises, operations, supply chains, transport needs, and employee safety, and may have financial implications for organizations, such as direct damage to assets and indirect impacts from supply chain disruption. For example, the floods in West Germany in July 2021 had a severe impact on infrastructure and industrial activities. The automotive manufacturers faced disruptions due to damaged facilities and supply chain interruptions (Koks et al., 2022). In 2022, one of the worst droughts in decades in Europe severely affected agricultural production, particularly cereals and vegetables (?). Food and beverage companies such as Danone, Mutti, Barilla, Nestlé, InBev, and Unilever all experienced supply shortages and cost increases. Flooding in China in 2022 impacted local and global food supply chains (Ali et al., 2023). Additionally, droughts and wildfires in Canada deprived French processing companies of mustard seeds, as Canada accounts for 80% of their supply (Raux, 2022).

For managers, adapting operations to climate risks is a new and complex challenge. It is complex because, by their very nature, physical risks involve a multitude of perils: heat waves, cold snaps, river and coastal flooding, storms, wildfires, and flash floods. Processes and metrics to measure or monitor their exposure are lacking (Lawrence et al., 2020; Ali and Golgeci, 2021). It is also complex because each peril evolves at its own pace, and this evolution over time depends both on a global scenario of greenhouse gas emissions and on the specific location to which it applies. The speed of climate change is not uniform across the world. Europe, for example, is warming more than twice as fast as the global average, and the number of severe and extreme weather events has increased by 35%, causing economic and financial losses to rise by 60% over the past two decades (Monasterolo, 2020; European Environment Agency, 2022). Only a third of executive boards have discussed the physical risk affecting their own operations, and even less have seen an analysis of the physical risks affecting their counterparties (Paisley, 2022).

Physical risks have become macro supply chain risks that pose significant threats to the global supply chain (Shu and Fan, 2024; Liang et al., 2024). They can cause disruptions, asset[1] damage, production setbacks, and drops in productivity, resulting in potential operational and financial losses (Pankratz and Schiller, 2022). In 2021, 432 events including heatwaves, droughts, floods and other climate events resulted in $252 billion in economic losses, with 2022 recording damages of $313 billion, marking a 25% increase in catastrophic events and a 64% surge in economic losses compared to the 2001-2020 averages. Half of these losses were uninsured (Aon, 2023).

Managers need to acquire new knowledge to understand climate-related disruption, select suitable suppliers, design adapted mitigation strategies, and enhance resilience across the supply chain (Ali and Golgeci, 2021; Ali

[1] In this paper, the term asset is used interchangeably in reference to production, distribution, supplier facilities or products.

et al., 2023; Ivanov, 2023).

This leads us to the following research questions: How can operations and supply chain managers measure climate risks to subsequently adopt suitable strategic and operational decisions? To what extent assets in a supply chain are exposed to disruptive events, and to what climate risk? Which critical suppliers are most at risk? Few methods and metrics address the multiple dimensions of physical risks and their evolution over time, applied at the granular level of each asset and its supply chain (Ghadge et al., 2020; Sodhi and Tang, 2021).

This is the knowledge gap we address in this paper. We present a blueprint with two major contributions. The first is a managerial one: (a) to help managers understand the current and projected risks affecting each element of the value chain in a way that facilitates decision-making on adaptation strategies. The second is a scientific one: (b) to provide scholars with a framework and new methods to broaden the study of supply chain risk by including both the short and long-term effects of climate-related disruptive events and patterns.

The methodology we present is based on meteorological risk calculation methods (Walsh et al., 2020). It involves different Global Climate Models (GCM) to mitigate potential biases and the fifth generation of atmospheric European ReAnalysis (ERA5) data (Hersbach et al., 2020). We introduce three innovative quantitative measures of climate risk for each peril: (i) the average level of risk (climate anomaly), (ii) the risk of a significant deviation from the average (climate extreme variability), and (iii) the speed of risk evolution (climate change acceleration).

Thanks to its open-source and granular nature, the methodology can be applied both to small and medium-sized firms (particularly at risk because they are generally highly dependent on a small number of assets and suppliers) and to multinational supply networks and their critical Tier 1 and Tier 2 suppliers. In the latter case, the metrics are used primarily to classify the elements of the value chain most at risk. Managers report that the measures helped understand the risks involved and that the corresponding precautionary managerial decisions are easy to identify.

In this paper, we apply the methodology to the network of a logistics service provider with 181 temperature-controlled warehouses spread across Western Europe, either directly owned or owned by a critical supplier. We evaluated the vulnerability of each warehouse to ten climate-related risks, enabling the company to identify the sites most exposed to each hazard. Managers then characterized the importance and degree of urgency associated with each peril and each site, providing the necessary decision support to enhance the resilience of the supply network with appropriate mitigation strategies.

The paper is organized as follows. In the next section, we review the related three streams of literature: climate risk and transmission channels, existing climate risk scores, and climate risk assessment in operations management. We describe the methodology and data in section 3. In section 4, we discuss its effectiveness and present the case of a logistics network. We provide the implications for practice and for research in section 5.

2. Related Literature

The literature on physical climate risks in operations management is sparse. Therefore, we reference relevant research from adjacent fields, focusing on three key aspects. In subsection 2.1, we define physical risks, analyze how they affect business activity, and review how they interact with financial performance. In §2.2, we examine existing aggregate physical risk scores and their inability to provide operational managers with useful, granular, and actionable information necessary to identify a supply chain's weaknesses and strengthen its resilience. In §2.3, we discuss how physical risk has been assessed in the operations management literature and draw on its contributions and limitations to identify the gaps that need to be filled in order to build the methodology presented in this paper.

2.1. Physical Risks: Definition, Transmission Channels, and Risk Assessment

Physical risks fall into two main categories: chronic, including slow-evolving perils like sea-level rise and gradual temperature and precipitation shifts; and acute, encompassing events such as floods, droughts, heatwaves, wildfires, and storms, whose frequency and severity climate change amplifies (Carney, 2015). Physical risks influence business through revenues, operating costs, and asset values (TCFD, 2017). Reduced sales, increased production costs, and interruptions caused by these risks directly impact firms' loan repayment abilities, indirectly affecting the financing banks and institutions (Ivanov et al., 2022). Chronic risks mostly shape demand and sales across numerous industries (Bertrand et al., 2015; Parnaudeau and Bertrand, 2018), while acute risks disrupt working conditions and productivity (Schuldt et al., 2021), causing damage to assets, infrastructure, and supply chains (Brusset and Bertrand, 2018; Ghadge et al., 2020).

An extensive body of literature has demonstrated that climate conditions significantly impact demand and therefore revenues, production costs, and earnings across various economic sectors. These sectors include agriculture, tourism, mining, food, beverage, apparel, outdoor activities, transportation, construction, and online shopping, among others (Fergus, 1999; Dutton, 2002; Deschênes and Greenstone, 2007; Murray et al., 2010; Musshoff et al., 2011; Steinker et al., 2017; Stulec et al., 2019). Chronic and acute risks together are estimated to cost the global economy from USD 2 trillion per year (-0.9% of GDP) in an optimistic GHG reduction Representative Concentration Pathway (RCP) scenario (RCP 2.6), to USD 15.45 trillion per year (-6.4% of GDP) under a 'business as usual' scenario (RCP 8.5) (Lepore and Fernando, 2023). While seven out of ten businesses are considered to be exposed to weather risks (Larsen, 2006; Lazo et al., 2011), small and medium-sized enterprises (SMEs) are particularly vulnerable due to their lesser diversification. A UK business survey conducted by Federation of Small Businesses (2015) revealed that 93% of small business owners perceive bad weather as a threat to the survival of their businesses.

The initial studies linking climate and financial performance focused on the influence of weather conditions on mood, and indirectly attempted to demonstrate that the mood of market participants could affect the rise or fall of stock markets (Hirshleifer and Shumway, 2003; Cao and Wei, 2005; Chang et al., 2006; Chen et al., 2018). As the understanding of transmission mechanisms progressed and climatic anomalies increased, a second stream of literature shifted its focus to fundamentals, examining the influence of temperature anomalies on the performance of sectoral stock market indices and, subsequently, on individual stocks (Boudoukh et al., 2007; Bertrand and Chabot, 2020; Lemoine and Kapnik, 2024). The financial impact of physical risks is estimated by extending traditional econometric and risk assessment methods to investigate the influence of one or more climatic variables on one or more financial variables. It is calculated as the potential financial loss that each climatic risk can generate over a given period. This calculation is known as Climate Value-at-Risk (Climate-VaR), a concept initially introduced by Toeglhofer et al. (2012), and developed in Prettenthaler et al. (2015), and Dietz et al. (2016). Climate-VaR offers a probabilistic estimate of potential maximum losses, incorporating both historical and projected climate data distributions and factoring in the asset's sensitivity to selected climate hazards. The cumulative Climate-VaR, when applied to the assets most at risk, provides the content for mandatory financial disclosure reporting[2].

The financial and insurance literature has extensively described methods for estimating the financial impact of a climatic hazard on an firm or an activity sector (Burke and Hsiang, 2015; Newell et al., 2021). For chronic risks, Pres (2009) reviews the most commonly used methods for estimating the evolution of financial losses as a function of the evolution of each climate hazard. From agricultural yields to clothing sales, from agri-food to energy consumption, from tourism to cultural events, and from consumer goods to seasonal products, most sectors of activity have been studied[3] to determine the level of sensitivity, thresholds, and probabilities of occurrence to be translated into economic impact (volume) or financial impact (Value at Risk). Most methods are empirical, leading to models that provide information

[2]From a regulatory standpoint, starting in 2024, companies with more than 250 employees, above €50m turnover and/or €20m total assets are required to comply with new accounting and sustainability regulations. These companies will need to disclose information about climate-related risks and opportunities that could reasonably be expected to affect the entity's cash flows, its access to finance or cost of capital over the short, medium or long term.

[3]see for instance Starr-McCluer (2000), Pres (2009), Auffhammer et al. (2013), Dell et al. (2014), Toeglhofer et al. (2012), Dietz et al. (2016), Dellink et al. (2017), Hsiang et al. (2017), Brusset and Bertrand (2018), Parnaudeau and Bertrand (2018), Bertrand and Brusset (2018), Surminski et al. (2018), Dellink et al. (2019), Bertrand et al. (2021), Zhao et al. (2021), and Dawkins et al. (2023)

on the sensitivity of a company, sector or product to changes in climate risk. Risk managers and academics now have access to a comprehensive repository of sensitivity and damage functions that can be used to determine the average and maximum financial impact of variations in climate risk parameters, and price climate insurance, also known as parametric insurance, whose applicability has been widely illustrated in the operational research literature (see for instance Bertrand et al., 2015; Bertrand and Parnaudeau, 2017; Prettenthaler et al., 2018).

In the case of acute risks, impact estimation methods rely on insurers' databases to determine the financial impact resulting either from the average number of days of business interruption or the average amount of damage based on indemnities paid by insurers (Nobanee et al., 2022). For over 20 years, insurers, reinsurers, and research institutes have been methodically recording all climatic events, their locations, extents, intensities, and the associated damage in financial and human terms. These databases are used to establish the damage functions utilized to price multi-peril or parametric climate insurance policies. The most widely used databases are managed by Munich Re and Swiss Re (reinsurance companies), and CRED (maintained by the University of Leuven in Belgium). Other providers of extreme event databases include BD Catnat in France, the Asian Disaster Reduction Center, EMA (Australia), the Federal Emergency Management Agency (USA), and ReliefWeb. In both cases, the academic literature abounds with empirical studies linking the intensity of an anomaly or one-off climatic event to its economic and financial consequences.

While global warming is commonly measured by the average temperature increase over pre-industrial levels, the primary financial risk concern lies in the associated rise in the frequency and intensity of extreme temperatures

(Cohen, 2023). A 2021 survey of finance academics, professionals, and public sector economists identifies physical risk as the top concern (Stroebel and Wurgler, 2021). Although there is some evidence of acute risks being factored into credit and equity markets, findings are preliminary, scarce, and mixed (Eren et al., 2022). In sovereign debt markets, Mallucci (2022) demonstrates deteriorating borrowing conditions in the Caribbean post-extreme events. Announcements of Corporate Environmental Initiatives that provide information about self-reported corporate efforts to avoid, mitigate, or offset environmental effects have limited or no impact on the financial value assessment of the announcers (Jacobs et al., 2010; Chen et al., 2020). The municipal bond market presents conflicting research results (Goldsmith-Pinkham et al., 2022), while the corporate bond market shows investors paying premiums for companies benefiting from natural disaster announcements (Huynh and Xia, 2021). Cevik and Miryugin (2022) found credit access challenges in high climate variability regions. In both academia and industry, the consensus is that physical risk impacts are under-studied and under-evaluated (Rising et al., 2022).

To date, most of the studies that demonstrate a link between climatic conditions and financial performance, although producing conclusive and significant empirical results, suffer from the same bias. The climatic data used are often highly aggregated both geographically and temporally (e.g., national average temperatures on a monthly or annual time scale) and are applied to financial data that are themselves aggregated (e.g., sales, stock market value). Additionally, these studies generally lack the ability to weight the climatic data according to the geographical distribution of the company's business volume due to the unavailability of detailed data. Identifying the vulnerabilities of a company's production assets and suppliers requires the use of granular, geolocalized climate data. While an operational manager may be able to list key sites and suppliers according to their degree of criticality for the company, they often lack the methodology and expertise to construct the risk metrics necessary to diagnose physical risks. Our methodology bridges this gap.

2.2. Physical Climate Risk Scores: Background and Limitations

The field of physical climate risk measurement is relatively new. Investors and asset managers were among the first to seek climate risk measures for their investment portfolios or loans (Calabrese et al., 2024). Faced with the urgency of climate change, investment advisors and asset managers have taken the lead in looking for ways to assess the extent to which physical risks affect investment portfolios (GARI, 2016). Rating agencies and vendors developed proprietary methodologies to produce climate scores (Hubert et al., 2021; UNEP FI, 2023). Chronic risks most commonly covered are sea level rise, heat and cold stress, drought, and flash flood. Acute risks are storms, floods, and wildfires (UNEP FI, 2023). In essence, investors expect an overall single aggregated rating or score, similar to what exists for credit or ESG ratings, taking into account vulnerability to each of the aforementioned climatic hazards. Four Twenty Seven, a California based vendor acquired by Moody's was one of the first to provide physical climate scores on about 2,000 listed companies (Mazzacuratti et al., 2017). Today, UNEP FI (2023) lists over ten vendors, some providing physical climate risk scores only, others providing both physical and transition scores. Using these scores, investors can compare potential investments with each other and rate exposure levels for asset portfolios on a 1-to-5 or colour-shaded scale, from low to catastrophic risk based on probability of occurrence.

Due to the commercial nature of scoring services, information regarding methodologies and underlying data used by climate score providers is restricted. In particular, this applies to how each peril is measured, and the way an overall climate risk score is aggregated. The same opacity extends to scores that encompass risk assessment and loss evaluation, whether relying on estimations at regional or sector levels, proprietary asset-level data, or satellite images. Hain et al. (2022) explored whether existing climate scores are sufficiently reliable to improve financial decision-making. They compared six score providers on a sample of listed US corporations. They observed significant divergences in scores at company level, and suggest that the choice of score provider alters the results of climate risk assessments. Several explanations account for discrepancies in climate risk assessments. Firstly, the granularity of metrics is often too broad to be pertinent at the asset level. Secondly, the lack of transparency in methodologies and risk metrics can result in varying outcomes. More critically, assets subjected to climate risks are derived from databases informed by satellite data and diverse sources about Tier 1 and Tier 2 suppliers. Asset criticality is frequently gauged by site size, whereas operations managers prioritize criticality based on the volume of activity managed by the supplier or its irreplaceability in the value chain. While site size and supplier rank can approximate business volume, they fail to capture the supplier's unique value proposition. Managers, who are best positioned to identify key suppliers and production sites, must be involved in determining which sites to apply climate risk metrics to, thereby ensuring an objective risk assessment. Hain et al. (2022)'s findings emphasize that existing physical risk scores, while scientifically rigorous and adequate for financial asset managers, are inadequate for tactical and operational decisions. For the latter detailed exposure information for each climate peril are required at the facility and supplier level to make informed decisions. This paper addresses this gap by offering a more actionable climate risk assessment methodology.

2.3. Climate Risk Assessment in Operations Management Literature

Physical risks are related to the operational or disruption risks identified in the SCRM literature (Tang, 2006). They can be classified in both of two primary identified risk categories: (1) risks stemming from coordination challenges between supply and demand, influenced by chronic climate risks, and (2) risks related to disruptions in normal operations, which include acute climate risks. The pioneering work of Kleindorfer and Saad (2005) and Tang (2006) highlighted natural disasters as significant supply chain risks, emphasizing their more substantial impact on business compared to operational risks. Tang (2006) acknowledged that while most companies recognize the importance of risk assessment programs and employ various methods, from quantitative models to qualitative plans, for evaluating supply chain risks, the scarcity of reliable data poses a significant challenge. This lack of data makes it difficult to accurately estimate the probability of specific disruptions and assess the potential impact of each disaster.

Subsequent works have been analyzed in a literature review with the purpose of answering the question: 'How can climate change risks be managed in global supply chains?' (Ghadge et al., 2020). However, in that work, the mitigation strategies identified centre on sustainable practices (Pagell and Shevchenko, 2014) rather than actionable measures to assess or protect operations against physical risk. As early as 2014, Prof. Howard-Grenville, Simon Buckle, and Sir Brian Hoskins highlighted the high uncertainty of climate change outcomes in an editorial, urging scholars to explore shifts in supply networks, relationships, and risk-mitigation strategies (Howard-Grenville et al., 2014). To date, this appeal appears to remain largely unaddressed.

Er Kara et al. (2020) emphasizes the necessity of modeling the influence of climate change risk on supply chain performance and the need for established approaches to capture the complex interaction between these factors. In line with this study, Ghadge et al. (2020) discuss the management of climate change risks in global supply chains, highlighting the importance of understanding the complex behavior of risk and its cascading impact on the network. They emphasize the need for designing and managing unique supply chain networks to effectively address climate change risks. However, neither work proposes a methodology to measure such risk.

The questions operations decision-makers must address involve resilience enhancement and regulatory obligations. They need to identify the physical risks impacting their assets, pinpoint the assets with the highest vulnerability, and determine which assets demand immediate focus. However, existing climate score methodologies generally lack the necessary analytical capabilities (Saunders and Skinner, 2023).

We observe that the literature predominantly relies on empirical methods that involve a comparative analysis of historical data series to assess the impact of the weather on operational costs and performance (Cachon et al., 2012; Dell et al., 2014; Kahn et al., 2021). Typically, operational managers utilize assessments of weather conditions' impact on sales and operating costs to manage short-term challenges (Badorf and Hoberg, 2020). Steinker et al. (2017) showed that integrating climate variables into sales forecasts a week ahead can effectively align workforce allocation with expected sales, thereby leading to cost savings. Brusset and Bertrand (2018) demonstrated how understanding the relationship between climate conditions and sales facilitates the development of financial protection strategies for manufacturers of seasonal products. These strategies enable firms in the supply chain to manage risks of lost sales and overstocking due to adverse climate conditions, specifically targeting protection for the upcoming season or, at most, two consecutive seasons.

Studies modeling climate change impacts on organizations and facilities often face challenges due to high uncertainty and the lack of suitable data, typically relying on limited data sets or focusing on restricted geographical areas. For instance, Wang et al. (2019) proposed a real-options model for infrastructure investments to mitigate rainstorm disasters in urban areas. Er Kara et al. (2020) adopted a three-phase mixed-method approach to identify how various climate risks affect supply chain performance, including resource availability and stockouts. Bertrand et al. (2015) found a relationship between apparel sales in France and unseasonal temperatures to lay the ground for specific climate insurance mechanisms. Bertrand and Brusset (2018) developed a methodology for supply chain managers to manage risks of unseasonal weather through financial insurance policies, and Bertrand et al. (2021) focused on protecting franchises from unseasonal weather in specific territories by hedging against identified weather variable fluctuations. Scott et al. (2020) asks the rhetorical question of whether we should resist climate change induced disruption or "retreat" by moving or relocating assets which could be subject to such risk. Liang et al. (2024) propose a method to evaluate the loss of labor productivity due to heat and other extreme weather shocks in China. No mitigation or other strategy is proposed except that firms should take a full inventory of their entire infrastructure to ensure security of both physical and digital infrastructure. Lai et al.

(2023) review recent economic literature and find that the negative effects of extreme temperatures are widespread, and that in addition to lower physical outputs, extreme temperatures impair mental productivity. The effect of heat stress is corroborated by Song et al. (2023). They note that however an initial improvement on labor and energy efficiency between 2007 and 2016 as temperature progressively increased in their panel of cities mostly situated in temperate areas. This is consistent with the concept of an optimal temperature identified by Burke and Hsiang (2015), above which productivity falls rapidly. Caputo et al. (2023) estimate resilience to physical disruptions including both accidents and weather-induced ones in supply chain. They measure the damage impact and recovery using a software which models the recovery of production buildings. Besides the limitation due to a computer model, the authors do not propose a measure of climate risk nor managerial recovery measures beyond suggesting that systems be constructed in a resilient and robust way. Shu and Fan (2024) propose an analysis of supply flexibility in US firms exposed to extreme weather risk and propose that flexibility in supply chains requires that sourcing take into account such risks when choosing suppliers. Yang et al. (2024) study the impact of heavy haze as a weather disruption on operational efficiency on firms in China. Saura et al. (2023) developed a data-driven model to identify the main impacts of extreme weather on economic production using the user-generated content from the social network Twitter as a source of information, but there is no suggestion as to how managers could operationally deal with such risks. Li (2023) review the adaptation of listed companies through the lens of self-disclosed information and find that improving firms' adaptive capabilities and extending their time horizons can be considered. The measurement of different adaptation strategies can also be informative for managers seeking to identify best practices.

However, the methodologies are often applied to a restricted number of assets or area and do not encompass a comprehensive list of risks, both chronic and acute, that typically affect a whole supply chain. None aim at addressing the complexities of managing hundreds of facilities and assets across multiple countries with the need to produce granular risk metrics that can easily be used to make adaptation decisions. Furthermore, they focus mainly on protecting short-term sales or profits, but do not integrate physical risks in longer-term strategic decisions regarding the location of a new production asset, the choice of a supplier, or the need to adapt or close a facility. To address this, current risks must be projected over longer-term time horizons. The methodology we present closes these gaps.

3. Methodology and Data

Conceptually, climate risk assessment combines three dimensions: the climatic hazard, the probability of occurrence, and the criticality of the asset to which the risk applies (UNEP FI, 2023). These three dimensions are covered in steps 1 to 3 of our methodology (Figure 1). Step 4 converts the climate risk into economic and financial impact. The economic and financial impacts of chronic and acute risks is reflected in lower productivity or higher operating costs (see section 2.1 on climate sensitivity, value at risk, and damage functions). Hence, the challenge for an operational manager is not merely to estimate the financial impact on the asset, but to understand the type of peril, determine how to measure it, and estimate its intensity and probability distribution. This observation was corroborated by the feedback from one hundred company representatives[4] consulted prior to the development of this methodology. Recognizing that existing aggregated climate risk scores do not help improve the resilience of the supply chain, their foremost objective was to identify the physical risks affecting each element of the supply chain, assess their significance, prioritize the sites most at risk, and obtain the risk metrics necessary to estimate potential losses and determine the appropriate investment in adaptation solutions.

In developing our methodology to address these needs, we engaged both collectively and individually with the delegates to draft a comprehensive specification of the expected deliverables. The climate data had to be certified and open-source. The methodology had to be designed to elucidate the multi-dimensional aspects of climate risk, and to enable the comparison of assets through precise risk measurements. Additionally, the list of perils had to adhere to the recommendations of accounting and sustainability standards, thus serving as a foundational basis for the preparation of various reports. These are the challenge to which our methodology contributes.

The methodology presented in this paper builds upon the limitations observed in existing solutions while preserving transparency, data accessibility, practicality, and actionability (see an overview in Figure 1). Following the steps of the methodology, this section is divided into five subsections. In §3.1 we first present the scope and objectives that drive data requirement. In

[4]The delegates were part of "The Great Challenge of Businesses for the Planet", which is a collective intelligence initiative to select 100 proposals aimed at accelerating the ecological transition (https://www.legranddefi.org/). Participating firms were selected from a pool of 120,000 firms. From an initial list of 65,000 suggestions and contributions made by these firms, the ability to assess the exposure of the supply chain to physical risks was selected as part of the final 100 proposals. It is part of the operations and production tools category (proposition number OP5, page 36 of the summary report (Raisson-Victor et al., 2023). The final 100 proposals were presented to the Prime Minister of France in February 2023.

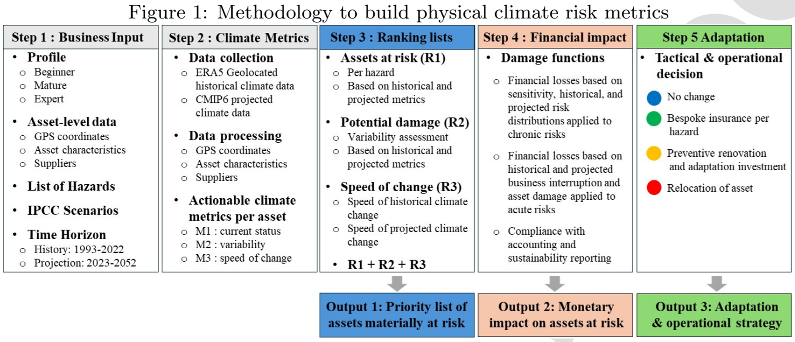


Figure 1: Methodology to build physical climate risk metrics

The methodology to design actionable climate risk metrics and rank assets most at risk is composed of step 1 and step 3, and leads to the priority action list. The step '4: Financial' is not in the scope of this paper. The adaptation strategy decision tree is detailed in subsection 4.2

§3.2, we describe how data is collected and climate metrics are calculated. In §3.3, the assets most at risk are ranked. Finally, in §3.4, we present the decision-making process based on climate-related exposures.

3.1. Business Input : Asset-level data and Strategic Objectives Data

As we worked with operational managers over several sessions, we identified three climate risk maturity profiles. The first profile, which we termed Beginners, aims for minimal compliance with accounting and sustainability reporting standards. Implementing a resilience strategy is not a priority for these entities. They are typically small to medium-sized entities lacking integrated climate risk management systems. The second profile we termed Mature, is in active transition toward formal climate management. These entities are aware of the risks and are seeking solutions to manage them and adapt their supply chains to enhance resilience. They generally have robust risk management processes in place and aim to integrate climate risks into their decision-making and adaptation strategies. The third profile, termed Experts, demonstrates a high level of expertise and recognizes the value of climate risk assessment. These entities deploy sophisticated risk management practices and aspire to extend climate risk evaluation to their supply networks.

Hence, the profile of the firm determines the objectives and the required level of information on assets. Geolocation is sufficient for 'beginners' whose objectives are limited to identifying assets at risk. Asset-level characteristics (asset type, book value, number of employees, contribution to financial results, etc.) are required for 'mature" and 'expert' firms looking to make operational decisions on adaptation and resilience improvement. Asset-level data are any type of quantitative or qualitative information regarding physical assets (i.e., tangible assets of economic value). Whereas the geolocation may be relatively easy to obtain, the characteristics of each asset, such as book value, market value, production methods or throughput, number of employees, are generally hard to obtain, even within companies. In step 1, the list of hazards is selected. While reporting initiatives like the TCFD suggest a list of standard hazards, additional specific hazards may be added depending on the asset considered. Climate scenarios are also selected in step 1. For risk management purposes, managers are interested in making decisions based on the most unfavorable climate scenario. This is often scenario RCP 8.5, also referred to as 'business as usual' or 'hot house scenario'. Finally, risk managers choose the time horizon on which to project climate change which conditions the ranking of assets most at risk. In practice, the time horizon is aligned with that of the financial resources available to firms to invest in transformations aimed at improving resilience. This time horizon rarely exceeds ten years.

3.2. Building the Physical Climate Risk Metrics

In step 2, we collect geolocated climate data for each asset and transform it into hazard indicators.The methodology requires transforming hourly worldwide climate data into actionable climate measurements scaled down at the level of each location.For each asset, we collect a minimum of thirty years of hourly weather data. For projection data, we collect 5 daily data sets for four scenarios, 11 global climate models, and two values (median and max). In the case study used to illustrate the methodology, the data required to produce climate risk metrics on 181 locations represents just over one billion data points.

While a set of standard hazards are defined by regulators (see Table A.5), asset-level characteristics may require adjustments in climate metrics. Typically, this involves adjusting a trigger threshold of an existing metric. For instance, if an asset is insulated against cold or heat, the threshold for measuring vulnerability to extreme temperatures can be modified, either lowered or raised, to more accurately represent the actual risk faced by the asset. Similarly, the nature of a supplier, or the material supplied may entail evaluating specific climate risk metrics. For instance, a food company sourcing wheat, sunflower, and rapeseed may need to evaluate the risk of supply shortages. This evaluation requires information on the geographical area of sourcing and tailored risk indicators. These agro-climatic risk indicators might include temperature sums 'base 0' or 'base 6' (depending on the crop), cumulative rainfall, dates of the first and last frost, number of scalding days, etc. (Walsh et al., 2020).

One major contribution of this paper lies in steps 2 and 3 of the methodology. Historical climate data used to produce risk metrics are hourly data on single level representing the fifth generation atmospheric European

ReAnalysis (ERA5) provided by Copernicus at the European Centre for Medium-Range Weather Forecasts (Hersbach et al., 2020). Copernicus is the Earth observation component of the European Union's Space programme. It offers free, open access information services that draw from satellite Earth Observation and in situ (non-space) data. For the purpose of this paper, historical data covers the period 1993-2022.[5] A minimum of 30 years of data is required to calculate normal climatic conditions and deviations from these conditions at each site under consideration (WMO, 2017). As the raw data are provided in one-hour time steps, this entails downloading a large volume of data, as well as the metadata associated with each data point (i.e., longitude, latitude, altitude, and time). The file format commonly used by corporate managers, namely Excel, is unsuitable for collecting data or working on worksheets in this context. The maximum memory or file size allowable for any site and hazard metric would quickly be exceeded. The same applies to projected data. Copernicus climatic data are available in the NetCDF (Network Common Data Form) format. NetCDF, a file format designed to facilitate the creation, access, and sharing of scientific data, is widely used in oceanographic and atmospheric communities. It stores variables like temperature, pressure, precipitation, and wind speed. NetCDF files can contain large arrays of multi-dimensional data. Constructing climate indicators requires a High-Performance Computing (HPC) platform to convert NetCDF data into Python-compatible data structures, like Xarray. The

[5]We construct all metrics from hourly data except for the Fire Weather Index and Sea Level Rise that are directly collected from Copernicus. The calculation of the Fire Weather index (FWI) follows Van Wagner (1987) and Vitolo et al. (2020). FWI ranges from 0 to 100, with values above 30 indicating high fire danger conditions. Sea level rise (SLR) is measured against sea level of the reference period 1986-2005. ERA 5 Data can be downloaded on : https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form

code we designed was run on a high performance computing (HPC) system, which featured dual Intel Xeon Platinum processors (2.60 GHz) and 512 GB of RAM. Python packages used in this work are provided in Table A.3. User-friendly Excel files are generated so that corporate managers can use them to calculate risk metrics M1, M2, and M3 for each assets.

Measuring exposure to climate hazards requires taking several dimensions into account: the nature of each hazard, the current average and projected level of risk applied to each location, the intensity of deviations from the current and projected average, and the speed at which the climate is changing applied to each location. The metrics we have developed reflect these dimensions. Risk metrics M1, M2, and M3 are estimated on annual bases (e.g., number of days > 25°C in a year). The first metric M1 aims to identify and rank the company's assets for each risk in relation to the indicator's current and projected anomaly. For each indicator i and each *site*, M1 is defined as the difference between the average value of the indicator for *site* and the average value of the same indicator when all assets are considered.

Let *sites* be the set of asset $j \in \{1, \ldots, N\}$, *clim* the set of possible climate indicators with $i \in \{1, \ldots, n\}$, and the calculation period $t \in \{1, \ldots, T\}$ covering the period from 1993 to 2022. The site average $M_{j,i}$ for all values taken by each indicator over the period is

$$Avg_{j,i} = \frac{1}{T} \sum_{t=1}^{T} x_{ij,t}, \qquad \forall i \in clim, j \in sites \tag{1}$$

where $x_{ij,t}$ is the average value taken for an indicator i, on site j over T. We use 10 hazard indicators (see the list in Table A.5). This calculation is iterated for the N assets in the study set. We introduce the standard deviation calculation for each climate indicator over the specified period.

The standard deviation $\sigma_{j,i}$ for each indicator on site j is given by:

$$\sigma_{j,i} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_{ij,t} - Avg_{j,i})^2}, \qquad \forall i \in clim, j \in sites \tag{2}$$

We then use the mean and the standard deviation to calculate the z-Score for an indicator i, on site j over T, represented as:

$$M1_{j,i} = \frac{1}{T}\sum_{t=1}^{T}\frac{x_{ij,t} - Avg_{j,i}}{\sigma_{j,i}}, \qquad \forall i \in clim, j \in sites \tag{3}$$

The value of M1 determines the associated level of risk. The risk is low if M1 is less than 1.5 (green), moderate if M1 is between 1.5 and 2 (orange), and high if M1 is greater than 2 (red). This classification follows McKee et al. (1993) and the recommendations of the National Center for Atmospheric Research[6].

For the development of projected data, we adopted a multi-model approach. This involves generating a set of projected values for hazard indicators fro each Global Climate Model (GCM). The list of GCMs is in Table A.4. The models and time periods used are part of the sixth phase of the Coupled Model Intercomparison Project (CMIP6), which forms the basis of the Intergovernmental Panel on Climate Change's 6th Assessment Report (Eyring et al., 2016; IPCC, 2021). With this multi-model approach, we mitigate potential biases associated with using a single model, thereby enhancing the robustness of our analysis. We use the trend-preserving Quantile Delta Mapping (QDM) bias correction (Cannon et al., 2015) and apply the down-

[6]See example of the Standardised Precipitation Index (SPI) on https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-index-spi

scaling method called Quantile-Preserving Localized Analog Downscaling (QPLAD) developed by Gergel et al. (2023), which also preserves trends in the distribution tails.

The projected value of each metric M1, M2, and M3 is the average over all GCM of each M1, M2, and M3 over a planning horizon (usually several years). We projected data according to IPCC RCP 4.5 and RCP 8.5 scenarios, i.e., respectively the median and worst case scenarios in terms of expected rise in global temperature. Let μ be the projection period. In the empirical application for the logistics group, which is discussed in the following section, μ is equal to 10 years. This aligns with the group's time horizon for adaptation investments and return calculations. We denote $M1p$ the projected value of $M1$. Equation 3 on projected data becomes:

$$M1p_{j,i} = \frac{1}{T+\mu} \sum_{t=T}^{T+\mu} \frac{x_{i1,t} - M_{j,i}}{\sigma_{j,i}}. \tag{4}$$

The second metric, M2, measures the indicator's probability of a significant deviation from the mean. To calculate deviations from the mean, we rely on the mean calculation defined using Equation 1 and the standard deviation with Equation 2. Based on this, we calculate the number of days where indicator i at site j deviates from the mean by more than two standard deviations:

$$M2c_{j,i} = \frac{1}{T} \sum_{t=1}^{T} \theta_{\{x_{ij,t} > Avg_{\mathrm{j},i} + 2\sigma_{\mathrm{j},i}\}}. \tag{5}$$

where $\theta_{\{x_{ij,t} > Avg_{\mathrm{j},i} + 2\sigma_{\mathrm{j},i}\}}$ is the indicator function, with $\theta = 1$ if the condition $x_{ij,t} > Avg_{\mathrm{j},i} + 2\sigma_{\mathrm{j},i}$ is true, and 0 otherwise. The choice of a trigger set at two standard deviations reflects the non-linear nature of the empirical damage caused by severe climatic events and is consistent with Alfieri et al.

(2015), Nordhaus and Moffat (2017), Gosling et al. (2018), and Vousdoukas et al. (2019). The projected metric follows the same logic but is calculated on projected data from 2023 to 2032. As for $M1$, the value of $M2$ determines the level of risk. The risk is low (green) for M2 equal to 0. The risk is moderate (orange) if M2 is less than 0.3. The risk is high (red) if M2 is greater than 0.3. In practice, M3 over 0.3 means that the asset is not insurable.

M3 measures the extent to which the risk is increasing. Based on the values obtained per *site* from the two previous metrics, the objective is to select assets that require priority attention. To identify priority action areas, we first calculate, for temperature-related indices, the following averages:

$$M_{\mathrm{j},i(1993-2012)} = \sum_{1993}^{2012} \frac{x_{i1,t}}{(2012-1993+1)} \tag{6}$$

$$M_{\mathrm{j},i(2013-2022)} = \sum_{2013}^{2022} \frac{x_{i1,t}}{(2022-2013+1)} \tag{7}$$

We calculate the growth rate risk per site for each indicator:

$$M3_{j,i} = \left| \frac{M_{\mathrm{j},i(2013-2022)} - M_{\mathrm{j},i(1993-2012)}}{M_{\mathrm{j},i(1993-2012)}} \right| \times 100 \tag{8}$$

We proceed with the same calculations for wind and precipitation indices. Finally, we replicate the same calculation with projected data, relying on the IPCC RCP 4.5 and RCP 8.5 scenarios.

3.3. Ranking Assets and Creating the Priority List

In step 3, assets are classified according to their exposure to each hazard. The R1 ranking, based on M1 metrics, identifies the assets most exposed to each hazard over the chosen time horizon. The R2 ranking, based on M2 metrics, classifies assets according to the climatic variability that applies to each hazard and location. This variability and the associated probability distribution are synonymous with a high risk of deviation from normal, in other words, a high risk of loss or damage. The R3 classification, based on M3 metrics, ranks the assets selected as most at risk by the R1 and R2 classifications. The interest of such a ranking is because the speed of change varies according to hazard and location.

Assets that simultaneously meet the risk criteria of classifications R1, R2, and R3, constitute a priority list of assets for which mitigation decisions must be taken. Such mitigation strategies include either insuring the asset against the consequences of a specific hazard (if still insurable), carrying out preventive work to reinforce the asset's resilience and lower insurance cost, or selling or relocating the asset.

3.4. Operational and Strategic Adaptation Decisions

Our methodology (step 1 to 3) enables the identification of assets where physical risks have a significant impact over the chosen time horizon due to their abnormal situation (M1), extreme variability (M2), and the speed at which these risks evolve (M3). In step 4, managers can translate physical risk into monetary impacts. When the potential loss is significant on a company-wide scale, the options are to implement insurance where possible, select one or more adaptation actions, or relocate the site or change suppliers (Figure 2). The final step is to identify and prioritize adaptation measures. In some cases, few measures may seem feasible due to implementation challenges or cost constraints. In such instances, adaptation may not be possible, making relocation the most viable option. Conversely, in other cases, multiple measures are feasible. For instance, to mitigate the impact of heat waves on employees, a company can insulate its premises, install air-conditioning units, repaint roofs white, plant vegetation, adopt heat-appropriate workwear, or introduce staggered working hours.

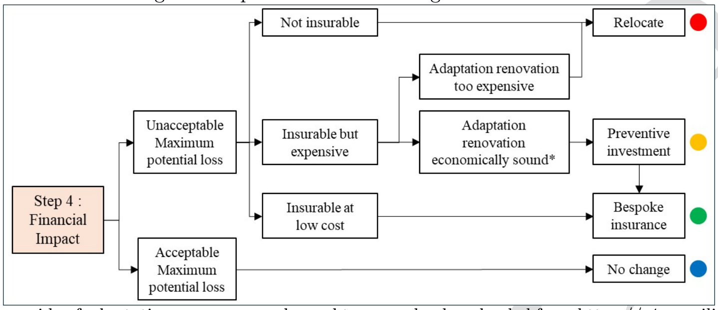
Adaptation solutions can be categorized into two types: no-regrets solutions, which are beneficial regardless of future climate change (e.g., reducing water dependency), and evolutionary solutions, which allow for the integration of feedback and the combination of multiple measures. To support operational managers in their adaptation efforts, the European Commission has published a technical guide on adapting buildings to climate change. This guide consolidates existing methods, specifications, best practices, and guidelines for climate-resilient buildings, providing practical advice to professionals and serving as a reference in various EU policy documents (European Commission, 2023). Furthermore, a collaborative initiative of experts[7] has produced a comprehensive inventory of adaptation solutions. Each solution is detailed in a data sheet, which, for a given level of exposure determined by our methodology, allows for the selection of one or more solutions based on an index of technical implementation difficulty, a cost index, and an index of effectiveness for the specific climate peril under consideration (OID, 2024).

4. Application of the Methodology to a Case Study

The methodology can be applied to any type of supply or distribution network spanning any number of regions in the world. For illustrative purposes and without loss of generality, we present the case of a large pan-European group in temperature-controlled logistics, managing directly and

[7]The European Sustainable Real Estate Initiative is a collaboration between the United Nations Environment Programme, the Global Alliance for Buildings and Construction, the Agence de la Transition Écologique, and is supported by approximately twenty international technical partners.

Figure 2: Operational and Strategic Decision Tree



*: The guide of adaptation measures per hazard type can be downloaded from https://r4re.resilience-for-real-estate.com/documentation. The guide makes it possible to combine several adaptation actions according to the level of risk involved. Each action is assigned a score for technical difficulty and financial investment, and a score for effectiveness in relation to the risk incurred.

indirectly a network of over 200 warehouses spanning eight different countries, and whose profile in terms of knowledge and climate risk management objectives is that of a mature company. The first subsection details the application of the methodology and the second shows its effectiveness in providing managers with sufficient information for the ensuing strategic and operational decisions.

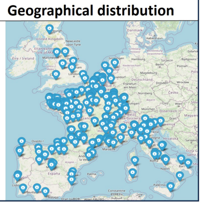
4.1. Assessing and Identifying Sites Most Vulnerable to Physical Risks

The critical assets consist of warehouses located in 181 sites across eight countries in Europe (Figure 3). Warehouses are temperature-controlled, with temperatures ranging from −25 °C to 15 °C. Warehouses are located on the city outskirts, along freeways or expressways, and some in port areas. The outside temperature and its fluctuations are significant factors, as they influence energy consumption and impact productivity. Severe weather events, such as heavy rain or storms, can also cause disruptions. The group aims to assess the current climate risks, project them onto a timeline that aligns with the investment horizon for adaptation, and identify which warehouses need close monitoring and may require decisions regarding refurbishment or relocation. Furthermore, due to its scale, the company is mindful of the new IFRS and CSRD directives pertaining to the disclosure of physical risks and is committed to fulfilling its reporting obligations. Existing high-level climate risk scores, which mirror credit and ESG risk scores, fall short of meeting the group's specific operational needs and strategic objectives. We therefore apply our methodology to identify the warehouses most at risk on 10 climate hazards. We consider two scenarios (RCP 4.5 and RCP 8.5), and a 10-year projection time horizon, which is aligned with the strategic time horizon of the company.

Figure 3: Location of 181 Sites in Europe

Country	Number of sites
Belgium	5
France	101
Italy	32
The Netherlands	3
Portugal	3
Spain	24
Switzerland	5
United Kingdom	8
Total	**181**

Geographical distribution

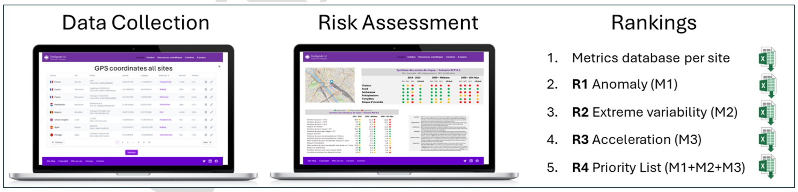


First, we collect raw hourly data such as temperature, wind, precipitation from Copernicus in NetCDF format. Using HPC, we extract the data for all 181 sites based on GPS coordinates. We calculate the historical values of the 10 climate metrics for the period 1991-2022. We project the climate metrics using 11 different Global Climate Models and calculate the median value for each year up to 2032. We construct M1, M2, and M3 for each site, we assign the corresponding risk levels (green, orange, red). Sites are then ranked according to their level of risk, from highest to lowest, based on the risk metrics M1 (anomaly), M2 (extreme variability), and M3 (acceleration). Sites that are simultaneously at the top of the ranking for all three risk metrics constitute the list of sites for which a decision must be made. This decision is either to relocate the site or to implement one or more adaptation actions.

Thanks to this methodology, the operational managers at each site have access to all changes in each risk metric for the ten identified perils from 1991 to 2033, provided in Excel format. Additionally, they can access the values of the M1, M2, and M3 metrics for each peril. This comprehensive data enables managers to fully understand the nature of the risks they face and make informed adaptation decisions based on the risk level associated with each metric. Moreover, the head of operations management can view the same information by site and access the M1, M2, and M3 metric rankings for all 181 sites by peril. To facilitate ease of use, we have created a dedicated website where all this information can be readily viewed and downloaded in Excel format by any authorized manager.

Figure 4 illustrates the data collection process and the output delivery of the physical risk assessment via the dedicated website, which enables all the information (data and associated risk probabilities) to be downloaded in Excel format for easy integration into the company's mapping software.

Figure 4: Data Collection, Risk Assessment, and Output Delivery



4.2. Identification of Sites Most at Risk and Adaptation Decisions

To save space, we focus only on the priority list of the 10% of sites most at risk, based on the worst-case yet currently most realistic scenario, i.e., RCP 8.5. In appendix, we have included a screenshot of heat stress from the interactive maps of the web site, to illustrate the dynamic visualization of the evolution of each peril for all sites (Figure A.5). We produce M1, M2 and M3 metrics for all sites and all perils. While M1 sorts the sites already at risk, M2 differentiates assets between insurable and non-insurable without prior adaptation measures. Assets with a high M2 (i.e., which frequently exceed two standard deviations) are deemed economically non-insurable. For such asset, one option is to adapt and improve the site's vulnerability attributes, provided risk reduction is cost-efficient. When the cost of adapting the asset exceeds the potential benefit in risk reduction, a decision to relocate the asset is taken.

Table 1 lists the sites where anomaly (M1), extreme variability (M2), and accelerating climate change (M3) rank among the highest risks[8]. These comprise a total of 74 sites out of 181 that require one or more adaptation actions. Temperature is the most frequent hazard (52 sites). Heat, either episodically or in waves, is present at 32 sites, while cold represents a risk at only 20 sites. The risks associated with flooding, flash floods and sea level rise are on the priority list 35 times. However, the economic and financial consequences of flooding (business interruption and property damage) are greater than those associated with temperature changes (lower profitability, higher operating costs). Therefore, we have prioritized sites exposed to

[8]The complete set of results including M1, M2, and M3 individual rankings, can be obtained upon request from the authors, subject to authorization by the company on which the case study is based.

fluvial and pluvial flooding, as well as flash floods, at the top of the table. A total of 17 sites are at high risk of flooding, 3 of which are exposed to both flooding from water accumulation and rising groundwater, and flooding from runoff. In addition to this list of flood-prone sites, 14 others are at risk from sea level rise. For each of these sites, remediation strategies identified and evaluated by the European Sustainable Real Estate Initiative are considered in relation to the required investment, their effectiveness for the peril under consideration (Table 2). The choices to be made depend on the company's financial capabilities. Adaptation often involves multiple measures, which can be combined. Some strategies are mutually exclusive, while others can be implemented concurrently. Additionally, certain actions are considered "no-regrets" measures, meaning their implementation will be beneficial regardless of future climate developments, particularly when the required investment is low. An evolutionary approach is also possible, initially reducing risk until funds can be secured for a more transformational measure.

Our methodology is particularly effective for assessing the risk of very large supply chains, as it enables centralized operations management to compare sites on a granular and comprehensive basis. Due to its granularity, it can also be applied locally to small and medium-sized businesses, providing them with a comprehensive assessment of the climatic risks they face. Some of the sites on the priority list, such as La Rochelle, Marseille, Quimperlé, and Vigo, simultaneously have to manage four climatic perils with a very high probability of occurrence. Additionally, six other sites face three major perils. This matrix and granular approach illuminates the strategic choices that need to be made, particularly in assessing the relevance of relocation versus adaptation to the identified perils. In addition, for the purpose of regulatory reporting, the assets our methodology identifies to be at risk of material damage (the priority list), in particular those exposed to floods, wildfires, and storms, are to be accounted for in the proportion of assets at risk, which is to date the figure on which companies over 250 employees, and sales in excess of 50 million sales, or total assets in excess of 20 million euros, will have to report (CSRD E1 and IFRS S2).

Table 1: R4 - Priority List (M1+M2+M3) - Standard Hazards - Scenario RCP 8.5 - 10 Years

Site	Heat Stress	Heat Wave	Cold Stress	Cold Wave	Flash Flood	Flood	Wildfires	Sea Level Rise	Storms	Total
Benavente					1	1				2
Ludres					1	1				2
Marcilla					1	1				2
Dover					1				1	2
St-Brieux					1			1		2
Burnhaupt le bas					1					1
Castellanos de Moriscos					1					1
Metz					1					1
St Martin des Champs					1					1
Vannes					1					1
Atton						1				1
Custines						1				1
Duppigheim						1				1
Reichstett						1				1
Rivalta di Torino						1				1
Valladolid						1				1
Villadangos del Paramo						1				1
La Rochelle	1	1		1				1		4
Marseille	1	1		1				1		4
Quimperlé	1	1		1			1			4
Vigo		1		1			1	1		4
Alicante	1							1	1	3
Branderion		1		1			1			3
Frontignan	1			1				1		3
Genova		1		1			1			3
Monteprandone	1						1	1		3
Tiriolo	1	1					1			3
Girona		1					1			2
Marcianise		1		1						2
Plouenan		1						1		2
Santa Iria		1						1		2
Santa Palomba		1		1						2
St-Sever	1	1								2
Aix en Provence				1						1
Albeda de Iregua		1								1
Amorebieta		1								1
Ascoli Piceno							1			1
Barnsley									1	1
Bodegraven								1		1
Boulogne	1									1
Bridgwater								1		1
Carros				1						1
Catania								1		1
Coruna								1		1
Eindhoven									1	1
Fontanil-Cornillon							1			1
Gardolo			1							1
Givers			1							1
Gorizia				1						1
Herminal les Vaux									1	1
Ibos		1								1
Ifs									1	1
Irun								1		1
La Garde				1						1
Langres			1							1
Lardier et Valenca				1						1
Liverpool									1	1
Llissa de Val	1									1
Mesagne									1	1
Miramas				1						1
Modugno									1	1
Motherwell									1	1
Olbia	1									1
Porrino	1									1
Povoa de Santa Iria								1		1
Redditch									1	1
Replonges			1							1
San Giovanu	1									1
Sestu		1								1
Sorgues				1						1
St Lo									1	1
Tombolo		1								1
Valencia	1									1
Verson									1	1
Total	14	18	4	16	10	10	9	15	13	109

Table 2: Remediation Strategies for Flood Risks

Remediation Strategy	Benefits	Investment
Designing a sponge plot	10	10
Creating a courtyard oasis	10	7
Creating a rain garden	10	3
Planting around the building	10	1
Raising structural elements	9	10
Installing rainwater management basins	8	7
Installing flood defence	8	5
Fixing outdoor furniture	8	1
Protecting networks	6	7
Organizing a temporary withdrawal strategy	4	7
Setting up emergency warning systems	4	4
Concentrating essential equipment and activities on upper floors	4	1
Setting up autonomous power generation	1	10

Source: European Sustainable Real Estate Initiative. Investment relates to the technical difficulty and cost of a remediation action. Benefits relates to the efficiency of the action for the peril considered. Both scores are normalized on a 1 to 10 scale to allow comparisons.

Based on the methodology presented in this paper, the logistics group reached the following decisions. The ten assets identified as priority assets for wildfire risk underwent preventive improvements, including the creation of water retention reservoirs, autonomous electric generators for emergencies, and land clearing to establish safety zones to delay the spread of fire. This allowed the group to improve resilience and revise insurance costs down. Taking budget constraints into account, not all assets will undergo adaptation work in the first year. Due to their current level of exposure and ten-year risk projections, the two assets most exposed to flood risk and the site most vulnerable to flash floods are likely to become non-insurable in the near future. Since the cost of refitting these assets and protecting them against flooding consequences is economically unjustifiable, all three assets are currently being relocated. Finally, significant improvements in energy efficiency have been agreed upon for the seven assets most exposed to heat stress and the eight assets with the highest heat wave risk score. Thanks to these operational decisions, managers estimate a reduction of nearly 60%

in the value-at-risk for assets identified in the priority list. This strategy reinforces the viability and resilience of their network. A next phase will be considered to include Tier 2 critical suppliers.

In the case study, the overarching issue stems from the need for decision makers' to quantitatively assess the exposure to physical risks for each site in a way that allows them to make informed and cost-effective strategic or operational decisions. The methodology we propose capitalizes on readily accessible open-source climate data and predictive global climate models to deliver actionable insights. The M1, M2 and M3 metrics resulting from this iterative work are transparent, as their definition and calculation are known to all stakeholders. By construction, they are replicable, comparable and auditable, and apply to all types of organizations. They are also flexible: additional bespoke risk metrics and thresholds can be chosen to best fit each activity or business sector. With our methodology, managers can identify climate risks and priority actions based on objective and systematic criteria, using data they own and control.

5. Conclusion and Implications for Practice and Research

Climate change and related physical risks challenge business resilience and profitability. From 2024, European regulatory requirements mandate disclosure of risk exposure to encourage proactive adaptation. We observe that existing risk assessment tools lack transparency and practicality, failing managers.

The research question asked in introduction, namely: How can operations and supply chain managers measure climate risks to then be able to adopt suitable strategic and operational decisions? is answered in the present article. The methodology provides the necessary metrics to back strategic and operational decisions. Our approach aligns with the Global Adaptation & Resilience Investment Working Group's objectives, in terms of using uniform data sets, disclosing data sets and calculations, and projecting data within widely accepted scenarios with available references (GARI, 2016). The resulting metrics are comparable across assets, and can be integrated with financial measures to assess the financial implications for operations, revenues, and capital expenditure. It is important to note that such metrics can be dynamically updated to reflect both new data as well as the evolution of a network.

The growing impact of climate change on supply networks underscores the necessity of the present research. Increasingly frequent climatic events are impacting supply chain performance, asset values (including those of suppliers), and delivery capabilities.

5.1. Implications for Practice

The methodology presented in this paper meets the specifications of a collective intelligence effort involving a large group of operational managers and academics for the construction of a comprehensive physical risk assessment tool. The aim is to provide an actionable risk assessment tool to accelerate the adaptation and enhance the viability and resilience of value chains. Nine additional companies, which participated in the initial design of the metrics, are in various stages of applying the methodology we present in this paper. Our methodology has a broad scope of application, benefiting a wide range of users and data types. Banks and financial institutions can employ it when requesting asset information from the firms they finance, while accounting firms can use it to validate the risk reports of the firms they audit.

Our research opens up new perspectives for operations and supply chain managers by providing a cost-effective, transparent, independent, and efficient way to address forthcoming regulations and adapt firms while safeguarding employees from climate impacts. The climate scores we developed can be integrated into existing risk management models and applied to assets by firms based on asset-level information they control or with whom they operate, over a time horizon in line with their strategic re-evaluation periods.

Measuring a company's exposure to physical risk involves quantifying known unknowns, a task that is challenging in most circumstances. It also means quantifying the cost of climate inaction, a cost which many companies are still unaware of. The ability to measure physical risks as outlined here offers a new perspective for operational managers. It enables the assessment of potential losses under current or planned supply chain networks, thereby revealing hidden costs and benefits. This endeavor was extended to their main suppliers in identifying assets at risk, often prompting a physical reorganization of the supply chain to decrease dependency on distant suppliers, despite their cost advantages. The ability to measure physical risks as described here provides operational managers with a new perspective.

As our approach is based on open-access climate data and models, it is also cost effective. It significantly benefits small firms often overlooked by rating agencies and regulatory frameworks. Paradoxically, small businesses, reliant on fewer assets, less diversified, and with fewer resources dedicated to risk management, are also the most vulnerable. These firms can now perform internal risk measurement and adopt adaptive strategies to increase resilience and seize opportunities arising from climate change. Thanks to the calculation algorithms, the methodology we developed result in climate scores that can be seamlessly integrated into existing risk management models. Operational managers can apply these scores to their assets, using asset-level information under their own control and aligning with their investment horizons.

We contribute to the literature by shifting the discussion from the inadequacy of existing climate risk measures and the lack of data to providing an operational evaluation of physical risks. This approach has significant implications particularly for small firms, overlooked by rating agencies and regulatory frameworks, which can now self-evaluate their supply networks or respond to the request of upstream partners on their resilience to physical risks. By applying our methodology, companies can upgrade their internal risk management skills to boost resilience and capitalize on opportunities arising from climate change. The approach we propose reduces their dependence on costly, opaque proprietary global climate scores, which lack the granularity required to implement adaptation strategies. Instead, they are empowered to determine the necessary actions for each component of the supply chain, thereby enhancing its overall resilience.

5.2. Implications for Research on climate risk

The field of physical climate risk measurement has historically been overshadowed by research predominantly focused on managing risks and uncertainties on product, supply, demand, and information (Tang, 2006). When considering wider networks, most contributions in the field of supply chain risk management deal with such risk at the margin or only for certain weather variables. Much fewer research deals with climate change induced risks. This research answers the call for a "better understanding of climate change risks in SCM" as it is "critical for future managers" (Ghadge et al., 2020, p. 44).

One of the most innovative aspects of this paper is the introduction of three dimensions for understanding climate risk: anomaly, extreme variability, and acceleration, applied to each peril from historical to projected data. This approach allows for the isolation of the components of climate change by peril, facilitating a better understanding of each component. Furthermore, it enables the development of adaptation responses tailored to each of the climate dimensions. The research presented is also innovative in the granularity of the climatic data used, measuring each peril as closely as possible to the provided GPS coordinates, and in the comprehensiveness of the perils considered.

The measurement of each climate risk is transparent, as we explicitly define the calculation of each metric. It is based on certified, up-to-date, open-access data, ensuring replicability. Our methodology can be extended to measure the exposure of supply chains to air quality, pollution, biodiversity, and clean water availability. Another direction for research could involve integrating this methodology with the flow dynamics of a supply network. By considering climate change risk probabilities when assessing potential throughput at a node and evaluating alternative flow scenarios in the event of a disruption, a more comprehensive understanding of supply chain resilience can be achieved.

5.3. Limitations and Future Research Directions

As with all research, this work is subject to several limitations, and presents promising opportunities for future work. The first limitation is the imperative need for access to a supercomputer to open and read the data files and produce the historical and projected geolocated risk metrics. While the computation time involved is not prohibitive for a large group, it represents an obstacle for small or medium-sized businesses. However, this limitation also presents an opportunity for the academic world to collaborate more closely with companies and validate the relevance and usefulness of their research. Increasingly, researchers have access to supercomputers or sandboxes on hyperscalers such as AWS (Amazon) or Azure (Microsoft), which they can share with companies as part of preliminary empirical validations that companies can then adopt.

The second limitation concerns risk metrics and the notion of local adaptation. To illustrate this, consider vulnerability to heat stress, which is currently measured according to regulators' recommendations by the number of days above 25°C (summer days) and above 35°C (hot days). The uniformity of measurements across a geographical area with a relatively homogeneous climate facilitates the comparison of vulnerability between two sites or two suppliers. However, as early as 1971, Burton demonstrated that heat tolerance can vary greatly from one place to another, such as from the north to the south of Europe. This tolerance is referred to as adaptive capacity or coping range (Hewitt and Burton, 1971), defined as the ability of systems to adapt to variations in local climatic conditions (Smithers and Smit, 1997; Smit and Wandel, 2006). Future research could benefit from applying different temperature thresholds to define hot days, thereby accounting for this coping range.

The third limitation concerns the metrics used in the context of workers' health and well-being, whether indoors or outdoors. The metrics as defined by the TCFD, then endorsed by accounting and sustainable development regulations, are essentially "purely climatic" metrics that apply more to buildings than to people. For example, a hot day is defined in relation to the crossing of a temperature threshold. However, the human body reacts very differently to the same temperature, depending on whether the humidity level is low or high (Saura et al., 2023). Other heat indices linked to occupational health are currently being developed, such as the Standard Wet-Bulb Globe Temperature (WBGT) index (ISO 7243), and the first comparative studies are appearing (Barzegar et al., 2024). Similarly, additional metrics should be developed that take into account air pollution and the nature of the products handled by workers. Some gases become highly volatile and dangerous to humans above certain thresholds. The metrics we have used do not incorporate these elements. The gradual availability of geolocalized air quality data from Copernicus should enable researchers to supplement our work, especially as health and safety in the workplace is one of the key elements of an ESG rating.

Conflict of interest

The authors hereby confirm that they have no conflict of interest to declare.

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Appendix A.

Table A.3: Python Packages and Versions used in the code

Python packages	Version	Online Documentation
Python version	3.10.11	https://docs.python.org/3.10/library/os.html
Jupyter Notebook	6.5.4	https://jupyter-notebook.readthedocs.io/en/v6.5.4/
pandas	2.0.1	http://pandas.pydata.org/docs/
folium	0.14.0	https://pypi.org/project/folium/
xarray	2023.8.0	https://docs.xarray.dev/en/stable/
openpyxl	3.1.2	https://openpyxl.readthedocs.io/en/stable/
planetary-computer	1.0.0	https://planetarycomputer.microsoft.com/docs/overview/about
pystac-client	0.7.5	https://pystac-client.readthedocs.io/en/stable/
tqdm	4.65.0	https://tqdm.github.io/
plotly_express	0.4.1	https://plotly.com/python/plotly-express/
numpy	1.24.3	https://numpy.org/doc/1.24/

Table A.4: Global Climate Models

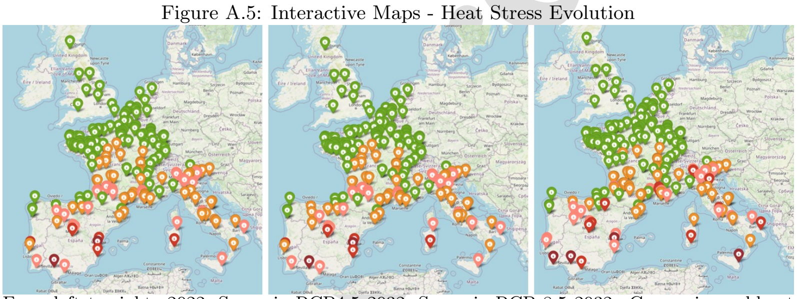
Modeling institution	Source model	Reference (doi)
CAS	FGOALS-g3	10.22033/ESGF/CMIP6.1783
INM	INM-CM5-0	10.22033/ESGF/CMIP6.1423
BCC	BCC-CSM2-MR	10.22033/ESGF/CMIP6.1725
CMCC	CMCC-ESM2	10.22033/ESGF/CMIP6.13164
MIROC	MIROC6	10.22033/ESGF/CMIP6.881
MOHC	UKESM1-0-LL	10.22033/ESGF/CMIP6.1569
MPI-M	MPI-ESM1-2-LR	10.22033/ESGF/CMIP6.742
NCC	NorESM2-MM	10.22033/ESGF/CMIP6.506
NOAA-GFDL	GFDL-ESM4	10.22033/ESGF/CMIP6.1407
NUIST	NESM3	10.22033/ESGF/CMIP6.2021
EC-Earth-Consortium	EC-Earth3	10.22033/ESGF/CMIP6.181

Table A.5: Standard Hazard Indicators

Hazard	Indicator	Description
Heat stress	HD25	Number of Hot Days with temperature in excess of 25°C
Cold stress	ID	Nb of Ice Days, days for which temperature does not exceed 0°C
Heat wave	WSDI	Warm Spell Duration Index
Cold vave	CSDI	Cold Spell Duration Index
Flash flood	R20mm	Nb of days with daily rain in excess of 20mm
See level rise	SLR	Sea Level Rise index
Floods	CWD	Consecutive number of Wet Days
Storm	WMax	Number of days with wind above storm level (> 20 m/s)
Wildfires	FWI	Fire Weather index
Drought	CDD	Consecutive number of Dry Days

Detailed explanations of each hazard indicator and the calculation formulas are available at https://www.ecad.eu/indicesextremes/indicesdictionary.php.

Figure A.5: Interactive Maps - Heat Stress Evolution



From left to right: 2022; Scenario RCP4.5 2032; Scenario RCP 8.5 2032. Green: insurable at reasonable cost; Orange: Insurable provided adaptation investments are made; Red and Dark red: Relocation to be considered.

Highlights

Identifying assets exposed to physical climate risk:
a decision-support methodology

- Climate change causes increasingly damaging disruptions to production sites
- A new methodology provides risk metrics for the 10 climate hazards
- Metrics are built on prospective variance of hazards over 10 years
- All existing Global Climate Models are used
- A case study illustrates the application with 181 sites over 8 countries