

## RESEARCH ARTICLE



# Sustainability risk in insurance companies: A machine learning analysis

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## Abstract

Sustainable development constitutes a global challenge today, and the sustainable development goals (Agenda 2030) will probably set the course for the coming decades. This paper discusses sustainability in insurance companies by combining two aspects: a social approach (the environmental impact) and a business approach (the prediction of claims due to climate change). Our objective is to analyse the impact of physical risk in a home insurance portfolio and to measure in economic terms the effect of climate change in the future, by applying machine learning methodologies. Two data sources are used: a Spanish insurance portfolio with 31,998 policies and claims from 2017 to 2022, and daily meteorological variables from 290 Spanish weather stations from 2000 to 2022. Two climate scenarios are considered: RCP 4.5 (medium impact) and RCP 8.5 (high impact). On average for the period 2023–2052, the results reveal that claims will increase by 105% for the 4.5 scenario and by 129% for the 8.5 scenario. Our paper makes a clear contribution to sustainability by analysing climate risks and their impact on an insurance portfolio. It shows the grave consequences of climate change for the insurance sector's solvency and the political implications for the financial system in general.

## 1 | CLIMATE CHANGE AND ITS FINANCIAL EFFECTS

Sustainable development has become a global challenge nowadays. Efforts to define and specify how it may be achieved led the United Nations to establish 17 Sustainable Development Goals in 2015, called the 2030 Agenda (United Nations, 2000). This action plan reminds us that the future will be marked by growing uncertainty generated largely by the impact of 'the highly improbable' or 'black swans' (Taleb, 2007), much like the coronavirus or the recent wars.

This paper explores sustainability in insurance companies as the main factor to be implemented and one that directly affects insurance products. The relationship between sustainability and the insurance sector is a topic of growing interest in academic and practical literature, as insurers play a crucial role in promoting sustainable practices and managing sustainability-related

risks (Sood & Özen, 2024). Climate risk assessment and management constitute a critical area in sustainability, and this is where insurers can help societies to adapt to and mitigate the effects of climate change. As climate change worsens, many natural disasters are becoming more frequent and severe. Households and businesses cover the risks of damages due to natural disasters with insurance. Therefore, before we discuss the insurance sector's ability to withstand climate change, we must understand insurers' exposure to climate risk. Moreover, insurers can exert an influence on sustainability when underwriting, by incentivising sustainable practices in various economic sectors. They can also develop innovative insurance products, such as parametric insurance and catastrophe bonds that provide more effective solutions for emerging climate and sustainability-related risks (Chiaramonte et al., 2020; Nogueira et al., 2018). Finally, the integration of ESG (environmental, social and governance)

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criteria in investment decisions has improved the sector's overall sustainability and contributed to broader sustainable development goals (Sood & Özen, 2024).

This research seeks to bring together two aspects of the effect of climate change on insurance. Firstly, a social approach within a development context, which will be related to the environmental impact and its effect on insurance portfolios. Secondly, a business approach based on actuarial practice, which will focus on a methodology for predicting claims and the monetary impact of climate change scenarios on non-life insurance products, in this case home insurance. Both aspects have a direct impact on insurance activity due to the sector's growing motivation to integrate into a more sustainable economy. It also includes the possible effects of climate change, thereby representing an opportunity in terms of product design for this market.

There is increasing awareness among academics and financial supervisors of the fact that unmitigated climate change and a disorderly transition to a low-carbon economy may affect the profitability of several economic activities and cause significant losses in insurance companies' portfolios (Battiston et al., 2017; Carney, 2015; NGSF, 2018). Among them, Munich (2019) estimated an economic impact of around USD 160 billion for 2018, of which only 50% had been insured. In 2022 they updated their estimates, concluding that the economic impact would reach USD 270 billion with an increased uninsured population of 55%. This figure shows the importance of various environment-related risks for the insurance sector. Furthermore, authors such as Maynard (2008) and Stechemesser et al. (2015) mention the opportunities and challenges faced by insurers when considering changes in environmental factors, which will mean an increase in their range of products that must adapt to new realities. We must also consider the evidence of the last few years of climate change on insurance pricing.

One of the drawbacks of insurability in the case of environmental impacts is that, although the industry accepts that it ensures a risk, this is determined by the limits of their knowledge at the time of underwriting. This may result in either the parameters or the magnitude of the risk subsequently being very different from those used for underwriting and pricing. Consequently, it is extremely important to correctly measure and predict risks arising from environmental phenomena. In other words, it is necessary to make sure that the premiums charged are sufficient to cope with possible unexpected events. In this sense, it is essential to study both the frequency of claims associated with climate change and the average cost of these claims, so their impact on a given portfolio in the future may be estimated.

In line with the above, new tools and approaches are required to measure and understand such risks. Therefore, measuring financial risks associated with

### Policy Implications

- Financing policies to prevent climate change: National, regional and local governments must invest the necessary resources to prevent climate change.
- Promoting all the political measures to tackle climate change. The political authorities must develop regulations to implement the agreements on the fight against climate change, especially the agreements of the last United Nations Climate Change Conference (COP26).
- Enhancing Awareness of climate risk: Policies aimed at increasing investor awareness of the impact of climate change can help investors make more informed decisions. This can lead to greater investment in sustainable firms.
- Developing additional mechanism for insurance supervisors. The policymakers should increase the controls to supervise the climate risk in insurance sector, as it may seriously affect the solvency of insurance companies in the future.
- Facilitating the control over climate risk by the design of corporate policies for insurance companies. It is essential that the underwriting, risk management and the reserve policies of the insurance firms remain aligned to minimise the possible future impact of this risk and to avoid its transference directly to people in economic terms or the financial system.

climate change can be complex because it involves assessing the effect of multiple impacts. Thus, this research seeks to propose a predictive model of environmental impact on the frequency and severity of climate risk in an insurance portfolio, and based on this prediction, to measure monetary impact by geographical area. Moreover, its aim is to implement different ways of measuring environmental risk since, according to Garcia (2020), sustainability contingencies are generally considered differently from the rest. This is because they are hazards for which there is no previous experience and whose effects may be manifested in the long term. They require a different treatment from the usual one that is based on impact history and geared towards the short term. Thus, while they are managed together with other risks, they require specific techniques such as scenario analysis (together with stress testing) or the inclusion of a long-term approach in their management.

Having defined and justified the line of research, the main objective of this paper is to analyse the

impact of physical climate risk in a home insurance portfolio and quantify in economic terms, the effect of climate change in the future, by applying different climate scenarios.

In order to achieve this general objective, we propose to quantify sustainability risk in non-life insurance portfolios by defining a 'stress-test' and thus viewing its impact in monetary terms. Based on this result, we intend to measure the impact based on their location within a specific geographical area.

Consequently, this paper presents several new ways forward, firstly with regard to how the proposed analyses are carried out. The data were analysed using non-supervised models to create clusters between a given risk (claims portfolio) and the nearest associated weather station. Supervised models are developed to measure sustainability risks in a non-life insurance portfolio (Burkart & Huber, 2021). Within these supervised models, a combination of several machine learning methods such as nonlinear regression, generalised linear model (GLM) and generalised additive model (GAM) has been used (Nguyen et al., 2023). By combining these techniques, we can carry out a more comprehensive analysis of the problem from several points of view, thus allowing us to apply the results in a more generalised manner.

Secondly, two data sources have been used for this analysis: a multi-risk home insurance portfolio of an important insurer in the Spanish market, with 31,998 policies and claims from 2017 until 31st December 2022 and information from 290 weather stations, each one providing data for the period 2000–2022 with daily frequency of meteorological variables. Additionally, two climate scenarios defined by the Intergovernmental Panel on Climate Change (IPCC, 2014; Pachauri et al., 2014) have been used: the RCP 4.5 scenario (medium-impact scenario where temperature increases on average by 2.6 degrees Celsius, and carbon emissions increase until 2040 and then decrease) and RCP 8.5 scenario (high-impact scenario where temperature increases by 4.8 degrees Celsius, and carbon emissions increase until 2100).

The results reveal that the future projection of claims will increase for both climate change scenarios. Thus, for the period 2023–2052, the results indicate that in the RCP 4.5 scenario, total losses will increase by 105% compared to current values. Similarly, in the RCP 8.5 scenario, there will be an increase of 129%, considering that the projected periods from the year 2040 onwards are expected to have the most significant impact.

The main contributions of this paper to the existing literature are as follows. Firstly, to the best of the authors' knowledge, it is the first study that analyses the impact of sustainability risks, specifically physical risks, in a non-life insurance portfolio and measures them

in economic terms. Secondly and equally innovative, it uses a data-driven approach to the problem by employing two data sources: insurance portfolio data and meteorological variables. Finally, the paper validates the usefulness of a variety of machine learning tools in predicting sustainability risks associated with climate change. To sum up, this paper improves the analytical comprehension of the effects of climate risks in a financial company and their measurement and estimation to calculate their economic impact.

The following sections begin with the theoretical framework. Subsequently, information on the dataset, variables and methods applied in this study is provided. After that, the main results of the study are presented, and the paper ends by drawing certain conclusions.

## 2 | THEORETICAL BACKGROUND

### 2.1 | Sustainability risk in insurance: Current context and regulation

Since its founding in 1957, the European Union has sought to establish an internal market that works towards the sustainable development of Europe based, among others, on balanced economic growth and a high level of environment quality protection and improvement (Article 3 of the Treaty on European Union). There has been increasing regulatory and institutional activity in this regard in recent years. In fact, the adoption of SDGs in 2015 by the United Nations may be considered as a starting point, linking sustainability and different industries, including the financial system. The SDGs comprise 17 social and environmental goals, where each goal has specific targets to be achieved by 2030 and are applicable to both developed and developing countries. They seek to end poverty, protect the planet and ensure prosperity for all by 2030.

The recommendations of the Task Force on Climate-Related Financial Disclosures (TCFD, 2017), established in 2017, are aimed at assisting investors and companies to identify climate change risks and opportunities, thereby offering a roadmap for effective responses. Applicable to companies of all sizes and sectors, the recommendations emphasise disclosure in financial reporting. They provide specific guidance for both financial (banks, insurance companies, asset owners and asset managers) and non-financial sectors that are most affected by climate change: energy, transport, materials and buildings, agriculture, food and forest products (TCFD, 2022).

Both Europe and Spain have implemented various regulations to address sustainability, especially in the insurance sector. In 2019, Regulation (EU) 2019/2088 was approved by the European Parliament and the Council, covering rules on financial information disclosure, and defining sustainable investments.

Concurrently, the European Banking Authority outlined a three-step action plan in 2019, which focused on strategy and risk management, conducting stress tests related to climate change and addressing the prudential treatment of 'green' exposures. Additionally, in 2020, the European Green Deal was established, outlining a roadmap for a sustainable EU economy. This initiative intends to transform climate challenges into opportunities in order to achieve climate neutrality in the EU by 2050.

In 2021, the insurance sector made significant strides towards sustainability by amending the Solvency II directive through Delegated Regulation (EU) 2021/1256. These changes have an impact on governance, risk management, actuarial functions, investment processes and information disclosure by insurance companies, seeking to integrate risks and sustainability factors. Furthermore, in the same year, the European Insurance and Occupational Pensions Authority (EIOPA) issued an opinion on the supervision of climate change scenarios in the Own Risk and Solvency Assessment (ORSA). EIOPA considers it 'essential' to promote the forward-looking management of these risks for the long-term solvency and viability of the insurance industry.

According to the Delegated Regulation (EU) 2021/1256, sustainability risk is defined as: 'Any environmental, social or governance event or condition that, if it were to occur, could have an actual or potential material adverse effect on the value of the investment or on the value of the liability.' According to the Bank of England (2019), climate change can materialise as different types of risks for financial institutions, including physical risks and transition risks. Physical risks arise from the increasing frequency and severity of environmental or climate changes. They are, therefore, incidents related to property, infrastructure, changes in agricultural production and may even lead to loss of life. Therefore, these risks directly affect financial institutions by impacting their assets. Specifically, in insurance companies, they would cause risks on the liabilities side, in pricing or reserves due to changes in the risk profiles of policyholders and changes in mortality, thereby causing changes in demographic trends (IAIS, 2018). According to Ancos (2015) all segments within the insurance industry have a degree of vulnerability due to the likelihood of climate change and environmental damage, since they cover property damage (infrastructure, automobiles, marine vessels, aviation industry); crops and livestock; pollution claims; business interruptions; value chain disruptions; or loss of service utility; equipment damage from temperature extremes; data loss from power outages or surges and a wide spectrum of consequences to life and health. However, the research also mentions that based on environmental impacts, the insurance products most likely to be affected are property insurance, followed

by agricultural, engineering, marine, aviation and transport insurance.

However, the risks classified as transition risks may arise from the adjustment of public policies towards bioeconomics. According to Mohammadian (2005), bioeconomics will be the future basis for a sustainable society that prioritises biological or environmental capital, as opposed to the current economy based on business competition and exploitation of natural resources. This transition will require significant structural changes in the economy, leading to a re-evaluation of asset values, changes in commodity prices and a fall in the income and creditworthiness of borrowers. For an insurer, this transition may have an impact on market risks due to shrinking demand in specific sectors, or they may in turn be affected by changes in financial asset prices (Breitenstein et al., 2021, 2022).

In line with the above, the World Economic Forum (2017) highlights that most global risks in 2017, in terms of probability and impact, are caused by climate change. Furthermore, some studies suggest that potential impacts could reduce global GDP by 2%–3% annually by 2060, and that the lack of action to reduce the effects of climate change and physical risks to the global economy are likely to continue increasing in the future. Analysis suggests that the frequency and severity of extreme weather events may increase non-linearly and become increasingly correlated with each other over time (OECD, 2015). Additionally, climate change forecasts and its impact on humans and ecosystems contain irreducible uncertainties given the nature of the earth system, including the presence of tail events (Weitzman, 2009) and tipping points (Solomon et al., 2009), which cannot be overcome by model consensus (Knutti et al., 2010). This means that the largest shocks are expected to occur in the mid-to long-term, but their exact location and magnitude is unknown.

Authors such as Berz (1999), Dlugolecki (2000) and Golnaraghi (2018) note that, historically, many sectors of the insurance industry did not consider climate change to be a significant issue. However, progressive companies have conducted research and analysis, recognising it as a fundamental concern. Amendments to regulations not only influence the nature of insurance risk but also shape public policy responses to natural hazards. The insurance industry worldwide has experienced a considerable rise in the scale and frequency of major natural disasters. Climate change is expected to affect pricing, capacity, loss reserves, assessment of insured liabilities, preventive planning and the effective adjustment of catastrophe losses. The connection between climate change risks and economic development is pivotal. Hence, effective mitigation, adaptation and management of associated risks are vital. The insurance sector plays a crucial role in minimising or transferring these risks through diverse products and services.

## 2.2 | The impact of climate change on insurance

Climate risks are those related to the natural variability of the climate which, due to their severe nature, affect natural and human systems and cause damage. Risks related to windstorms, heavy rainfall, hail, droughts and cold and heat waves are some major ones (Campiglio et al., 2023).

Climate risks carry a significant challenge for insurance companies, affecting their operations and financial stability. The insurance industry's effectiveness in managing the consequences of natural disasters is one of its strengths, emphasising the need to adapt to climate crisis challenges. Overall, it is essential for insurers to address climate risks so they may adjust their risk assessment, product offerings and operational strategies to minimise damages and ensure financial resilience in the face of global climate changes (Golnaraghi, 2023; Lukić et al., 2022).

Insurance companies assess climate-related risks by various methods such as analysing the financial impacts of climate change in insurance contracts, conducting asset-level risk assessments on energy infrastructure investments and considering their contribution to climate adaptation by encouraging risk reduction by policyholders and supporting resilient resettlement (Lukić et al., 2022). It is also becoming mandatory to consider green aspects in financial markets, evaluating investments according to their alignment with regulatory standards and their impact on natural resources. In general, insurance firms are increasingly engaging in climate risk management by adjusting products and risk assessments to minimise potential damages (OECD, 2023). Today, machine learning plays a significant role in assessing and managing these risks (Zhang & Xu, 2023). The use of data analytics and data mining enhances prediction capabilities and pricing accuracy of policy premiums by insurance companies when estimating climate risk, as well as assessing the risk of catastrophes such as storms, hurricanes, tornadoes, earthquakes, floods and fires (Hassani et al., 2020). Moreover, the literature has demonstrated the use of machine learning to forecast future claim dynamics and evaluating associated uncertainties (Dey et al., 2021), to analyse catastrophe insurance (Zhang & Xu, 2023) or to identify extreme flood and drought events (Cesarini et al., 2021).

However, the effects of climate change will depend very much on the geographical area in question. For example, according to the Swiss RE Institute (2018), hurricanes are the most damaging climate risk in the United States and the Caribbean; in Europe, winter storms, floods, cold snaps, droughts and high temperatures; in Asia, monsoon rains and associated floods; in Latin America and the Caribbean, hurricanes, floods and forest fires; in Oceania, cyclones, wind, rain and

associated storm surges; and in Africa, forest fires and storms.

Specifically, climate change has significant effects on the insurance sector in regions such as Latin America (Cárdenas et al., 2021; Taboada et al., 2021) and the Asia-Pacific (Jain et al., 2022) affecting risk management strategies and the pricing of insurance products (Lukić et al., 2022). Extreme weather events such as hurricanes, droughts and floods in both Latin America and Asia-Pacific countries are becoming more frequent and severe, leading to increased financial losses and risks for insurers (Alam et al., 2020; Cesarini et al., 2021). In these exposed regions, the insurance sector is increasingly involved in managing risks related to climate change, requiring the inclusion of weather change considerations in risk assessments to adjust insurance products accordingly (Jain et al., 2022; Olarewaju & Nomlala, 2021; Zhou et al., 2023). Moreover, the technology applied to the study and prediction of weather events has improved insurance techniques, enabling better risk pricing and the development of models to enhance risk management strategies in these geographical areas (Broberg, 2020; Horton et al., 2021). As the world grapples with the impact of climate change, the insurance industry is playing a critical role in building resilience, supporting socio-economic development, and addressing the global transition towards a more sustainable future, especially in the most vulnerable areas (Jain et al., 2022; Vyas et al., 2021).

Not all areas of the world are subject to the same climate risks, and within the same country, not all regions suffer the same risks with the same intensity. For our empirical analysis, we will use a Spanish insurance portfolio. According to Olcina-Cantos (2010), the main climate risks in Spain are floods, storms and sea storms, which are traditionally the adverse climatic phenomena that cause the greatest damage to property and people (Gil Olcina & Olcina Cantos, 2017).

Hassani et al. (2020) points out that multi-risk insurance, especially in the case of home insurance, may witness an increased number of claims due to various weather-related damage such as wind, rain and forest fires. Wind and rainstorms can result in damage to homes, including water filtrations, leaks during persistent rainfall, damage from falling objects, broken windows, etc. Water damage is responsible for over a third of all home insurance claims in Spain. Snowfall can damage roofs due to excess weight, potentially causing structural collapse. Furthermore, electrical storms and lightning strikes contribute to an increased claims rate for electrical damage in homes (UNESPA, 2017). In this context, according to Cooperative Research between Insurance Entities and Pension Funds (Spanish acronym, ICEA) data, the volume of gross premiums earned in the non-life insurance sector reached 40,239 million euros in December 2022,

representing 62.10% of the total insurance business. Within the non-life insurance sector, the multi-risk sector represents a 21% share, with a volume of gross earned premiums of 8578 million euros, demonstrating the importance of this specific sector in the Spanish market even more when discussing non-compulsory insurance (ICEA, 2022).

### 3 | METHODOLOGY

#### 3.1 | Data

Two different databases were used to achieve the objectives proposed in this research:

a. A multi-risk home insurance portfolio of a prominent insurer in the Spanish market. Specifically, information on 31,998 policies and claims catalogued by the entity as weather claims was analysed. This database obtained from the company only contains information on the claim, geolocation and the weather event responsible for the claim. The data was

gathered between 2017 and 31st December 2022, grouped together on a monthly basis. Given the size of the monthly data used for the analysis, Table 1 displays an example of the claims distribution according to cause grouped by quarters for the final analysis, the same distribution is used but grouped by month.

b. The other source is Spanish weather data, given that the claims in the policy portfolio are related to Spain. Therefore, weather station information was obtained from AEMET. Specifically, the data were obtained from 290<sup>1</sup> meteorological stations, each providing data for the period 2000–2022 with the daily frequency of weather variables such as: precipitation, wind gust, maximum temperature, minimum temperature, etc. In order to maintain consistency with the database described above, the daily data were grouped on a monthly basis. The meteorological variables were thus grouped, and the maximum value of each variable per month was obtained. This allowed us to compare two time series that were grouped by month.

**TABLE 1** Claims portfolio distribution.

Date	Wind (%)	Rain (%)	Hail (%)	Snow (%)	Flood (%)
2017 I	72.98	26.28	0.53	0.12	0.08
2017 II	66.40	30.45	2.89	0.13	0.13
2017 III	44.11	39.64	15.65	0.15	0.45
2017 IV	70.05	25.61	2.94	1.25	0.15
2018 I	55.03	41.94	1.09	1.89	0.04
2018 II	39.70	54.06	5.58	0.47	0.19
2018 III	30.61	36.85	32.21	0.08	0.25
2018 IV	33.30	65.26	1.35	0.00	0.09
2019 I	64.45	34.38	0.63	0.36	0.18
2019 II	53.18	44.70	2.12	0.00	0.00
2019 III	33.80	47.95	17.89	0.07	0.29
2019 IV	65.09	34.49	0.38	0.03	0.00
2020 I	66.60	31.72	1.53	0.05	0.10
2020 II	40.26	51.76	7.67	0.11	0.21
2020 III	35.80	24.55	39.50	0.16	0.00
2020 IV	61.83	37.35	0.71	0.10	0.00
2021 I	30.55	28.05	0.63	40.69	0.08
2021 II	35.89	45.81	17.22	0.84	0.24
2021 III	33.20	45.32	21.38	0.00	0.10
2021 IV	33.38	63.13	2.20	0.99	0.30
2022 I	39.57	58.38	1.77	0.19	0.09
2022 II	42.87	48.74	8.05	0.23	0.11
2022 III	56.67	32.82	10.27	0.00	0.24
2022 IV	42.81	56.00	1.06	0.00	0.13

Source: Own elaboration.

### 3.2 | Variables

The dependent variable to be analysed will be the number of claims classified as ‘weather claims by the company,’ that is the 31,998 policies. The independent variables are weather variables obtained from weather stations in Spain: flood, rainstorm, snow, hail and wind. For this research and based on the observed frequency of the portfolio analysed, only variables associated with rain (maximum precipitation<sup>2</sup>) and wind (maximum wind gust<sup>3</sup>) will be used, since both causes together account for 89% of the insurer’s claims. Next, and as an example, different stations (Tables 2 and 3) were selected to observe their main statistics for the period analysed. Although the

analyses are monthly, due to the large amount of data, we have grouped them by year for the table.

#### 3.2.1 | Precipitation

Please see Table 2 for maximum and average precipitation.

#### 3.2.2 | Maximum wind gust

Please see Table 3 for maximum and average wind gust speeds from the weather stations.

**TABLE 2** Maximum and average precipitation – weather stations.

Date	Barcelona (airport)	Bilbao (airport)	San Sebastián (Igueldo)	Fuengirola	Madrid (Retiro)
Weather station – Maximum precipitation (L/m <sup>2</sup> )					
2017	64.7	65.6	59.2	52.8	25.2
2018	74	44.6	58.8	41.4	28.9
2019	72.9	53.1	84.8	49.4	38.4
2020	87.9	35.8	62	29.7	37.8
2021	50.6	50.3	84.2	56.9	67.7
2022	45.9	59.9	55.8	32.1	26.6
Weather station – Average precipitation (L/m <sup>2</sup> )					
2017	0.97	3.60	4.30	1.09	0.70
2018	2.06	3.63	4.82	1.21	1.61
2019	1.84	3.47	5.21	0.71	1.07
2020	2.77	3.04	4.86	0.79	1.30
2021	0.92	3.51	4.59	1.11	1.71
2022	0.91	2.33	3.67	0.88	1.23

Source: Own elaboration.

**TABLE 3** Maximum and average wind gust – weather stations.

Date	Barcelona (airport)	Bilbao (airport)	San Sebastián, (Igueldo)	Fuengirola	Madrid, (Retiro)
Weather station – Maximum wind gust (m/sec)					
2017	30.8	26.4	33.6	20.8	40.8
2018	22.8	23.6	31.4	24.4	24.7
2019	24.7	30.8	35	18.6	29.2
2020	29.2	26.7	35	23.3	21.1
2021	24.2	24.7	33.9	24.2	26.4
2022	23.3	25.3	28.1	25	40.8
Weather station – Average wind gust (m/sec)					
2017	30.8	26.4	33.6	20.8	40.8
2018	22.8	23.6	31.4	24.4	24.7
2019	24.7	30.8	35	18.6	29.2
2020	29.2	26.7	35	23.3	28.9
2021	24.2	24.7	33.9	24.2	21.1
2022	23.3	25.3	28.1	25	26.4

Source: Own elaboration.

### 3.3 | Machine learning techniques

This section describes the methodology and the process to be implemented to achieve the objectives set out in the earlier sections. The analysis has been carried out using supervised and non-supervised models. Supervised models are defined using labelled data sets to train algorithms that classify data or predict outcomes accurately based on historical information. Regression models belong to this category. Non-supervised learning uses unlabelled data through which patterns are discovered that help solve grouping or association problems. Common clustering algorithms are hierarchical models, k-means, principal components, etc.

In our study, non-supervised models have been used to create clusters by a specific risk (claims portfolio) and the nearest weather station associated with it. Supervised models have been developed to measure sustainability risk in a non-life insurance portfolio. Moreover, a combination of several machine learning methods (namely nonlinear regression, GLM and GAM) has been used in the supervised models. Therefore, this research extends the literature by using several categories and types of machine learning methodologies to analyse financial problems and, more specifically, to improve analytical comprehension of the impact of climate risks in a financial company and their measurement and estimation for economic impact calculation (Rolnick et al., 2022).

#### 3.3.1 | Non-supervised learning models

Non-supervised learning models were applied initially, starting with a Haversine model to geolocate the loss associated with a climate event and to assign it to the nearest weather station. In other words, the information from the closest weather station was assigned to each claim in order to deduce whether the claims were caused by one of these meteorological variables. Authors such as Valero et al. (2021) and Monawar et al. (2017) have shown that the Haversine distance method is best applied for risk and geolocation studies. This is due to the fact that it is based on trigonometric principles and is useful for calculating distances in geographic coordinates on a flat map, thus making this method suitable for problems involving location data and geolocation. The Haversine distance equation is described below.

$$D(x,y) = 2 \arcsin \sqrt{\sin^2\left(\frac{x_1 - y_1}{2}\right) + \cos(x_1) \cos(y_1) \sin^2\left(\frac{x_2 - y_2}{2}\right)}$$

After the risks have been geolocated, a general database is obtained where each claim has the

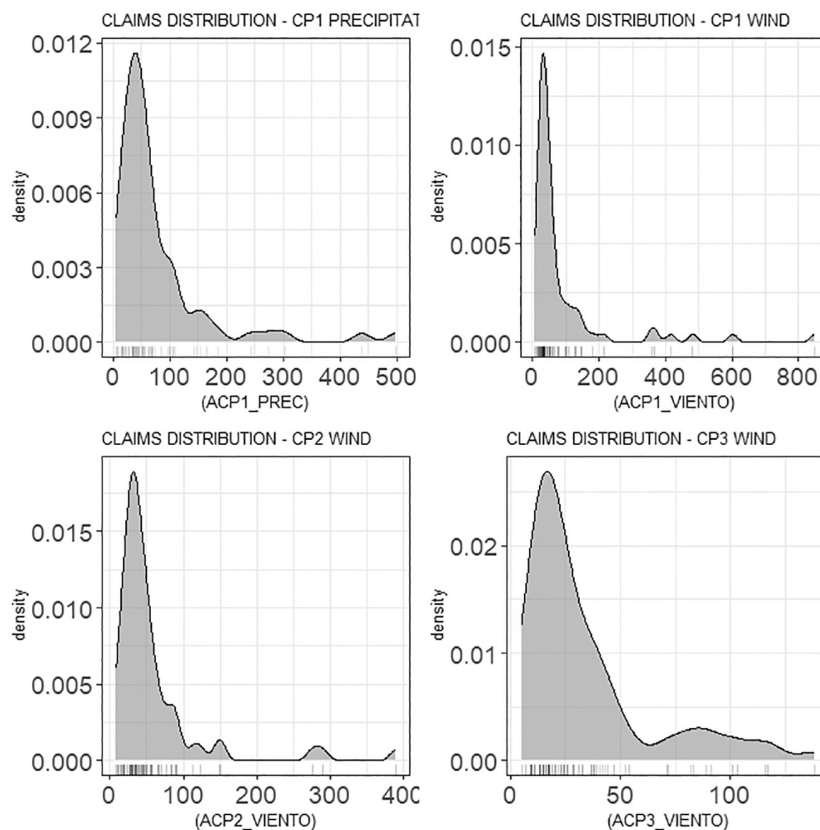
information of the nearest weather station. Through this process, the risk associated with a specific station is assigned to the insurance portfolio analysed. In this way, by having a geographical location-based measure of risk, the total claim ratio of the insurance portfolio analysed is measured. A clustering analysis for the total database has been conducted with this information. We have used Principal Component Analysis (PCA), aiming to reduce the database's dimensionality and to group stations according to the number of claims within their respective geographical zones. As described by Jolliffe (2002), PCA is a widely recognised and effective multivariate technique for reducing high-dimensional data matrices. It involves obtaining principal components as linear combinations of the original variables. The principal components are selected based on eigenvalues greater than or equal to 1, and the chosen set should explain more than 70% of the data variance.

As the wind and rainfall variables account for the entire company's claims portfolio, we have identified one component related to rainfall and three components related to wind. Component 1, related to precipitation, groups provinces located in the southern part of Spain along with the province of Madrid (region in central Spain). In total, this component accounts for 75% of the losses related to precipitation. Regarding wind-based components, Component 1 groups provinces located in the Basque Country (region in northern Spain), Component 2 groups non-coastal provinces and Component 3 groups coastal provinces. In total, these three components account for 78% of all wind event claims.

The distribution of the dependent variables (one for each component) is plotted in Figure 1. It thus becomes evident that the distributions in all cases are asymmetrical with a positive skewness, indicating that the response variable is not normally distributed.

The following is a summary of the variables used and the process followed:

- Dependent variable: monthly frequency of claims classified as rain-based, and independent variables: maximum monthly temperature and maximum monthly precipitation.
- Dependent variable: monthly frequency of claims classified as wind-based and independent variables: maximum monthly temperature and maximum monthly gust.
- The relationship between average temperature and precipitation and wind gusts is used for future predictions. The goal is to see whether these variables increase if the temperature increases.
- To avoid creating a model for each station (290 models), PCA was used to reduce the dimensionality of the database. Accordingly, four components were obtained in order to identify the geographical areas.



**FIGURE 1** Claims distribution of dependent variables for all components. Source: Own elaboration.

### 3.3.2 | Supervised learning models

After obtaining the components, different models are applied to each component in order to explain the relationship between the number of claims and the meteorological variables. Given the nonlinear nature of this relationship, both GLM and GAM are employed. Both models consist of three steps: (i) specifying the distribution of the response variable; (ii) defining the systematic component in terms of explanatory variables; and (iii) establishing the link between the mean of the response variable and the systematic component. The foundation of these models is outlined below (David, 2014, 2015; Gschlößl & Czado, 2007).

The GLM model distinguishes three components: the random component, the systematic component and the link function. The random component is represented by  $y_i$ , the target-endogenous variable for  $i=1, \dots, n$  policies, where  $y_1, \dots, y_n$  follow an exponential family distribution. The systematic component is defined through the  $j=1, \dots, k$  exogenous explanatory variables for  $i=1, \dots, n$  policies, denoted as  $X_{i1}, \dots, X_{ik}$  and their estimated coefficients  $\beta=(\beta_0, \beta_1, \dots, \beta_k)'$ . The link function  $g(\mu)$  will enable us to relate the value of claims (dependent variable) with the linear predictor of the explanatory variables:  $g(u) = n_i = X_i' \beta$ .

The parameters of the linear predictor will be estimated on the basis of the chosen model using the maximum likelihood method (Alemany et al., 2020)

$$f_Y(y; \theta; \phi) = \exp\left\{\frac{y\theta - b(\theta)}{a(\phi)}\right\} + c(y, \phi)$$

Here,  $\phi$  is a dispersion parameter that includes a weight  $\omega_i$ ;  $\theta_i$  represents the parameters to be estimated, and the functions  $b(\theta)$  and  $c(y, \phi)$  depend on the probability density function of the exponential family, whose distribution set will be adapted to this structure.

As the dependent variable is a count variable, we must adjust the distributions accordingly. Traditionally, the distributions used for counting data in actuarial theory include Poisson and Negative Binomial distributions. However, in this case, considering the observed variability in the data over the period, various count models were tested. Of them, the generalised Poisson model displayed the best fit to the data.

With regard to the generalised Poisson regression model (Consul & Famoye, 1992; Johnson et al., 2005), the probability function is given by the following equation:

$$P(Y = y | \theta, \lambda) = \frac{\theta(\theta + \lambda y)^{y-1} e^{-(\theta + \lambda y)}}{y!}$$

For  $y=0, 1, 2, \dots$ , where  $\theta > 0$  and  $0 \leq \lambda \leq 1$ . The mean and the variance of the generalised Poisson distribution are given by

$$E(Y) = \frac{\theta}{1 - \lambda} \quad \text{Var}(Y) = \frac{\theta}{(1 - \lambda)^3}$$

We have evaluated the performance of the proposed models using the metrics associated with regression problems, as the variable analysed is a discrete variable (number of claims), seeking to estimate the total loss in economic terms. The Akaike Information Criterion (AIC) was chosen for this purpose. The AIC is a mathematical method used to assess how well a model fits the data used to generate it. In statistics, AIC is employed to compare different models and determine the best fit for the data (Cavanaugh & Neath, 2019).

### 3.3.3 | Process to estimate climate change scenarios

Once a relationship has been established between the number of claims and the environmental variables, different climate change scenarios may be applied. To make the predictions and to model climate change scenarios, it is necessary to make certain economic and social assumptions regarding physical changes that affect our environment. The IPCC<sup>4</sup> (2014) has adopted different scenarios known as Representative Concentration Pathways (RCPs), which capture all climate change hypotheses according to different social or economic changes. The following scenarios are commonly used in the literature on climate change (Buras & Menzel, 2019; Nilawar & Waikar, 2019) and have been used for the projections here.

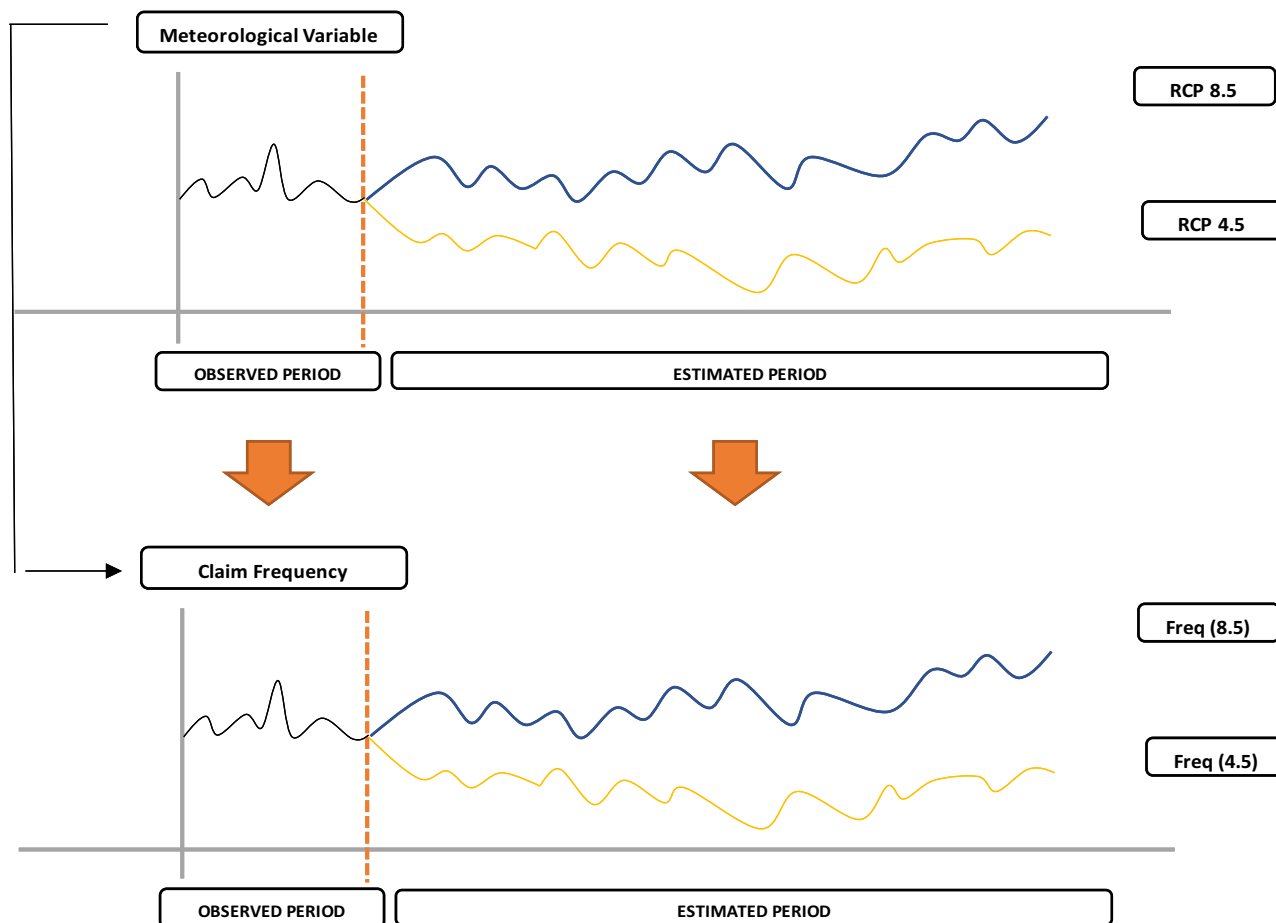
- RCP 4.5: Classified as a medium-impact scenario where changes in meteorological variables are expected due to an average temperature increase of 2.6 degrees Celsius and carbon emissions increase until 2040, and then decrease.
- RCP 8.5: Classified as a high-impact scenario where changes in meteorological variables are expected due to an average temperature increase of 4.8 degrees Celsius and carbon emissions increase until 2100.

To obtain these two scenarios, we must first verify whether there is a relationship between the increase in average temperature and precipitation or maximum wind gust. To obtain this relationship, we used the historical dataset obtained from the AEMET to applied polynomial regressions (nonlinear regressions) to measure the impact of increased average temperature on precipitation and maximum wind gust. The applied equations may be verified in Table 4.

TABLE 4 Nonlinear regressions.

Group	Nonlinear regressions	Coefficient of determination
C1 - Precipitation	$\text{Max\_Prec\_C1} = 0.0045(\text{Avg\_Temp})^4 - 0.3784(\text{Avg\_Temp})^3 + 11.467(\text{Avg\_Temp})^2 - 149.47(\text{Avg\_Temp}) + 744.33$	$R^2 = 0.69$
C1 - Wind	$\text{Max\_wind\_Gust\_C3} = -0.0134(\text{Avg\_Temp}^2) - 0.0473(\text{Avg\_Temp}) + 30.27$	$R^2 = 0.62$
C2 - Wind	$\text{Max\_wind\_Gust\_C2} = 0.0266(\text{Avg\_Temp}^2) - 1.5483(\text{Avg\_Temp}) + 39.04$	$R^2 = 0.63$
C3 - Wind	$\text{Max\_wind\_Gust\_C3} = 0.0033(\text{Avg\_Temp}^3) - 0.17(\text{Avg\_Temp}^2) + 2.2265(\text{Avg\_Temp}) + 18.97$	$R^2 = 0.64$

Source: Own elaboration.



**FIGURE 2** Stress scenario estimation process. *Source:* Own elaboration.

Once the relationship is obtained for each component, a stress test exercise based on climate change scenarios is carried out. In this way, the two estimated future time series for each component are obtained and implemented in our models obtained in the previous section. The result of applying different scenarios will be the estimation of the frequency of a stressed insurance portfolio (Figure 2).

Finally, once the two series of meteorological variables associated with the implemented frequency model for a non-life insurance portfolio have been projected, the goal is to quantify these scenarios based on their materiality (Valero et al., 2021). That is, we determine the total cost of claims for an insurer given variations in climate change scenarios by applying the average cost of the claims associated with these meteorological factors.

## 4 | RESULTS AND DISCUSSION

### 4.1 | Models for component 1 – precipitation

Various generalised linear models (generalised Poisson, GAM (GPD), Poisson Inverse Gaussian, Sichel and Beta Negative Binomial) were used to estimate the

monthly number of claims over the years, including precipitation and average temperature as independent variables. The selection of the optimal model to predict the number of claims was guided by the AIC. For Component 1 associated with precipitation, the best estimation within the GLM family was achieved via a generalised Poisson distribution as the link function. A generalised additive model was then implemented for validation (Stasinopoulos & Rigby, 2007) and its fit to the data was assessed. The results of the chosen model are presented in the next table (Table 5).

The results of the generalised Poisson regression for Component 1 show that both precipitation and average temperature are significant at a 95% confidence level. Nevertheless, the effect of precipitation is positive on claims numbers, with a coefficient of 0.04, while average temperature has a negative effect with a coefficient of  $-0.91$ .

### 4.2 | Models for Components 1, 2 and 3 – wind

Following the same procedure, the same GLMs were used to estimate the monthly number of claims over

**TABLE 5** Generalised poisson regression – Precipitation.

Coefficients and <i>p</i> value (model CP1)				
Variable	Estimate	SE	<i>p</i> Value	Significance
Intercept	5.8752	1.091	0.000001	***
Precipitation	0.0461	0.007	0.000000	***
Average temperature	−0.9190	0.007	0.005150	**

Note: Significant codes: 0; \*\*\*\* 0.001; \*\*\* 0.01; \*\* 0.05; \* 0.1; † 1.

Source: Own elaboration.

**TABLE 6** Generalised poisson regression – Wind.

Variable	Estimate	SE	<i>p</i> Value	Significance
Coefficients and <i>p</i> Value (model CP1)				
Intercept	−1.9184	2.213	0.003890	**
Maximum wind gust	2.7172	0.384	0.000000	***
Average temperature	−0.8612	0.361	0.020000	*
Coefficients and <i>p</i> Value (Model CP2)				
Intercept	−9.2137	1.746	0.000001	***
Maximum wind gust	3.4846	0.390	0.000000	***
Average temperature	0.8760	0.266	0.001590	**
Coefficients and <i>p</i> Value (MODEL CP3)				
Intercept	−1.7200	1.964	0.038640	*
Maximum wind gust	2.5957	0.411	0.000000	***
Average temperature	−0.9802	0.308	0.002220	**

Note: Significant codes: 0; \*\*\*\* 0.001; \*\*\* 0.01; \*\* 0.05; \* 0.1; † 1.

Source: Own elaboration.

the years, with maximum wind gust and average temperature as independent variables. The selection of the best model, optimising claims predictions, was based on the AIC. For Components 1, 2 and 3 related to wind, the best estimation within the GLM family was achieved via a generalised Poisson distribution as the link function, similar to precipitation. As a validation step, a GAM was implemented to assess its fit to the data, but the results remained unchanged (Table 6).

Regarding the wind components, both maximum wind gust and average temperature are significant predictors of claims in Component 1. The maximum wind gust has a positive effect, with a coefficient of 2.7, while the average temperature has a negative effect with a coefficient of −0.86. In Component 2, both predictors are significant, with a positive effect of 3.4 for maximum wind gust and 0.8 for average temperature. Component 3 displays similar results with a negative coefficient of −0.98 for temperature and a positive effect of 2.5 for maximum wind gust. All variables in all models are significant at a 95% confidence level.

**TABLE 7** Average cost by component in Euros.

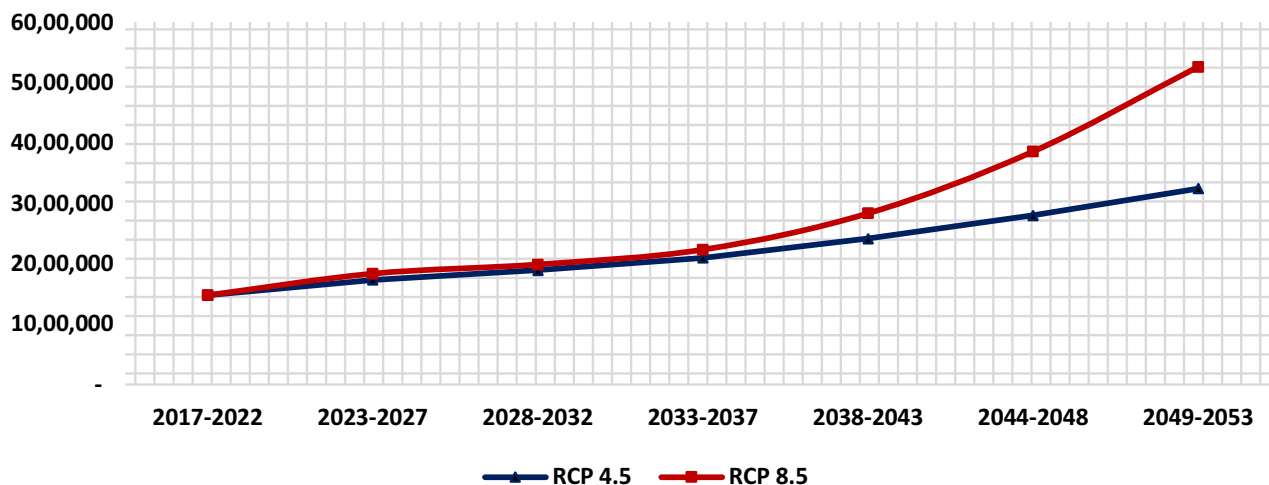
Year	ACP1_ PREC	ACP1_ WIND	ACP2_ WIND	ACP3_ WIND
2017	394.98	172.49	327.93	315.65
2018	371.73	245.39	360.23	416.21
2019	333.67	190.73	380.87	363.44
2020	278.60	242.50	400.97	399.45
2021	292.77	259.11	319.61	334.55
2022	258.16	360.28	469.61	373.25

Source: Own elaboration.

### 4.3 | Climate change scenarios

To project future losses for the portfolio affected by different climate change scenarios, various assumptions were applied:

The historical average costs for each principal component, considering both precipitation and wind, were determined and an annual increase applied until 2050. This timeframe was selected in accordance



**FIGURE 3** Total loss C1 – Precipitation. *Source:* Own elaboration.

with EIOPA (2021) guidelines, emphasising the analysis of climate change impacts over medium to long-term scenarios. Table 7 details a matrix of the average cost per component.

The results for Component 1 of precipitation (non-coastal cities) in the projected scenarios display increased losses from climate events linked to both precipitation and average temperature. Compared to 2023, losses are projected to increase by 189% in the average scenario and 273% in the stressed scenario by 2050. Figure 3 illustrates the trends at 5-year intervals, projecting losses of 3.4 million and 4.1 million for 2050 in both cases.

Similarly, for wind-related components, both climate change scenarios are analysed. In Figure 4, the trends for the total loss in the 3 wind groups are observed. For Component 1 (provinces located in the north of Spain), temperature increase has a greater impact on the average scenario due to its negative relationship with maximum wind gust. In the stressed scenario, with a more significant temperature increase, losses related to wind claims are lower. Compared to 2023, the projected losses for 2050 increase by 172% in the average scenario and 135% in the stressed one. For Component 2 related to wind (non-coastal provinces), the average scenario has a greater impact, albeit less than Component 1. Compared to 2023, the projected losses for 2050 increase by 210% in the average scenario and 191% in the stressed one. Finally, the results for Component 3 (coastal provinces) also display an increase in total loss. However, as in the previous components, the average scenario has a greater impact on total loss than the stressed scenario. Compared to 2023, the projected losses for 2050 increase by 180% in the average scenario and 150% in the stressed one.

Another relevant result is related to the total effect that may be seen in Table 9. For the portfolio under analysis, the impact of climate change on claims related to precipitation is greater than those related to

wind. Thus, the longer the term of analysis, the more significant this impact becomes. In fact, this impact can be seen in the areas corresponding to the coastal areas of northern Spain, which have a warm oceanic climate. Unlike the climate in the rest of Spain, this climate is characterised by mild, rainy summers and cold, rainy winters. Rainfall being abundant throughout the year, a climate change that aggravates this factor is, therefore, of great importance. This result is of great interest to insurers so they may make future forecasts and include them in future premiums. The projection of the total loss shows a cumulative increase for both climate change scenarios. In fact, the total loss for the average scenario will increase on average by 105% if we compare the last period with the baseline, and in the case of the stressed scenario, by 129% (Table 8).

We would like to mention that the analysis and results focus only on the impact of meteorological variables on an insurance portfolio and do not take other factors into account. It therefore assumes a 'ceteris paribus' analysis, meaning that everything else remains constant. Other variables such as inflation may also have an impact on the cost of claims. This variable may be included in the analysis, that is, the projected loss ratio may be multiplied by an increase (inflation) but the results of the impact of climate change on the portfolio would be maintained.

## 5 | CONCLUSIONS

Climate change will affect the frequency of weather events including precipitation, temperature fluctuations and wind gusts, potentially leading to increased insurance claims. It is essential for the insurance industry to systematically evaluate the risks associated with climate change, affecting both liabilities and assets. This effect will lead to several risks known as physical risks and transition risks. Transition risks arise from



**FIGURE 4** Total loss – Wind. *Source:* Own elaboration.

regulatory (limits on carbon emissions) and technological changes (innovations in the field of electric vehicles, for example) that are required to achieve the decarbonisation objective set out in the Paris Agreement. This risk will generate impacts at the financial level. However, physical risks are the result of physical impacts or increased severity and frequency of the extreme weather events (Breitenstein et al., 2021, 2022). In addition to affecting insurers' tangible assets and investments, this would affect their liabilities by increasing them due to a higher claims ratio. This analysis considers only the maximum precipitation and maximum wind gust as an

influencing factor in increased claims associated with climate change. It is important to highlight that there are other variables in the area of insurance that may result in increased claims. However, the objective of this work is to demonstrate that meteorological variables affect insurance portfolios and to quantify said effect.

Rising temperatures can lead to increased flooding from heavy rainfall and storm surges linked to hurricanes. Increased atmospheric moisture, expanding oceans and rising sea levels contribute to heightened economic damage from said events. To ensure sufficient risk coverage, insurers and reinsurers must set

appropriate premiums in line with risks and exposure, as well as set suitable limits on insured capital and exposed territories.

This study highlights the significant impact of climate risks on society, especially within the insurance sector, as events related to these risks generate high-impact economic claims, which vary according to geographic exposure. The projection indicates an increase in claims if the climate change scenarios are developed (RCP 4.5 and RCP 8.5). According to the results, the total loss is projected to increase by an average of 105% in the 4.5 scenario as compared to the baseline scenario, and by 129% in the 8.5 scenario. These findings underscore the direct importance of understanding the impact of climate change, especially the increased impact of meteorological variables on an insurance portfolio since this knowledge is crucial to ensure the stability and solvency of insurance companies. The comparison of the scenarios (4.5 and 8.5) with the current or baseline scenario reveals that increases in maximum precipitation and wind gusts require adjustments in subscription policies or greater reserves to face future meteorological events. In this sense, our paper makes a clear contribution to sustainability by demonstrating the importance of analysing climate risks and their impact on

an insurance portfolio by revealing possible serious consequences of climate change for the solvency of the insurance sector and for the financial system in general.

This study is not without its limitations. Although the selected country - Spain - may be considered a representative country (with a wild climate, the main climate risks are floods and storms that cause the most damage to property and people, akin to similar conditions in many other countries), the data only cover one country and future studies are needed to corroborate and generalise our conclusions. Another question is that we have selected two scenarios commonly used in the analysis. Therefore, as future lines of research into the risk of climate change and insurance companies, it is worth expanding the data to other countries, and making more projections with other scenarios, so we may obtain more robust results and perceive an impact closer to reality. We also propose the use of more advanced artificial intelligence techniques that enable algorithms to optimise financial and environmental objectives.

Certain important implications may be highlighted for two main stakeholders: governments and international regulators on the one hand, and insurers on the other. Given our results, we urge national, regional and local governments to invest the necessary resources to prevent climate change from progressing and to attempt to mitigate existing effects. Specifically, all political measures to implement the agreements of the last United Nations Climate Change Conference (COP26) must be urgently taken. Moreover, the results show the high impact of climate change on insurance firms and, therefore, policymakers should increase controls to supervise climate risk in the insurance sector, as it may have a serious impact on the future solvency of insurance companies. Regarding insurance companies, our recommendation is to permanently monitor the potential effects of changes in different meteorological variables. For this, it is essential that underwriting, risk management

**TABLE 8** Projection of total loss.

	Average scenario	Stressed scenario
2017–2022	0%	0%
2023–2027	10.24%	13.94%
2028–2032	20.38%	22.03%
2033–2037	32.14%	33.07%
2038–2043	52.29%	55.37%
2044–2048	76.82%	85.91%
2049–2053	104.98%	129.45%
Average increase	49%	57%

Source: Own elaboration.

**TABLE 9** Total Loss – Analysed portfolio in millions of euros.

YEARS	PRECIPITATION		WIND		TOTAL	
	RCP 4.5_P	RCP 8.5_P	RCP 4.5_V	RCP 8.5_V	RCP 4.5	RCP 8.5
2017–2022	1.48	1.48	3.32	3.32	4.80	4.80
2023–2027	1.73	1.84	3.56	3.63	5.29	5.47
2028–2032	1.89	1.99	3.88	3.87	5.78	5.86
2033–2037	2.10	2.24	4.24	4.15	6.34	6.39
2038–2043	2.42	2.84	4.89	4.62	7.31	7.46
2044–2048	2.80	3.86	5.68	5.06	8.49	8.92
2049–2053	3.25	5.27	6.59	5.75	9.84	11.01

Source: Own elaboration.

and reserve policies of insurance companies focus on minimising the possible future impact of this risk and to avoid transferring it directly to people in economic terms or to the financial system.

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## CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## DATA AVAILABILITY STATEMENT

Research data are not shared.

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## ENDNOTES

<sup>1</sup> <https://portal.mapa.gob.es/websiar/SeleccionParametrosMap.aspx?dst=1>.

<sup>2</sup> Precipitation:  $mm = \frac{\text{litres}}{m^2}$ .

<sup>3</sup> Wind: Maximun wind gust =  $\frac{\text{metres}}{\text{second}}$ .

<sup>4</sup> IPCC: Intergovernmental Panel on Climate Change <https://www.ipcc.ch/>.

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