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Research Article

Using Artificial Intelligence to Predict the Financial Impact of Climate Transition Risks Within Organisations

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Addressing climate change represents one of the most pressing challenges for organisations in developing nations. This is particularly relevant for companies navigating the shift towards a low-carbon economy. This research leverages artificial intelligence (AI) methodologies to evaluate the financial implications of climate transition risks, encompassing both direct and indirect energy usage, including expenditures on electricity and fossil fuels. Advanced machine learning (ML) and deep learning (DL) models are employed to predict electricity and diesel consumption trends along with their associated costs. Findings from this study indicate an average prediction accuracy of 90.36%, underscoring the value of these tools in supporting organisational decision making related to climate transition risks. The study lays a foundation for comprehending not only the added costs linked to climate risks but also the potential advantages of transitioning to a low-carbon economy, particularly from an energy-focused perspective. Additionally, the proposed climate transition risk adjustment factor offers a framework for visualising the financial impacts of scenarios outlined by the Network for Greening the Financial System.

Keywords: artificial intelligence; climate scenarios; climate transition risk; prediction

1. Introduction

Climate risk management is a critical business process for many companies, particularly in the face of the ongoing climate crisis. It involves gathering and enhancing understanding of predictions, patterns and future scenarios to safeguard or even enhance business value. This process requires a cross-disciplinary strategy that considers different socioeconomic and ecological factors [1].

Artificial intelligence (AI) has emerged as a transformative tool in climate risk management by enabling more accurate predictions, improving decision-making processes and identifying innovative solutions. AI-driven models can help address both physical and transition risks by offering advanced data analysis capabilities, automating the monitoring of climate-related variables and optimising energy consumption patterns. These technologies present numerous opportunities for organisations to not only mitigate the effects of climate change but also capitalise on the transition to a low-carbon economy. A recent review highlights the great potential of AI to provide solutions that accelerate climate action and enhance organisational resilience. The authors emphasise how AI can mitigate climate change by optimising energy efficiency, reducing emissions and improving resource management in key sectors such as energy, agriculture, transportation and construction. AI can reduce energy consumption in buildings by up to 50%, improve the precision of fertiliser application by over 40% and lower CO_2

emissions in transportation by 60%, while its use in smart grids enables 10%–20% savings in electricity costs. In addition, AI improves carbon capture and storage, extreme weather forecasting and the design of resilient cities. AI-based solutions can play a crucial role in mitigating the effects of climate change by providing accurate models that help organisations anticipate regulatory, technological and market changes [2].

Incorporating AI into climate impact forecasting not only enhances an organisation's ability to manage future uncertainty but also supports sustainable and resilient business practices. By predicting potential climate-related risks, AI helps organisations develop strategies to mitigate these risks. AI-driven models can automate complex calculations and analysis, reducing the time and resources required for traditional or manual assessments.

There are two main categories of climate risk, namely, *physical risks* and *transition risks*. Although physical climate risks refer to the potential economic and social losses resulting from sudden and gradual weather phenomena [3], transition risks refer to the potential challenges and uncertainties associated with the transition to a more environmentally sustainable low-carbon economy [3]. Based on their nature, transition risks are commonly further categorised into *regulatory*, *market*, *technological* and *reputational risks* [4].

The Task Force on Climate-Related Financial Disclosures (TCFD) [5] highlights that the financial effects of climate-related challenges within businesses are not always straightforward or immediately evident. Numerous organisations encounter obstacles in recognising risks, assessing their potential impacts and incorporating key climate considerations into financial statements. These challenges often stem from factors such as insufficient organisational awareness of climate-related matters, a focus on short-term risks at the expense of long-term concerns and the inherent difficulty of quantifying the financial implications of climate-related factors [6].

Effectively, reducing the increase in temperature to below 2°C will require the development of models that can successfully navigate the multiple challenges that arise from the impact of climate change on socioeconomic systems [7], suggesting an external perspective, with particular emphasis on exploring the implications associated with transitioning to a low-carbon economy. As AI continues to evolve, it can play a pivotal role in helping organisations tackle these challenges by enhancing scenario modelling, improving energy efficiency and forecasting the financial impact of climate transition risks [2].

As the effects of climate change escalate and the imperative to transition to a low-carbon economy intensifies, organisations face the obligation to disclose these impacts to stakeholders and demonstrate that they are addressing these important issues. It is crucial to assess financial implications on various aspects, such as revenues, expenses, assets and liabilities [8]. However, the European Central Bank (ECB) suggests that organisations consider various elements when assessing climate-related risks [9]. In addition to examining the effects on individual economic entities, it is crucial to consider the particular channels through which climate risks are transmitted. For a complete assessment, it is therefore essential to consider variables such as technology investments, greenhouse gas (GHG) emissions, carbon pricing, fossil fuel prices, energy use, fuel consumption and energy costs (ECs).

The transition to a low-carbon economy involves not only reducing GHG emissions but also transforming the energy sources used in production. However, climate change can significantly impact the progress and viability of renewable energy sources. As discussed previously [10], the costs, resilience and environmental impact of renewable energy can be adversely affected by extreme weather events, adding uncertainty to transition processes [11].

Our study aims to provide organisations and stakeholders with the tools and insights necessary to anticipate factors associated with the transition risks of climate change. This knowledge facilitates the identification, assessment and management of climate-related risks and their financial implications for organisations. Such climate change risk data enable investors to comprehensively assess a company's risk landscape and the effectiveness of its risk management strategies [12]. In this context, companies can use historical data, scenarios and assumptions as input for analysis. However, challenges such as data accessibility create barriers associated with these factors. Therefore, it becomes advisable to emulate climate scenarios to identify sensitivity ranges with respect to material risks to the organisation. It is important to note that scenarios may involve confidential assumptions tailored to specific organisational needs. According to experts, the incorporation of climate scenarios represents a valuable strategy for organisations to address uncertainties related to the risks and opportunities associated with climate change from external sources [8].

Our study focusses exclusively on climate transition risks, leveraging AI techniques to predict their financial impacts on organisations. Using machine learning (ML) and deep learning (DL) models, our objective is to improve decision-making processes and foster a deeper understanding of how transition risks affect financial outcomes. Although not all variables suggested by the ECB are covered, we focus on four key variables that we use in our case study as our research approach to generate a better understanding of the financial impact of climate transition risks on companies. Specifically, we examine the usage of energy in production systems and the consumption of diesel as a fossil fuel within the logistics fleet. The results we present serve as valuable data for future analyses, providing insight into how climate transition risks—ranging from regulatory and market factors to technological challenges—impact organisations financially.

In this context, our research is closely aligned with Sustainable Development Goal 13, which is Climate Action. Specifically, we focus on target 1 of this goal. The aim of this target is to strengthen the resilience and adaptability of organisations to climate-related risks. Our specific focus lies in developing a software prototype capable of predicting the financial implications of risks encountered by organisations during their transition towards a more climate-friendly approach.

To present our work effectively, the remainder of this article is structured as follows:

- Section 2 presents related research.
- Section 3 details our case study research methodology. It describes the methodology for collecting data for the four critical variables selected for our study, data preprocessing, prediction and validation and financial impact assessment.
- Section 4 presents the results obtained, specifying how the risks associated with a changing climate affect the financial health of the organisation.
- Section 5 concludes and offers future research directions.

2. Related Research

Researchers have used various methods to analyse climate risks, including physical and transition risks. These methods include economic and financial approaches, prospective analysis, statistical modelling and AI-based techniques.

2.1. Analysis to Assess Climate Risk. Several approaches available in the vast literature for forward-looking analysis to assess risks and consequences related to current and future climate factors use scenarios [13]. These are based on the GHG emission scenarios (RCP, Representative Concentration Pathways), which are used in IPCC AR5: RCP2.6 (early response), RCP4.5 (effective measures), RCP6.0 (2°C exceedance) and RCP8.5 (business as usual).

The nature of the data to be analysed to determine the risks of climate change can be very diverse. In [14], the authors examine different market indicators of climate change risks and analyse the participation of carbon-intensive assets in the overall portfolio. The study in [15] presents two climate indexes derived from media reports sourced from the Wall Street Journal, using a predefined set of climate-related terms. These indexes serve as tools for analysing market fluctuations driven by media coverage of climate change. Similarly, the authors in [16] proposed a "carbon beta" to measure an asset's exposure to climate risk, correlating high and low emissions in response to increasing climate concerns. This approach examines a climate policy uncertainty (CPU) index, which considers the frequency of climate news, as well as volatility in the stock market. To conclude, the authors in [17] used historical data to explore the correlation between temperature change and gross domestic product (GDP), to understand how temperature change affects the global economy. Since temperature serves as a direct measure of climate change and is easily quantifiable, changes in global warming can have substantial effects on both natural and human systems, leading to significant reductions in economic output. This impact is quantified by assessing changes in GDP, which can also serve as a proxy indicator of a country's capacity to adapt to and mitigate the effects of climate change.

2.2. Assessment Procedures. There are three approaches identified by the European Banking Authority to assess environmental, social and governance (ESG) risks [18]:

1. Portfolio alignment method.
2. Risk framework method (climate stress tests).
3. Exposure method.

In addition, carbon beta is a market-based indicator of climate risk. This measure reflects how assets, for example, global equities or commodities, relate with a carbon risk factor [16].

As stated in [19], the information required for stress testing or evaluating the financial implications of climate change on organisations can be divided into two primary categories: macroeconomic data and climate-related data. Macroeconomic data encompass a range of financial indicators, including regional and global economic statistics, financial statements, inflation trends and interest rates. Conversely, climate-related data involve elements such as regulatory frameworks, market fluctuations, technological innovations, organisational reputation, sector-specific emissions data, carbon pricing and the energy and carbon mix, which includes electricity usage and fossil fuel consumption. This study concentrates on the latter category, with a particular focus on energy consumption and the utilisation of a specific fossil fuel—diesel—within logistical operations. Furthermore, it incorporates a market variable, specifically addressing price fluctuations related to energy consumption and diesel.

2.3. Modelling of Climate Risk. In the context of modelling, various approaches can be found in the literature. A notable approach involves dynamic system models that are applied to evaluate the relationships involving climate risks, financial outcomes and operational processes within companies. These models consider various types of risk, including physical, regulatory, reputational and legal risks. They also integrate aspects such as climate scenarios, the influence of policies related to climate change, stakeholder perspectives and extreme weather events [20]. In addition, open-source software, such as CLIMADA, has been designed to combine risk exposure and vulnerability, supporting the development of risk indicators and evaluating the wider economic impacts. These resources enable the calculation of probabilities for events occurring nationwide [21].

An interesting study on transition risk in South Africa suggests the use of static input-output frameworks combined with sector-specific financial risk metrics to evaluate exposure and financial responsiveness in transition scenarios [22]. The study highlights the necessity of including scope 3 emissions in impact evaluations. A wider approach in [23] considers scopes 1, 2 and 3 to project the impact on an organisation's operating expenses, given its level of exposure. This analysis employs an econometric approach applied to a dataset of US companies to determine the connection between GHG emissions and reputational risk.

Similarly, other studies such as [24–31] consider GHG emissions as a proxy to evaluate the effects of climate change on business operations and economic systems. In contrast, the authors in [28] proposed CRISK, an expected capital shortage factor using climate scenarios. This methodology consists of creating portfolios sensitive to climate transition risk, then calculating climate betas using the dynamic conditional beta (DCB) model, monitoring market factors and economic changes.

AI plays a central role in modelling, with various computational approaches described in the literature to manage and quantify climate risks. In risk management, studies use techniques such as artificial neural networks (ANNs) [32]. Furthermore, BERT [33], a key component of many natural language processing (NLP) systems, has been widely used to quantify climate risks. For example, it has been used to analyse the impact of climate change on credit default and to interpret regulatory disclosures in 10-K reports [33].

There are numerous other computational models. For example, the one discussed in [34] uses a daily proxy of transition and physical climate risks derived from news articles. This model applies advanced computational linguistic techniques to evaluate the influence of climate risks on fluctuations in oil prices. Other approaches rely on stochastic diffusion frameworks aligned with extreme emission scenarios reported by the Intergovernmental Panel on Climate Change (IPCC), effectively incorporating uncertainty when estimating sea level rise [10]. Studies such as [35] leverage the ISO 31000 guidelines to develop online tools for assessing climate risks. These studies make use of stochastic probability techniques to determine the value of assets impacted by climate-related events, establish connections between GHG emissions and portfolio structures and analyse variability in event probabilities. It can be noted that most of the studies referenced in the current literature concentrate on either macroeconomic perspectives or national-scale analyses, often adopting a top-down methodology irrespective of the specific techniques applied. On the contrary, we employ a bottom-up approach based on a specific use case, the Colombian food sector, and use AI techniques to explore the financial implications of specific climate transition risks. We believe that this targeted approach is crucial to achieving precise and meaningful results.

3. Methodology

We design a comprehensive methodology to analyse and predict two of the four types of climate transition risks, including market and regulatory risks, for which we have collected our original data. A graphical illustration is shown in Figure 1.

According to the recommendations of [36], we consider the various factors and projections influencing the economic impacts, both at the macroeconomic and sectoral scales, to evaluate potential climate risks. Subsequently, we encourage (and expect) the organisation that we used for our case study to conduct these assessments and actively consider the potential long-term financial consequences. For this study, the relevant factors include *energy consumption* and *diesel usage*, categorised as regulatory risks, as well as *diesel* and *energy pricing*, identified as market risks. We will utilise ML and DL models to predict the financial impact concerning operational costs in the Colombian food sector. Further details are outlined in the subsequent sections.

3.1. Data Collection and Preprocessing. Our dataset consists of historical records of electricity and diesel consumption, along with past prices of fuel and electricity. As explained in Section 3, these are the variables under study. We collected data covering monthly consumption from January 2013 to November 2022 for all the variables mentioned above from the databases of a Colombian food processing company that decided to remain anonymous. In this study, to preserve the confidentiality of company data, which we cannot share, we use them to generate their distributions. This allows us to draw datasets and simulate relevant scenarios. Table 1 offers comprehensive details, including the number of samples and other relevant information on the dataset utilised in this study. For the sake of reproducibility, we made the latter available in [37], together with the source code to process it. This also allows the reader to replicate our results and run other simulations with different data from the same distributions.

Note that to create a fully useable high-quality dataset, we used *imputation* [38, 39], i.e., averaging the available time series, to estimate the values for missing/null data points. Before training DL models, we applied a standardisation routine with a mean value of 0 and a standard deviation of 1. That is, we worked with normal distribution data, as this practice is well known to significantly improve the performance of the models employed [40].

The imputation method that uses the mean to fill missing data can indeed introduce biases and affect the accuracy of predictions. However, there are many alternative approaches. Advanced interpolation techniques: Methods like spline interpolation or polynomial interpolation allow for estimating values based on the trend of nearby data, which can be more accurate than a simple mean. ML-based imputation models: Techniques such as K-nearest neighbours (KNN) or regression models can use patterns in the data to predict missing values, potentially reducing bias. Incorporating uncertainty: Bayesian techniques can be applied, not only imputing values but also providing confidence intervals for the imputations. Although these methods can sometimes improve missing data handling, the mean imputation was chosen because pilot tests with other techniques led to abrupt changes or disrupted the patterns in the series. The differences introduced by the missing values were minor compared to the inherent noise in the data.

Furthermore, the dataset was divided into consecutive intervals using a data window, allowing a more accurate prediction of our measurements, which were measured at regular intervals. The data subset in each window is the input of the forecast system to predict the values at each time [41]. A smaller window size is highly recommended to identify short-term trends in the data. On the contrary, a larger

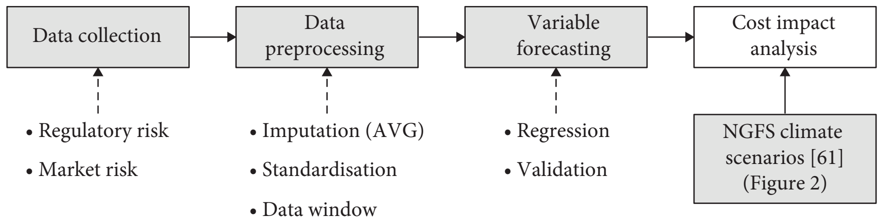

Figure 1: Methodology overview.

Table 1: Dataset description.

Variable	Data entries	Time horizon	Granularity
Energy consumption	2922	01/01/2015–07/31/2022	Daily
Energy price	84	01/31/2016–12/31/2022	Monthly
Diesel consumption	942	01/02/2020–07/31/2022	Daily
Diesel price	1218	04/19/2019–04/30/2022	Daily

window is preferred to detect long-term patterns [41]. Therefore, we adjusted the window size for the specific case, as indicated in Section 4.

3.2. AI Models Used. In this study, we address a regression problem. Specifically, we analyse the quantitative association between the independent variable ‘*date*’ and the dependent variables ‘*price or consumption*’ of electricity and diesel. This correlation analysis enables us to predict the financial impact linked to climate change risks within organisations.

To achieve this goal, we selected and compared 17 regression algorithms, reported in Table 2, which comprise a good number of statistical and AI-based methods.

We used different models to compare model performance. Different models have their own strengths and weaknesses. By training several models, we compared their performance and selected the one that best fit our specific dataset and problem.

We used both traditional/simple and modern/advanced models. We also implemented the ensemble methods because they can show better performance compared to a single method. Some models may be too simple (high bias) and underfit the data, while others may be too complex (high variance) and overfit the data. Evaluating different models helps to find a balance between bias and variance. This means that ‘there is a trade-off between the accuracy of the prediction and its precision, or equivalently between its bias (the opposite of accuracy) and its variance (the opposite of precision)’ [53].

Training different models allows a wider range of hyperparameters to be explored, potentially leading to better optimisation and performance. In addition, the use of different models helps to ensure that our predictive analytics solution is not overly dependent on a single model, making it more robust and reliable in different data scenarios. In summary, by using multiple models, we aim to increase the accuracy, reliability and overall effectiveness of our predictive analytics efforts. In selecting the criteria used to assess performance in different contexts, we have chosen standard criteria. These criteria or metrics are preferred because they provide a comprehensive view of a model’s performance from different angles, helping to identify strengths and weaknesses more effectively than using, for example, accuracy or MAE alone.

The models encompass both statistical and AI-based approaches, with a focus on ML and DL techniques. Our rationale for selecting these specific models stems from their proven effectiveness in handling nonlinear patterns, which are typical in time series data related to energy consumption and pricing [54, 55].

We included classical statistical models such as linear regression due to their simplicity and interpretability for linear trends, while the ML and DL models were chosen for their robustness in capturing complex nonlinear relationships. In particular, tree-based algorithms like random forest and gradient boosting have been widely validated in energy consumption forecasting due to their ability to model nonlinearities and interactions [56]. Furthermore, DL approaches such as LSTM and CNN are well suited to processing sequential data, making them ideal for time series predictions [57–59]. This combination, therefore, ensures comprehensive coverage of both linear and nonlinear dynamics within the dataset.

It can be seen that we have considered a larger number of AI-based regressors, as they are known to be more suitable for solving nonlinear time series problems [60]. Also, note that in Table 2, we further categorised AI-based approaches to distinguish between those based on classical ML frameworks and those based on DL models.

The hyperparameter tuning in this study was conducted through grid search, optimising parameters such as the learning rate, the number of hidden layers and the number of neurones in each layer. For each model, various hyperparameter combinations were evaluated using a validation set. The final selection of hyperparameters aimed to optimise performance in terms of MSE and R2. This approach ensures that the models are optimally tuned to the data, minimising the risk of overfitting or underfitting.

Table 2: The 17 regression models employed in this study.

Name	Acronym	Category
Linear regression [42]	LR	Statistical
Lasso regression [43]	Lasso	
Bayesian ridge regressor [44]	BRidge	
AdaBoost regressor [45]	AdaBoost	Machine learning
Decision tree regressor [46]	DT	
Light gradient boosting machine [46]	LGBM	
Gradient boosting regressor [47]	GBR	
Random forest regressor [48]	RF	
eXtreme gradient boosting regressor [49]	XGBoost	
Catboost regressor [43]	Catboost	
Bayesian automatic relevance determination regression [44]	B-ARD	
K-nearest neighbours regressor [50]	KNN	
Support vector regressor [45]	SVR	
Multilayer perceptron [45]	MLP	Deep learning
Convolutional neural network [51]	CNN	
Long-short-term memory [42]	LSTM	
Deep neural network [52]	DNN	

Regularisation techniques were implemented in DL networks, such as dropout layers and L2 regularisation, to improve the generalisation of the model. For time series validation, the time series split strategy was applied, ensuring temporal sequentially and preventing future information from influencing the predictions.

Throughout the process, continuous monitoring of performance metrics in the validation set was performed, with particular attention given to the divergence between training loss and validation loss. It is important to note that the results reported correspond exclusively to the validation set, not the training set.

3.3. Climate Scenarios. The Network for Greening the Financial System (NGFS) [61] has created a framework that features hypothetical scenarios (see Figure 2), aiming to offer a common reference to understanding the potential impacts of climate change and policies, highlighting different risk outcomes. These scenarios incorporate assumptions about technological advancements, climate policies and the general implications of climate change on the economic and financial conditions of countries, which should be taken into account in an informed risk assessment.

In this study, we used the six scenarios from the 2022 update version of the NGFS framework [61]. As indicated in Figure 1, these scenarios come into play as projections of the change or effect of climate change on a country's economy, derived from the analysis of integrated assessment models (IAMs) (which are expanded in the next section), are then compared with the prediction results using a method from Table 2 and help to estimate the financial impact of climate transition risks. Note that the quadrants in Figure 2 group the scenarios into the four classes explained below according to the definitions of [61].

1. Orderly scenarios occur when climate policies are implemented promptly and progressively strengthened, resulting in a significant reduction of both physical and transition risks. The two scenarios in this group are
   - Net zero (NZ) 2050, which limits global warming to 1.5°.
   - Below 2°C (B2D), which involves a gradual intensification of climate policies, providing a 67% probability of restricting global warming to below 2°C.
2. Disordered scenarios are those that can lead to greater transitional risks because policies are postponed or vary between countries and industries. For example, carbon prices tend to be higher for a given temperature result. The two scenarios in this group are
   - Divergent net zero (DNZ), which reaches NZ around 2050.
   - Delayed transition (DT), which assumes that annual emissions will not decrease until 2030.
3. Hot house world (HHW) poses a serious physical risk and a low transition risk because global efforts are not enough to stop global warming. The two scenarios in this group are
   - Nationally determined contributions (NDCs), which include all pledged targets.
   - Current policies (CPs), which assume that only CPs are implemented.
4. Too little, too late will contain scenarios of delays and differences in ambition for climate policy between nations, resulting in increased transition risks in certain countries and increased physical risks globally, as the general ineffectiveness of transition exacerbates these challenges.

The six scenarios studied belong to the first three groups. NGFS is currently adding more scenarios to the last group, but the data are not yet available.

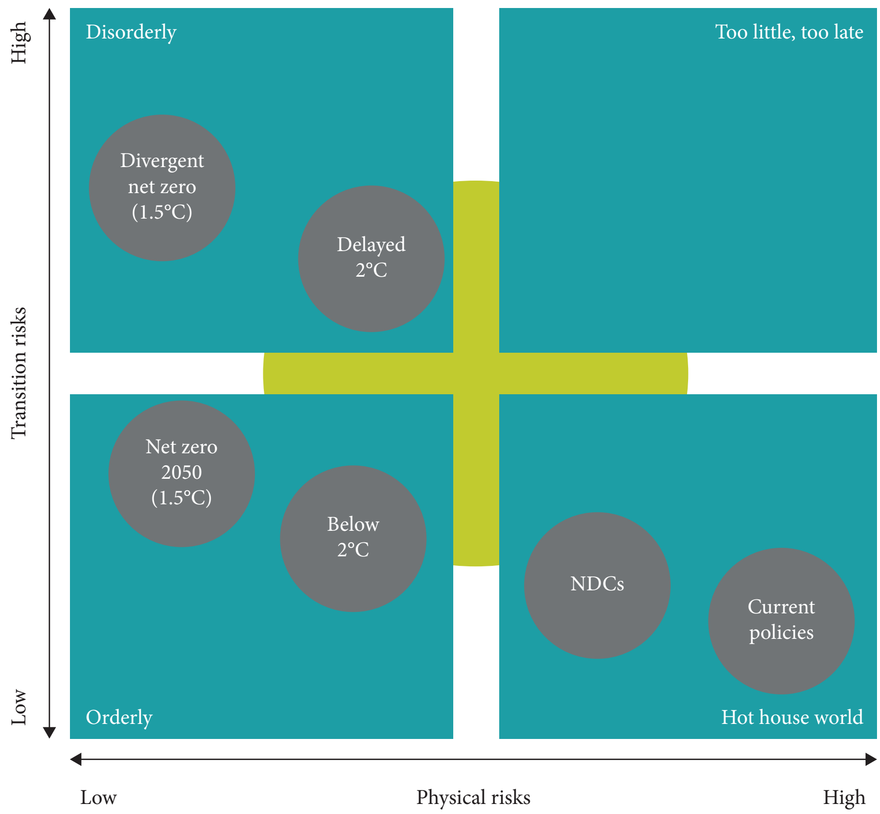

FIGURE 2: The NGFS scenario framework—image from [61].

Our idea is to use GDP as an economic indicator that encapsulates the level of stress induced by climate change, as suggested in [62], and in turn to assess the severity of climate scenarios. In Table 3, we report the projections of percentage changes in Colombian GDP, as generated by the AIM of the NGFS Global Change Assessment Model 5.3 (GCAM 5.3), which is described in detail [63, 64].

These scenarios combine climatological and economic data, using assumptions such as population growth, GDP growth and technological change to generate long-term projections, including mitigation costs and physical damages [65].

3.4. Metrics and Model Evaluation. We employ four established performance metrics to assess the performance of a model and select the best model [42]. These are

$$
\begin{aligned}
\text{Mean Squared Error (MSE)} &= \frac{1}{n}\sum_{i=1}^{n} e_i^2,\\
\text{Mean Absolute Error (MAE)} &= \frac{1}{n}\sum_{i=1}^{n} \left|e_i\right|,\\
\text{Root Mean Squared Error (RMSE)} &= \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2},\\
R^2\ \text{(Scored Error)} &= 1 - \left(\frac{\sum_{i=1}^{n} e^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2}\right),
\end{aligned}
\tag{1}
$$

Table 3: Projections of rate of change GDP in Colombia due to climate change under different scenarios obtained in the AIM GCAM 5.3 [63, 64].

Year	Below 2°C (%)	Current policies (%)	Divergent net zero (%)	Delayed 2°C (%)	NDC (%)	Net zero (%)
2025	−0.63	−0.62	−0.73	−0.62	−0.62	−0.63
2030	−1.12	−1.15	−1.05	−1.16	−1.09	−1.03
2035	−1.60	−1.73	−1.33	−1.79	−1.60	−1.46
2040	−1.94	−2.24	−1.46	−2.19	−2.04	−1.69
2045	−2.11	−2.63	−1.49	−2.33	−2.32	−1.72
2050	−2.31	−3.14	−1.57	−2.45	−2.71	−1.80
2100	−2.24	−7.02	−1.40	−2.28	−4.60	−1.62

where n is the number of data points available in the dataset, the i^{th} $(i = 1, \ldots, n)$ residual error $e_i = (y_i - \hat{y}_i)$ is denoted as the difference between the actual i^{th} value y_i (available in the dataset) and its predicted output $\hat{y}_i$, and y_i is the arithmetic mean of the data points.

3.5. Cost Impact Analysis. We use the climate transition risk adjustment factor (CTRAF) metric as a proxy that captures the economic changes in Colombia.

CTRAF is a useful tool for investors. It helps them understand the potential impacts of climate-related events on their investments. According to [25], it is recommended to use CTRAF as a proxy. This is particularly true in situations where data are absent or when modelling complex parameters. The CTRAF approach considers a vulnerability factor for the case study company, which is based on the IPCC's definition of vulnerability as a function of exposure, sensitivity and adaptive capacity [66]. However, most studies that analyse climate risk typically consider only physical risks and combine these factors, neglecting other variables of socioeconomic and systemic vulnerability that are difficult to characterise [67].

A traditional approach to defining vulnerability, see [68, 69] for details, is based on combining these components, as shown in the following equation:

$$V = E + S - C, \tag{2}$$

where V stands for vulnerability; E represents exposure, which is the nature and degree to which a system is exposed to climate variability; S represents sensitivity, which is the degree to which the system is affected by climatic stimuli; and finally C represents adaptive capacity, that is, the capacity of a system to adjust to the effects of climate change [69].

We approach the concept of vulnerability from a different angle, focussing on resilience instead of adaptive capacity. Resilience (R) is defined as the ability to anticipate and recover from the impacts of climate change [70], which is more comprehensive in this context. This leads to some modifications of equation (2). As suggested in [71, 72], the latter is replaced by the following equation:

$$V = E + S - R. \tag{3}$$

Subsequently, we define an index to understand the factors that influence each of the dimensions of vulnerability (i.e., exposure, sensitivity and resilience) in relation to the change in the climate transition. A semiquantitative approach is considered through expert validation, as vulnerability assessments to date have only been used to analyse physical climate risk [66, 73].

Note that the indicators obtained must be normalised to a common scale. The traditional Min-Max [25] scaler, indicated with the function $N(\cdot)$ for brevity here, is applied to rescale each value in [0, 1] using the following equation:

$$N_{(x_i)} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \tag{4}$$

where $x_{\min}$ and $x_{\max}$ are the lowest and highest values bounding any generic i^{th} data point x_i, respectively.

Following the assessment of any individual indicator I, each is independently combined in the three dimensions of vulnerability to produce a combined indicator (CI) using the weighted arithmetic aggregation method in [74]. This is calculated with

$$\mathrm{CI} = I_1 w_1 + I_2 w_2 + \cdots + I_n w_n, \tag{5}$$

where w_i $(i = 1, 2, 3, \ldots, n)$ is the weight assigned to the indicator (see [74] for more details).

The variables selected for the analysis of the three dimensions of vulnerability for our case study are described in the next section.

3.5.1. Calculation of Vulnerability Dimensions. The indicators in Table 4 are considered for calculating the exposure dimension.

Thus, exposure in this study is represented as

$$E = N(\mathrm{FFD}) \times w_1 + N(\mathrm{NEP}) \times w_2 + N(\mathrm{EV}) \times w_3 + N(\mathrm{DTCF}) \times w_4 + N(\mathrm{IAT}) \times w_5. \tag{6}$$

Table 4: Exposure dimension indicators.

Acronym	Description	Risk type
FFD	Fossil fuel dependence	Market
NEP	New environmental policies and regulations	Regulatory
EV	GHG emissions volume	Regulatory
DFT	Level of dependence on fossil fuel–based technologies	Technological
ITA	Investment in technological adaptation	Technological

The indicators in Table 5 are considered to calculate the sensitivity dimension.

Thus, the sensitivity in this study is represented as follows.

$$S = N(\mathrm{FC}) \times w_1 + N(\mathrm{SPM}) \times w_2 + N(\mathrm{DCS}) \times w_3 + N(\mathrm{LOT}) \times w_4 + N(\mathrm{CTC}) \times w_5. \tag{7}$$

The following indicators were considered for the calculation of the resilience dimension as shown in Table 6.

Thus, the resilience in this study is represented as follows:

$$R = N(\mathrm{CIT}) \times w_1 + N(\mathrm{SCF}) \times w_2 + N(\mathrm{DPS}) \times w_3 + N(\mathrm{ALC}) \times w_4 + N(\mathrm{AMS}) \times w_5, \tag{8}$$

where $\mathrm{Norm}(X)$ is the normalisation function that scales the variable X in a common range 0-1 and w are the weights assigned to each variable, which should add up to 1. Thus, the vulnerability is represented as

$$V = E \times w_E + S \times w_S - R \times w_R, \tag{9}$$

where E, S and R represent the 3 vulnerability factors and w represents the weights given to each of the components.

3.5.2. CTRAF. The proposed factor employs a top-down approach which applies the average exposure to climate risks of a specific sector and applies the averages to individual exposures of organisations belonging to that sector [75–77]. This factor considers GDP as a proxy in line with [65, 71, 78, 79], to translate the impacts of climate change on Colombia's GDP, considering the projections of the NGFS scenarios. On the other hand, the distribution of GDP by economic sector was identified; this procedure is known as downscaling [80].

The study by authors in [65] performs a long-term yield impact analysis where the effects on assets are calculated. The average annual impact on the performance of different asset classes is used as an impact indicator across using different climate scenarios, as shown in Figure 3.

This study uses variations in Colombia's GDP, obtained from various NGFS climate scenarios. In terms of asset sensitivity, the suggested vulnerability factor is used, considering not just sensitivity, but also exposure and resilience in relative terms, thereby producing a measure of the effect on the organisation's performance.

Studies such as [71] have shown the importance of analysing a country's economic activity. This analysis significantly influences the economic evaluation at the company level, often referred to as the top-down approach (see Table 7). The impact of climate transition risks, given a set of scenarios analysed by the NGFS, is determined by the interaction between factors such as exposure, vulnerability, resilience and adaptability, as proposed in equation (10). In the latter, CTRAF is the climate transition risk adjustment factor; V represents the vulnerability to climate change; $\Delta\mathrm{GDP}_S$ represents the adjustment factor for each economic sector, which in this case corresponds to the fluctuation of Colombia's GDP in the given climate scenario; σ denotes the proportional contribution of the sector, in which the subject company of the case study operates, to the GDP in the context of the climate scenario; and $N(\cdot)$ is the normalisation function that scales its variable within [0, 1] (equation (4)).

$$\mathrm{CTRAF} = V \times N\left(\Delta GDP_S\right) \times N(\sigma). \tag{10}$$

3.5.3. CTRAF Application. In this study, our objective is to capture the effects of climate shocks. As indicated in [79], we use CTRAF. This factor is multiplied by the forecast value of the prices of the variables analysed, which are electricity and diesel. This calculation proposed by the authors is used to estimate the price of stocks in different industries. Furthermore, in our study, we consider different scenarios by multiplying the decrease in stock prices by the transition vulnerability factors specific to the sector under analysis.

The forecasts of the variables produce monthly values. These are the forecasted energy price (FEP) and the forecasted consumed energy (FCE). These factors will generate the EC for a base scenario, known as S_0, as indicated in the following equation:

$$\mathrm{EC}_{S_0} = \mathrm{FPE} \times \mathrm{FCE}. \tag{11}$$

Cost projections associated with the consumption of these energies are obtained by applying the climate scenarios established by the NGFS. This proxy is represented as

Table 5: Sensitivity dimension indicators.

Acronym	Description	Risk type
FC	Susceptibility to fluctuations in energy and carbon costs	Market
SPM	Level of sensitivity to policy change and market demands	Regulatory
DCS	Degree of dependence on climate-sensitive sectors	Market
LOT	Level of asset obsolescence due to technological change	Technological
CTC	Capacity for technological change	Technological

Table 6: Resilience dimension indicators.

Acronym	Description	Risk type
CIT	Capacity for innovation in sustainable technologies and business practices	Technological
SCF	Supply chain flexibility	Regulatory
DPS	Diversification of products and services	Market
ALC	Adaptation and learning capacity	Regulatory
AMS	Adaptation and emission mitigation strategies	Regulatory

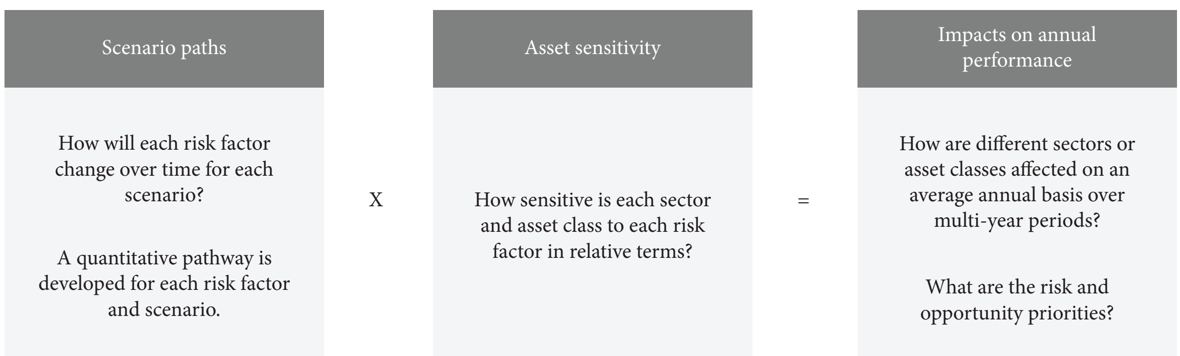

Figure 3: Annual return impact analysis inputs and outputs [65].

Table 7: Distribution of gross domestic product in Colombia by sector [81].

Economic activity	Share of GDP (%)
Commerce	17.76
Public administration and defence	15.09
Manufacturing industries	11.52
Taxes less subsidies	9.6
Real estate activities	8.43
Agriculture	7.43
Professional activities	6.65
Mining	5.29
Construction	4.72
Financial activities	4.48
Energy supply	3.48
Arts activities	2.85
Information and communications	2.7

CTRAF, which is added to the previous equation, as shown below. This will generate the EC for the scenario S to evaluate it, as illustrated in the following equation:

$$\mathrm{EC}_S = \mathrm{FPE} \times \mathrm{FCE} \times \mathrm{CTRAF}. \qquad (12)$$

The market cost overrun from the volatility of the energy price is the difference between the fuel costs in climate risk events and the costs in the base scenario S_0, typically projected without a climate event, as shown in the following equation:

$$\text{Total Cost} = \mathrm{EC}_S - \mathrm{ECS}_0. \qquad (13)$$

4. Results and Discussion

In this section, we analyse the findings from experiments conducted using ML and DL models. Comparisons focus on predicting energy consumption, diesel usage and associated pricing. For the assessment of the results, we use the metrics detailed in Section 3.4. Each of the previously mentioned 17 models (Table 2) undergoes testing for each variable, using various time windows for the predictions and different configurations of hyperparameters. The results derived for every variable are reported in this section.

4.1. Forecast of Electric Power Consumption, Fuel and Prices. Data for the four selected variables (electricity consumption and pricing, diesel usage and pricing as fossil fuel) were examined, and descriptive analytics methods were used to gain insight into data patterns over time and to identify anomalies or gaps in the data.

In the analysis of energy consumption, a total of 17 models were evaluated, including 13 ML models and 4 DL models. Among these, the DNN model demonstrated the best performance. The DNN model achieved an MSE of 1.69, an MAE of 28,236.48 and an R2 of 0.86, as reported in

Table 8. To determine the optimal forecast window for this model, various window sizes were explored. The most accurate results were achieved using a 30-data point window, which represents the 30-most recent observations in the time series. It is noteworthy that all time series data utilised had a monthly resolution. This window size proved to be effective in predicting the subsequent data point in the series.

On the contrary, Figure 4 illustrates the model's ability to apply the results obtained from the DNN training to both the training and the test datasets. The model's strong learning capability and accuracy are apparent, as the neural network's hyperparameters are very close to resemble the actual values.

In contrast, when analysing diesel consumption within the company's logistics operations, various models were tested, as presented in Table 9. Among these, the random forest regressor delivered the most accurate results, achieving an R^2 score of 0.93. A perfect R^2 value of 1 indicates that the model fully captures the variability of the dependent variable, whereas an R^2 value of 0 signifies a total lack of explanatory power [42]. For the optimal forecast window, the last 48 data points were used, resulting in an accuracy of approximately 93%.

The validation plot of the random forest regression model shows a good fit for diesel consumption (see Figure 5), which means a good level of learning.

After analysing consumption, we examined kilowatt-hour (kWh) electricity prices from the local energy supplier. This analysis facilitated the creation of a monthly consumption report for each of the company's facilities included in the study. The resulting data served as input for training the models, with the outcomes detailed in Table 10. In this case, the linear regression model was the one that obtained the best results by using a forecast window of 8 historical data points, i.e., we rely on the last 8 periods to forecast the following periods.

Similarly, Figure 6 presents the comparison between the observed and predicted values for energy prices. The test dataset indicates a fit of approximately 94%, which represents a good learning rate of the model.

For the diesel price variable within the logistics process, the analysis of trained models reveals that the Bayesian ARD regression provided the most accurate results, attaining an R^2 value of 0.87. Table 11 summarises the outcomes for all the models evaluated. In this case, a forecasting window of 12 historical data points was employed.

According to the findings presented in Figure 7, it can be concluded that there is a high level of accuracy in the prediction, reaching approximately 87%.

After training the models described in the previous section, predictions were generated for all the variables, including electricity usage, diesel usage, energy and diesel pricing.

The graphs presented in Figures 8, 9, 10, and 11 show the results of the predictions of the models. The blue line represents historical data for each variable, while the red line represents the forecast. The forecast time horizon covers 8 years, until 2030.

The exponential growth of electricity consumption can be seen in Figure 8, starting at the beginning of 2024 and continuing until 2030. This trend serves as a warning to the organisation, considering the energy consumption reduction target proposed for 2030.

In contrast, Figure 9 shows a consistent pattern of diesel consumption from 2023 onwards, with peaks ranging from low to high, persisting until 2030.

From a different point of view, Figure 10 illustrates the gradual increase in the cost of energy per kilowatt-hour (kWh) from 2023, consistently until 2030.

In contrast, Figure 11 shows the expected price of diesel for logistics purposes. The results indicate a price decrease and stable values starting in mid-2023. It should be emphasised that these findings represent an approximation of actual trends, and consequently, updating the model with more recent data in the future is likely to enhance the accuracy of the predictions.

4.2. Financial Impact Projection. Once the energy consumption and price forecasts were generated, we proceeded to calculate the expenses linked to this category of consumption. The analysis indicates that the projected costs are directly proportional to consumption levels, suggesting a notable rise in expenses driven by the trends observed in this parameter (see Figure 12).

Figure 13 illustrates the estimated costs for the diesel case in logistics until 2030. Similar to Figure 9, this one shows a constant pattern with high and low points, for the organisation analysed in this study.

It is evident that extended forecasts or those with lengthy time horizons can exhibit seasonality in the predicted results, as shown in Figures 9, 11, and 13. When the forecast horizon increases, the accuracy of the results becomes heavily reliant on preceding predictions. Consequently, long-term forecasts may deteriorate, leading to biased results that neither account for actual data nor accurately identify patterns within them [82]. To address this, it is advisable to retrain the models as new, real-world data become available, enhancing the precision of future forecasts.

The importance of data in training long-term forecast models is clear. In particular, data at the highest possible granularity can be valuable for evaluating the impact of climate risks. However, this requires increased computing power and a dataset with certain quality characteristics [83].

It is important to highlight that the example extending to 2030 is presented after model validation as a use case, given that companies usually need to make long-term forecasts. Long-term predictions are essential for companies to plan strategies and mitigate risks, but it is clear that they are susceptible to various variables that may change over time, such as policy changes, energy prices and market conditions.

We acknowledge the limitations of these models, as with any other, for long-term predictions, as they require the use of exogenous variables and significantly more data to improve accuracy, although bias will always exist. In this case, the use of ML and DL models, which are capable of adapting and learning from historical patterns, is an advantage,

Table 8: Forecast models and performance indicators—energy consumption.

Model	MSE	RMSE	MAE	R^2
DNN	**1.696610e + 09**	41,189.920324	**28,236.486094**	**0.860951**
MLP	2.241684e + 09	47,346.424559	32,677.868021	0.816278
Catboost	2.283084e + 09	47,781.623791	32,018.444658	0.812885
LGBM	2.426198e + 09	49,256.451484	34,023.228442	0.801156
GBR	2.568980e + 09	50,685.102708	33,761.013744	0.789454

Note: Bold values indicate the best results.

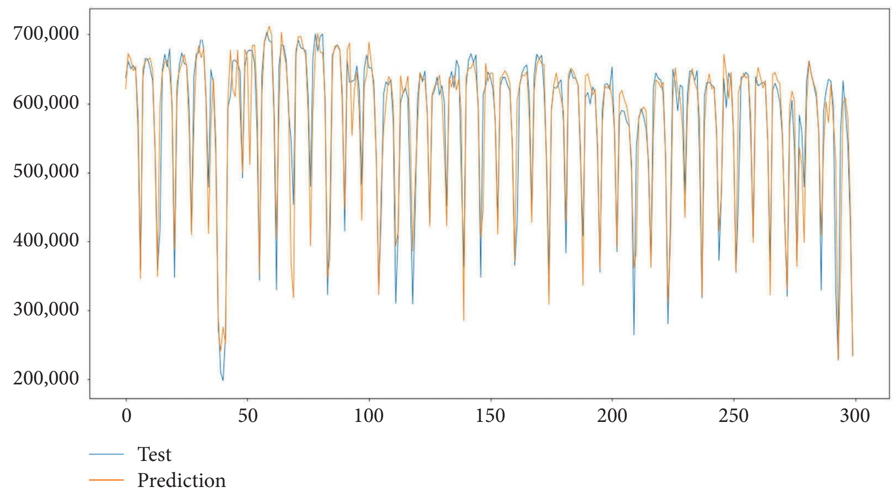

Figure 4: Fit of the data chart—energy consumption.

Table 9: Forecast models and performance indicators—diesel consumption.

Model	MSE	RMSE	MAE	R^2
RF	9.029042e + 04	300.483642	236.296525	**0.933340**
DT	9.081962e + 04	301.362944	**232.007473**	0.932949
LGBM	1.230149e + 05	350.734787	278.964027	0.909180
GBR	1.426821e + 05	377.732786	267.617305	0.894660
XGB	1.454580e + 05	381.389629	282.187783	0.892611

Note: Bold values indicate the best results.

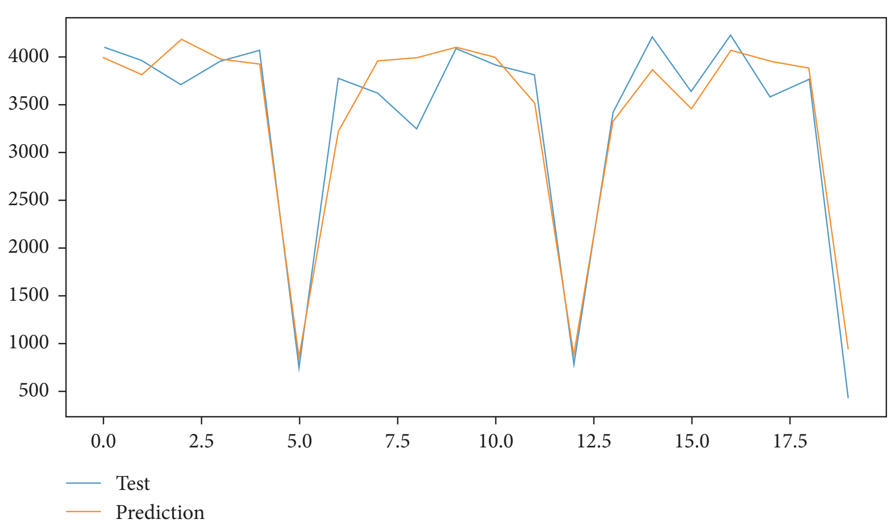

Figure 5: Fitting the data plot—diesel consumption.

Table 10: Forecast models and performance indicators—energy price.

Model	MSE	RMSE	MAE	R^2
LR	**81.974459**	**9.053975**	**7.316486**	**0.940489**
Lasso	88.141200	9.388354	7.759889	0.936012
BR	91.355604	9.558013	7.894933	0.933679
B-ARD	96.314222	9.813981	8.369255	0.930079
MLP	129.519848	11.380679	9.375882	0.905973

Note: Bold values indicate the best results.

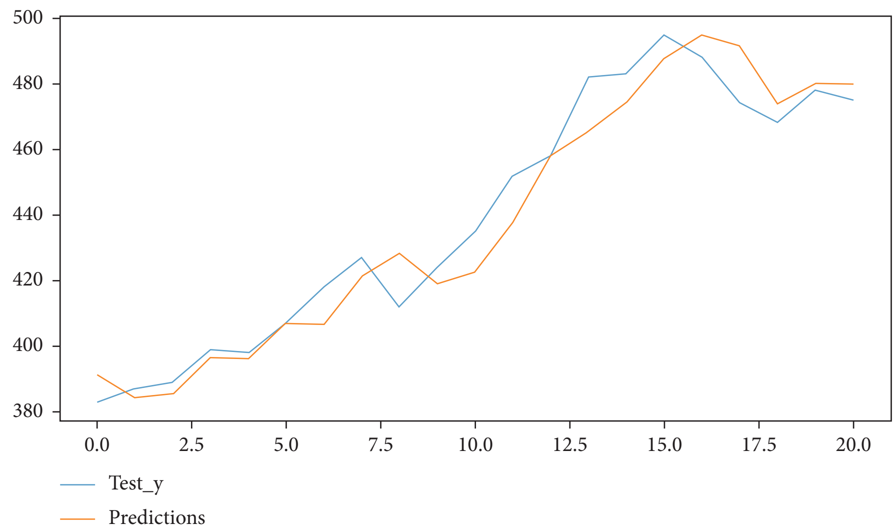

Figure 6: Fitting the data plot—energy price.

Table 11: Forecast models and performance indicators—diesel price.

Model	MSE	RMSE	MAE	R^2
B-ARD	3953.638785	62.877967	**44.252015**	**0.879945**
Lasso	3962.090573	62.945139	44.303752	0.879688
LR	3962.121258	62.945383	44.303725	0.879687
BRidge	3969.248544	63.001973	44.453659	0.879471
Catboost	4875.942522	69.827949	49.490207	0.851938

Note: Bold values indicate the best results.

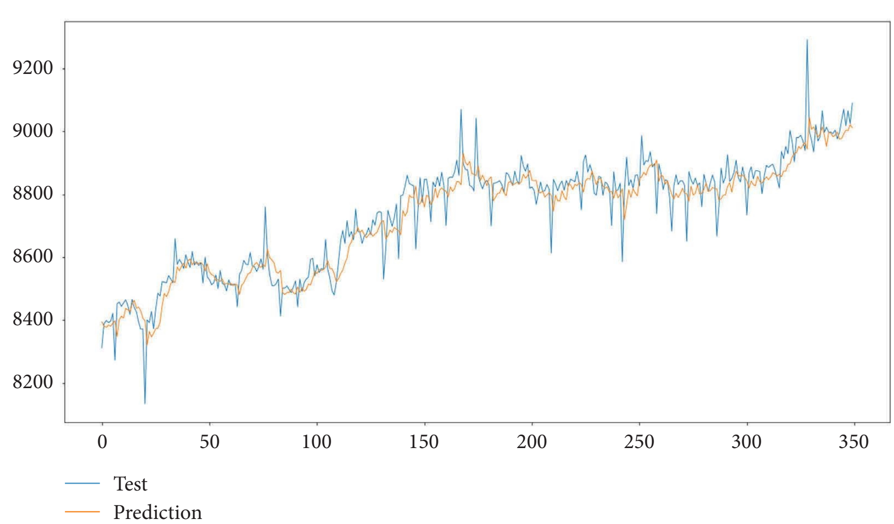

Figure 7: Fitting the data plot—diesel price.

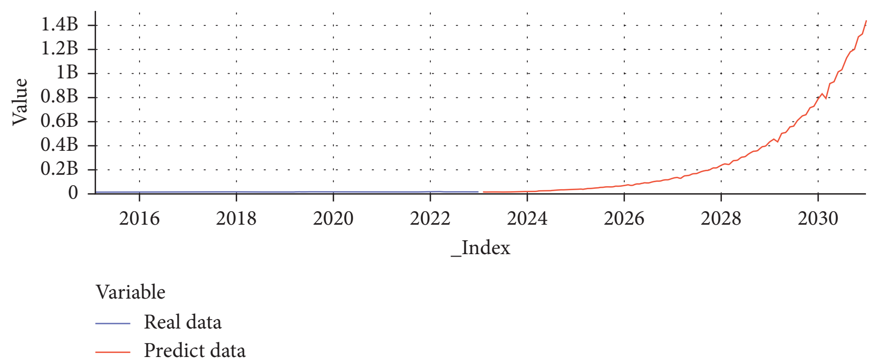

FIGURE 8: Forecast of energy consumption until 2030.

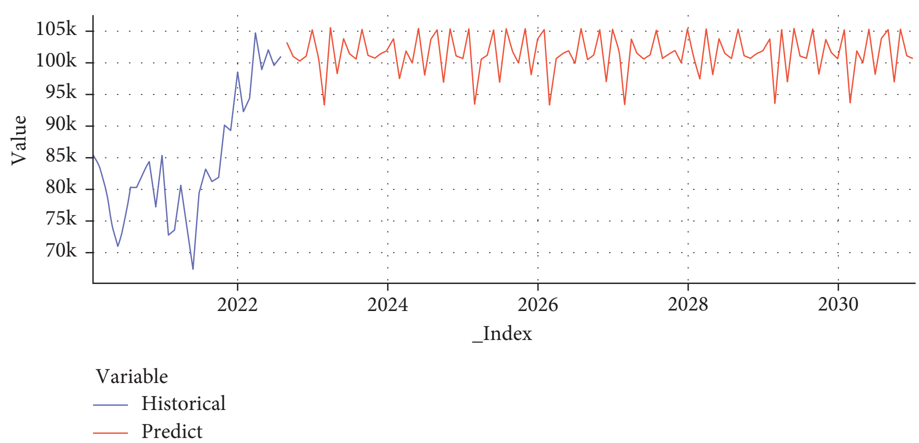

FIGURE 9: Forecast of 2030 diesel consumption.

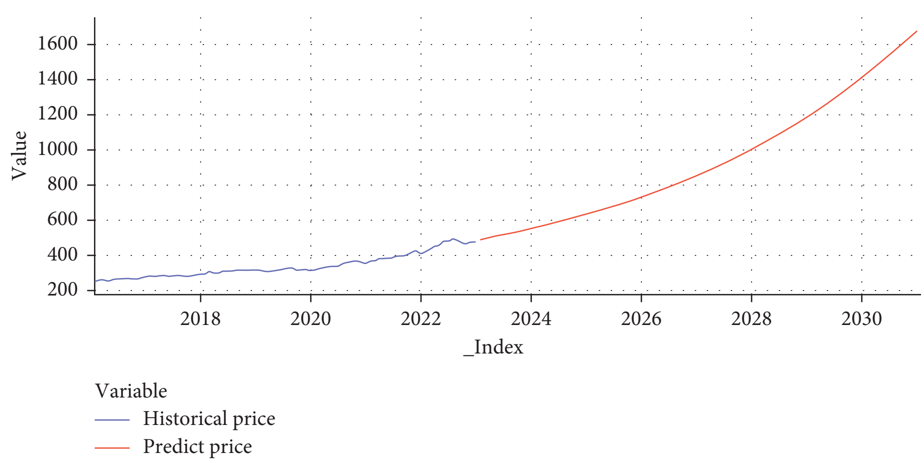

FIGURE 10: Forecast of energy price until 2030.

although they also heavily depend on the quality and availability of the data. We propose that the model continuously learns from new data over time, ensuring that future predictions become increasingly accurate, mitigating bias.

A simulation was conducted using different scenarios that could affect projections. By providing examples of various scenarios, our aim is to illustrate how companies can prepare for different scenarios and adjust their strategies based on the available information.

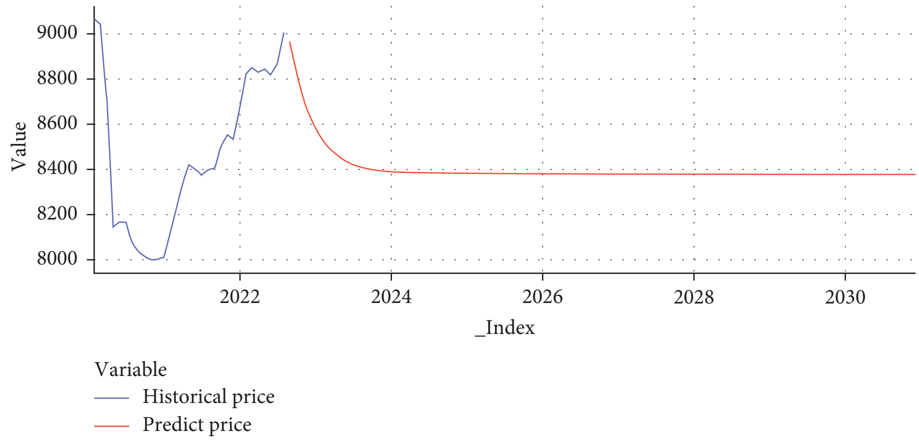

Figure 11: Forecast of 2030 diesel price.

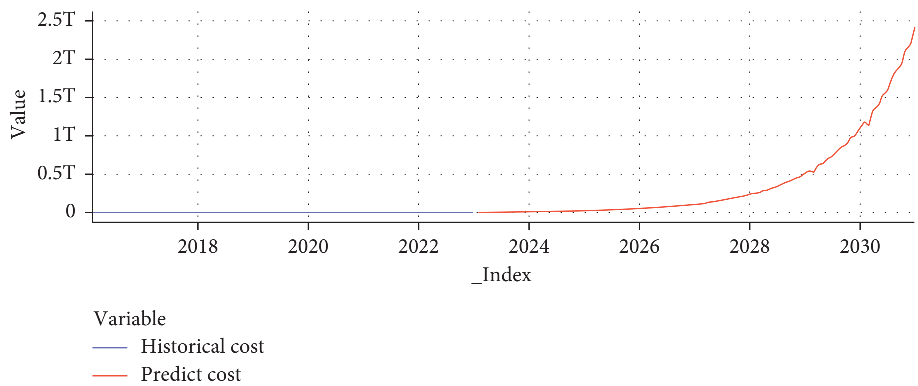

Figure 12: Forecast of the energy cost until 2030.

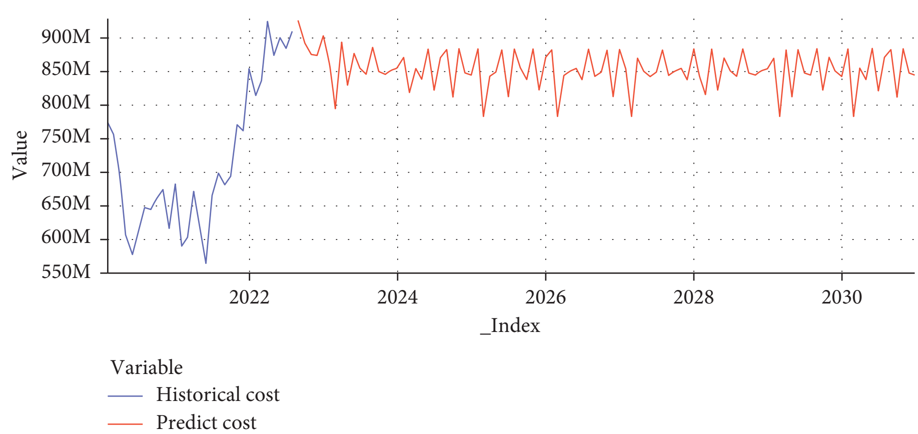

Figure 13: Forecast of the diesel cost until 2030.

This study has taken a different approach by applying bottom-up approach. This stands in contrast to the majority of suggested frameworks and models, which predominantly follow a top-down perspective [84]. The research and expert opinions advocate for the bottom-up approach, as it focuses on the firm or asset scale [77]. This method is considered to yield more precise outcomes within organisations.

This study aligns with the findings of Rao [85], who used a support vector machine (SVM) to examine fuel costs, CO_2 pricing and ECs in Italy. Similar to our approach, their research facilitated the estimation of ECs. However, unlike their methodology, our study employed a broader range of models—17 in total tailored to the specific variables analysed and the nature of the data used.

Currently, ML models are widely used to perform predictive analysis of production, consumption, demand analysis and other business variables. This is mainly due to their ability to provide high accuracy, efficiency and speed. In addition, these models also provide a better understanding of the operation of complex systems involving humans [85].

4.3. Application of Climate Scenarios. Once the forecasts for each of the variables in the previous section were made, we integrated the CTRAF for each of the six selected scenarios to understand the financial impact of climate change on the selected variables, adjusting the forecasts to the climate variations proposed by the NGFS. Figures 14 and 15 show the projections made in each climate scenario, after applying the adjustment factor.

For both diesel and electricity costs, it can be observed that costs begin to increase from 2023 onwards and maintain an upward trend until 2030. This may be partly due to changes in the organisation's logistics and the application of the CTRAF in each of the scenarios analysed. Towards the latter change, high costs are observed in the DNZ and NZ scenarios. This is because these scenarios require more mitigation to achieve zero emissions by 2050, requiring companies to take more drastic measures and governments to implement stronger policies, such as an increase in the carbon tax and an increase in fossil fuels tax, among other measures.

On the other hand, the DT and B2D scenarios present similar increases. These are inferior to those of the NZ scenario, and with those of B2D being always slightly higher than those of DT; this is because in the DT and B2D scenario, climate policy measures are just starting to reduce GHG emissions and ECs have not yet risen. Finally, the NDC and CP scenarios are the ones with the lowest cost increases because there are not yet strong policies in place to force companies to take action to mitigate and adapt to climate change and because there is not yet an increase in ECs.

The integration of this factor, a novel proposal generated by this study, adds a layer of analysis, which shows not only the direct impact of climate change on the costs of an organisation taking into account the energy sources analysed but also how this impact is distributed across different climate trajectories. This factor includes new environmental policies for each scenario, technological advances and changes in consumer and producer preferences, among other macroeconomic factors that modellers have included in their integrated models [65].

The outcomes of the applied scenarios range from an orderly and gradual transition to abrupt changes, allowing for a variety of outcomes and their impact on the organisation's financial and operational planning. The results highlight the differences between the scenarios and show that scenarios that take into account slow action to combat climate change bring significant additional costs, which shows the importance of taking measures related to the climate resilience of the organisation.

The predictions obtained in this study, based on the NGFS climate scenarios, provide a valuable framework for organisations to evaluate the financial implications of climate risks. Companies can integrate these predictions into their financial planning strategies, identifying critical points in their operations, such as rising ECs or potential fluctuations in fossil fuel prices. We recommend that organisations use these forecasts to establish adaptive budgets and develop climate risk mitigation strategies, adjusting their financial plans according to the various climate scenarios presented. This will enable them to improve their resilience and increase their resilience to future climate events.

Access to high-quality data remains a challenge for many organisations. To replicate this methodology in other contexts, we recommend following a data quality standards–based approach, such as those outlined in ISO 8000-60. This involves identifying data requirements, assessing data accessibility, verifying accuracy and managing data gaps. Specifically, we recommend that companies focus on the continuous improvement of their data management systems and the implementation of advanced data collection methodologies to increase the granularity and accuracy of datasets used in predictive models. The handling of missing data can be done using any method deemed appropriate for the given series. In addition, the window size should be adjusted as specified in the text, according to the specific study. However, the rest of the study can be replicated by following the steps of the methodology described.

Although these results are based on data from a single company in the processed food sector in Colombia, the methodological approach is generalisable to other sectors and industries. The selected variables (energy and diesel usage, energy prices and fossil fuel prices) are common in many productive sectors, suggesting that this methodology could be adapted for companies in various industries. However, we acknowledge that certain biases inherent to the nature of the studied company (e.g., the specific type of energy consumption) could limit the direct generalisation of the results. To mitigate these biases, we recommend that future studies conduct similar analyses in other industries or regions with different energy consumption profiles. Replicating this methodology in different contexts would provide additional validation and help identify potential sectoral differences.

The contribution of this research is twofold. First, it provides a methodology that can be replicated in any organisation, combining AI techniques with the strategic perspective of transitional climate risk management, allowing organisations to better anticipate the potential financial implications of climate change. Second, by considering a variety of climate scenarios, it provides a broader view of financial risks, facilitating informed and strategic decision making by

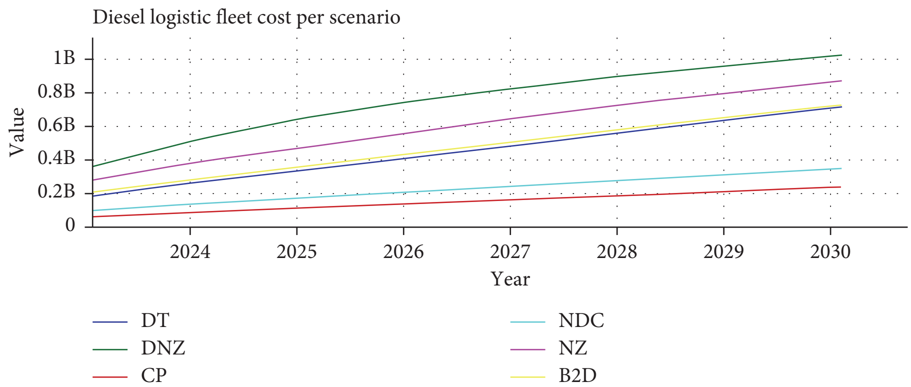

FIGURE 14: Total diesel cost per scenario.

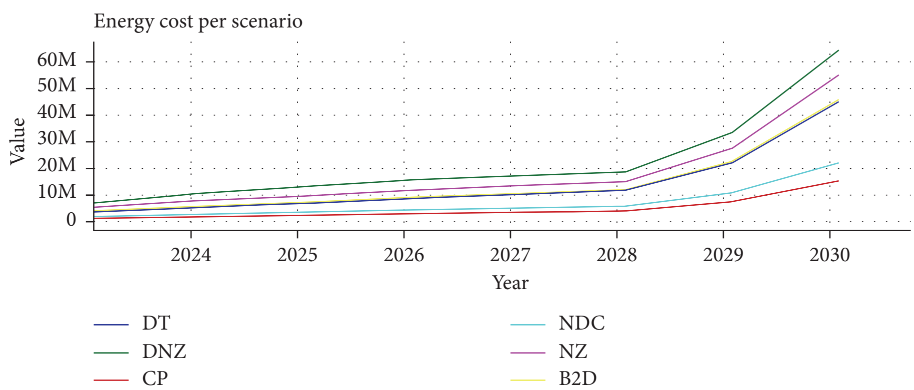

FIGURE 15: Total energy cost per scenario.

companies. Consequently, this study enriches the existing literature with a practical approach to financial planning and transitional climate risk management.

5. Conclusions and Future Work

Our research demonstrates that effectively applying predictive models empowers organisations to make well-informed decisions by leveraging historical data analysis. Consequently, this helps to manage financial resources efficiently and to monitor established objectives. This approach fosters stronger alignment with global climate transition targets, enhances comprehension of the scale of climate-related risks and evaluates the organisation's readiness to address such challenges.

Although managing limited datasets and low-resolution information presents challenges that may restrict the use of AI for analysis, AI-driven approaches remain an effective solution for addressing both climate transition risks and broader climate-related challenges.

Therefore, we stress the importance for companies to start identifying and collecting relevant data sources to leverage their predictive capabilities when making decisions about or even avoiding climate risks. In this context, it is essential to enhance understanding of effective data collection methods, including determining specific data requirements, evaluating the availability of data sources, adhering to industry standards, validating data, addressing data gaps and updating institutional frameworks. The International Organisation for Standardisation (ISO) supports this approach in the ISO 8000-60 series, which is specifically designed for data quality.

The average prediction accuracy of the selected models for each variable is 90.36%. This shows that AI has great potential as an option for organisations to improve their decision-making processes when managing climate change–related risks.

Our bottom-up approach is unique and competitive with the top-down approach prevalent in the existing literature. The latter is abundant with examples focussed mainly on the model, specifically for the financial sector. We believe that integrating bottom-up and top-down approaches can provide a more comprehensive understanding of these risks, encompassing both the macroeconomic system and the microeconomic level. We intend to analyse the joint use of these approaches in future studies.

The proposed methodology for calculating the CTRAF provides an important basis for making projections of the changes that different climate events can cause to a country's economy and an organisation's financial health. The results of this study are a first step towards understanding not only the potential additional costs caused by climate risks but also the opportunities for a transition to a low-carbon economy from an energy perspective.

Furthermore, the assessment in this study is an input for strategic budgeting in organisations, allowing them to anticipate and plan for financial adjustments in response to different climate trajectories. Although this research focusses on a Colombian organisation, the implications of the results are global, as climate change is a phenomenon that affects the whole world to varying degrees. In this sense, the additional costs of climate shocks can affect interconnected economies and sectors.

The application of the proposed adjustment factor shows that climate change has gone beyond a purely environmental concern to an economic one. This requires organisations to develop robust strategies for sustainable financial and operational planning. The results obtained highlight the need for more aggressive adaptation and mitigation measures.

The uncertainty associated with climate scenarios that can be considered for financial statement adjustments remains a challenge. This is an approach to analysing the financial impact of climate risks that builds on previous studies, including the World Business Council for Sustainable Development's recommendations to adjust values using weighted averages of the results of scenario analyses with the weighted according to proprietary but stakeholders' criteria.

Future studies will delve into additional aspects aimed at evaluating the impact of climate transition risks on institutions. These aspects include GHG emissions, carbon pricing and the utilisation of other fossil fuels. Efforts are required to enhance long-term forecasting methods to mitigate the influence of seasonal fluctuations on outcomes.

As the proposed method is new and not exact, it can be argued that it lacks validation and needs to be compared with other alternative methods. However, in our review of the literature, we did not find any alternative risk adjustment factors for climate change. Validation therefore implies not only the development of the method proposed here but also the development of alternative methods, which should be the subject of future work.

In conclusion, we have a vision for the future application of the methodology in this study. We plan to apply this in a wider context by increasing the number of variables related to climate transition risks. These risks include events related to the market and technological risk. Furthermore, we will develop, with the same organisation, a methodology for value-at-risk analysis to assess the potential losses (or gains) arising from climate transition risk.

Data Availability Statement

Data and the relevant code to replicate the results in this study are available at [37].

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

Juan F. Pérez-Pérez: conceptualisation, software, formal analysis, investigation, data curation, writing–original draft and visualisation. Isis Bonet: conceptualisation, writing–review and editing and supervision. María Solange Sánchez-Pinzón: validation and supervision. Fabio Caraffini: conceptualisation, visualisation, writing–original draft and writing–review and editing. Christian Lochmuller: conceptualisation, writing–review and editing and supervision.

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