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Research Article

Enhancing Credit Risk Assessment in the Era of Climate Change: A Machine Learning Approach for Loan and Lease Portfolios

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ABSTRACT

Given the growing risk of climate change to the financial sector's stability, institutions must modify their risk management practices to effectively evaluate and reduce potential impacts on their loan and lease portfolios. This paper investigates the use of sophisticated machine learning methods to create predictive models that measure the impact of climate-related risks on the likelihood of borrowers defaulting and the value of assets. These models allow for more detailed and future-oriented analysis than traditional methods by utilizing a modular, sector-specific approach and considering transition and physical risk factors. The paper introduces a thorough modeling framework, which includes architecture diagrams and pseudocode. It also illustrates how the model outputs can inform stress testing, portfolio management, and risk appetite setting. Moreover, it discusses the factors to consider when validating models and their constraints while suggesting continuous monitoring and re-validation methods in climate uncertainty. Financial institutions can effectively address the challenges of climate change and make better lending decisions by implementing machine learning-based climate credit risk models1.

Keywords: Climate Credit Risk, Machine Learning, Loan Portfolio, Stress Testing, Transition Risk, Physical Risk, Default Probability, Risk Management

1. Introduction

1.1. The growing importance of assessing climate risk for financial institutions

Financial institutions must now integrate climate risk assessment into their risk management frameworks due to the increasing occurrence and intensity of climate-related events and the worldwide shift towards a low-carbon economy. The financial consequences of climate change, which encompass physical risks (such as asset damage caused by extreme weather events) and transition risks (such as policy changes and technological shifts), can substantially impact borrowers' creditworthiness and the value of collateralized assets. Consequently, financial institutions must create robust techniques to measure and control climate-related risks in their loan and lease portfolios[2].

1.2. Challenges of quantifying climate impacts on credit portfolios using traditional approaches Conventional methods for evaluating the effects of climate on credit portfolios typically depend on past data and linear models, which may not sufficiently account for the intricate and non-linear connections between climate factors and financial results. These methods also have limitations in their capacity to integrate future climate scenarios and offer detailed insights at the level of individual borrowers or assets. As a result, there is an increasing demand for advanced and adaptable tools that can accurately represent the various effects of climate change on credit risk[3].

1.3. Machine learning for modeling complex relationships between climate scenarios and financial risks Machine learning has become a potent remedy for tackling these difficulties. Machine learning models can utilize extensive datasets and sophisticated algorithms to reveal complex patterns and connections between climate variables and credit risk metrics. This empowers financial institutions to make well-informed and proactive decisions. To thoroughly evaluate climate-related risks, these models can incorporate various data sources, such as climate scenario projections, borrower financial information, and asset-level characteristics. Moreover, machine learning methods can be customized to particular industries and types of assets, enabling a more detailed comprehension of climate-related risks in various segments of a credit portfolio.

Applying machine learning to climate credit risk assessment provides numerous significant benefits compared to conventional methods. Machine learning models can capture non-linear and interactive relationships between climate variables and credit outcomes, resulting in a more precise depiction of risk dynamics. Furthermore, these models can be readily updated and improved as fresh data emerges, guaranteeing that risk assessments stay pertinent and adaptable to evolving circumstances. Machine learning techniques can produce detailed insights at the individual borrower level, which can be used to develop specific risk reduction strategies and enhance portfolio management.

In the upcoming sections, this paper will explore the intricacies of applying machine learning to evaluate the effects of climate change on loan and lease portfolios. We will introduce a comprehensive modeling framework that integrates climate scenarios, risk drivers specific to each sector, and advanced machine learning techniques to produce practical and valuable insights for financial institutions. By implementing these innovative methods, institutions can bolster their ability to withstand climate-related risks and position themselves for success in the shift toward a low-carbon future[4].

2. Overview of Climate Scenarios and Credit Risk

2.1. Climate-related financial risks

There are two primary classifications of financial risks associated with climate change[5,6]. Climate-related financial risks can be classified into two primary categories: transition risks and physical risks. Transition risks emerge due to the worldwide transition towards a low-carbon economy, propelled by alterations in policies, regulations, technologies, and consumer preferences. These risks can appear in different ways, such as higher expenses for companies that produce a lot of carbon dioxide because of carbon pricing or a decrease in the desire for products that rely on fossil fuels. Conversely, physical risks pertain to the direct consequences of climate change on tangible assets and economic endeavors. The risks can be categorized into acute risks, which refer to damages caused by severe weather events like hurricanes or floods, and chronic risks, which pertain to long-term alterations in temperature and sea levels.

2.2. The impact of climate risks on borrowers' probability of default and asset valuations

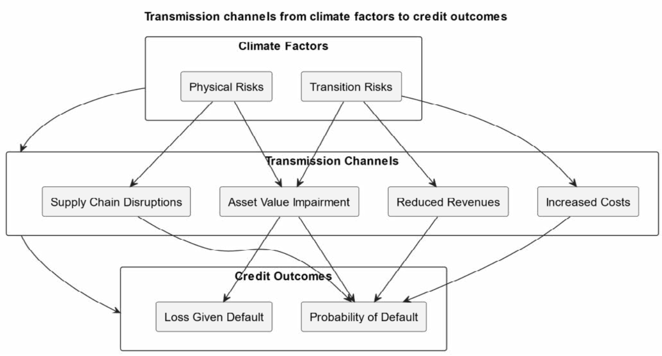
Both transitional and physical risks can significantly impact borrowers' creditworthiness and the value of assets used as collateral. Transition risks can harm borrowers' financial performance by causing an increase in operating costs, a decrease in revenues, or the abandonment of certain assets. For instance, a manufacturing corporation that heavily depends on fossil fuels might encounter increased production expenses due to carbon levies or reduced demand for its goods as customers transition to more environmentally friendly options. These factors can pressure the company's cash flows and elevate its likelihood of default.

Physical hazards can directly hinder borrowers' capacity to repay their loans by causing harm to production facilities, disrupting supply chains, or diminishing the worth of collateral assets. For example, suppose a coastal property is used as collateral for a mortgage. In that case, it may decrease in value or become uninsurable due to increasing sea levels or frequent flooding. Likewise, a farming enterprise may encounter diminished crop productivity and income due to extended periods of drought or shifting temperature trends, which can complicate the repayment of its loans.

2.3. Examples of specific transmission channels from climate factors to credit outcomes for different sectors

The transmission channels from climate factors to credit outcomes vary significantly across various sectors. Here are some examples:

1. **Energy sector:** Transition risks are particularly relevant for the energy sector, as the shift towards low-carbon energy sources can lead to stranded assets and reduced profitability for fossil fuel companies. This can increase the probability of default for loans and bonds issued by these companies.
2. **Real estate sector:** Physical risks, such as sea-level rise and more frequent natural disasters, can directly impact the value of real estate assets and the credit quality of mortgage loans. Properties in high-risk areas may experience declining values, higher insurance costs, or even become uninsurable, leading to higher default rates.
3. **Agriculture sector:** Both physical and transition risks can affect agriculture. Chronic physical risks, such as changes in temperature and precipitation patterns, can reduce crop yields and increase the volatility of agricultural revenues. Transition risks, such as shifting consumer preferences towards more sustainable food options, can also impact the sector's profitability and credit risk.
4. **Transportation sector:** The transportation sector is exposed to transition risks as the world moves towards lower-carbon modes of transport. For example, automotive companies that fail to adapt to the shift towards electric vehicles may face declining sales and profitability, increasing their credit risk. Airlines may also face higher operating costs due to carbon taxes or regulations on emissions.



3. Machine Learning for Climate Credit Risk Modeling

3.1. Comparing machine learning to traditional econometric approaches

Machine learning provides numerous benefits compared to traditional econometric methods when modeling climate credit risk. Conventional techniques, like linear regression, typically assume linear connections between variables and may face difficulties capturing the intricate, non-linear interactions between climate factors and credit outcomes. Unlike other methods, machine learning algorithms can accurately represent complex and non-linear relationships and interactions between variables, which helps understand the underlying factors contributing to risk[7].

Furthermore, machine learning techniques are particularly suitable for managing extensive, multidimensional datasets frequently encountered in climate risk modeling. These algorithms can automatically detect the most significant characteristics and patterns from large quantities of data, thereby minimizing the requirement for manual feature engineering. This is especially advantageous when working with various data sources, such as climate scenario projections, borrower financials, and asset-level characteristics.

One additional benefit of machine learning is its capacity to adjust and acquire knowledge from fresh data. Machine learning models can be readily retrained and updated to incorporate recent trends and insights as climate conditions change and new information emerges. Adaptability is essential when considering climate risk, as the factors contributing to this risk may evolve due to changes in policies, technologies, and the physical impacts of climate change.

3.2. Machine learning model types

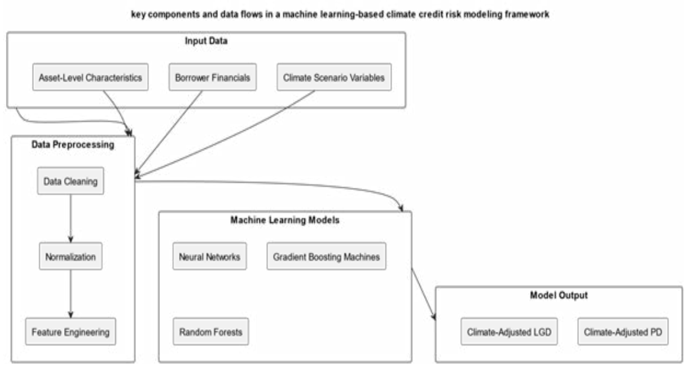
Several machine learning model types are particularly well-suited for climate credit risk modeling:

1. **Neural Networks:** Neural networks, intense learning models, are powerful tools for modeling complex, non-linear relationships. They can learn hierarchical representations of data, capturing intricate patterns and interactions among climate variables and credit risk factors. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are specific architectures that can be effective for analyzing spatial and temporal patterns, respectively, which are often relevant in climate risk modeling.
2. **Gradient Boosting Machines (GBMs):** GBMs, such as XGBoost and LightGBM, are ensemble learning methods that combine multiple weak learners (typically decision trees) to create a robust predictive model. They are known for handling large datasets, dealing with missing values, and capturing complex relationships among variables. GBMs have been successfully applied in various credit risk modeling tasks and can be adapted to incorporate climate risk factors.
3. **Random Forests:** Random forests are another ensemble learning method that constructs multiple decision trees and combines their predictions to improve accuracy and reduce overfitting. They can handle numerical and categorical variables and provide a measure of feature importance, which can help understand the relative contribution of different climate risk drivers.

3.3. Important data considerations for model training

When training machine learning models for climate credit risk, it is crucial to consider the quality, relevance, and representativeness of the input data. Some critical data considerations include:

1. **Climate scenario variables**: Incorporating forward-looking climate scenario data is essential to capture the potential impacts of future climate change on credit risk. These scenarios should cover a range of possible climate futures, including transition and physical risk pathways. Examples of relevant variables include greenhouse gas emissions, carbon prices, temperature and precipitation projections, and the frequency and severity of extreme weather events.
2. **Borrower financials:** Historical and projected financial data for borrowers, such as revenue, operating expenses, and cash flows, are critical for assessing their creditworthiness. When modeling climate risk, it is essential to consider how climate-related factors, such as changes in energy costs, market demand, or physical asset values, may impact these financials.
3. **Asset-level characteristics:** Detailed information on the physical characteristics and location of assets pledged as collateral can help assess their vulnerability to climate risks. For example, data on a property's elevation, flood risk, or energy efficiency can be valuable when modeling the impact of physical dangers on real estate portfolios.
4. **Data quality and completeness:** Ensuring input data's accuracy, consistency, and completeness is critical for developing robust climate credit risk models. This may involve data cleaning, normalization, and imputation techniques to handle missing or inconsistent values.



4. Modeling Framework and Methodology

4.1. The overall framework for incorporating climate scenario impacts into credit risk models

To effectively incorporate climate scenario impacts into credit risk models, we propose a comprehensive modeling framework that integrates climate risk drivers, sector-specific impact models, and machine learning techniques. The framework consists of the following key components[8,9]:

1. **Climate scenario generation:** This component defines and quantifies relevant climate scenarios, including transition and physical risk pathways. The scenarios should capture a range of potential climate futures and provide granular projections of essential climate variables, such as carbon prices, temperature changes, and the frequency and severity of extreme weather events.
2. **Sector-specific impact models:** Given the heterogeneous nature of climate risk impacts across industries, the framework employs a modular, sector-specific approach. A dedicated impact model is developed for each sector (e.g., energy, real estate, agriculture) to translate climate scenario variables into sector-specific financial and operating

metrics, such as revenue, costs, and asset values.

3. **Machine learning-based credit risk models:** The sector-specific impact models feed into machine learning-based credit risk models, which assess the creditworthiness of individual borrowers and estimate key risk parameters, such as the probability of default (PD) and loss-given default (LGD). These models capture the complex, non-linear relationships between climate-adjusted financial metrics and credit outcomes, enabling a more accurate assessment of climate-related credit risk.
4. **Portfolio aggregation and reporting:** The output of the credit risk models is aggregated at the portfolio level to provide a comprehensive view of climate risk exposure. This allows for the computation of portfolio-level risk metrics, such as expected loss and risk-weighted assets, under different climate scenarios. The results can be further analyzed and visualized to inform risk management decisions and support stakeholder disclosures.

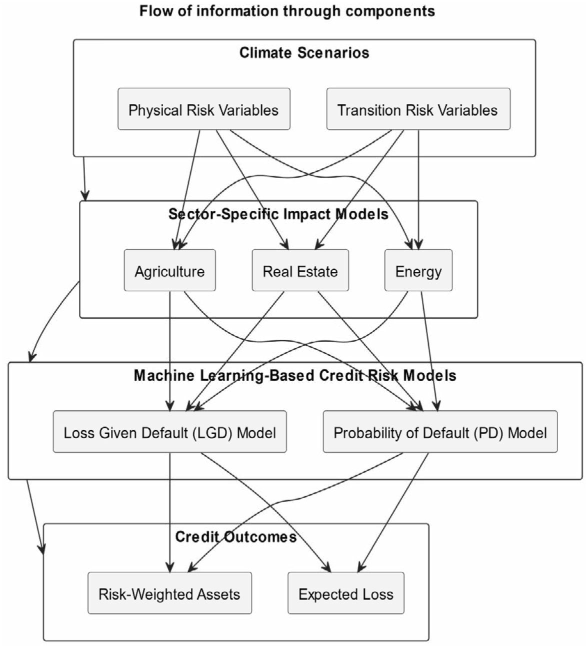
4.2. Modular, sector-specific approach for differentiated impact modeling

Adopting a modular, sector-specific approach is imperative in comprehending how climate risk can affect different industries. The framework can incorporate specialized impact models for individual sectors, allowing for consideration of the distinct factors that influence risk, how impacts are transmitted, and the ability of each industry to adapt.

In the energy sector, the impact model would specifically examine how transition risks, such as carbon pricing and the transition to renewable energy, influence the demand for fossil fuels, the profitability of energy companies, and the value of their assets. On the other hand, the impact model designed for the agriculture sector would prioritize assessing tangible risks, such as alterations in temperature and precipitation patterns, and their consequences on crop productivity, production expenses, and land prices.

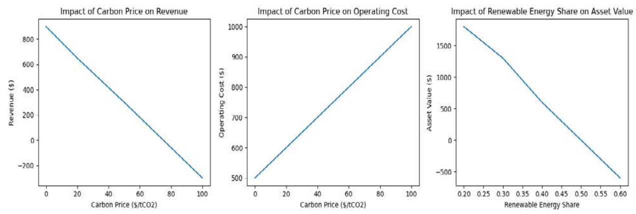
4.3. Core model components translating climate factors into financial drivers and credit outcomes

The core components of the modeling framework work together to translate climate factors into financial drivers and, ultimately, credit outcomes. The following diagram illustrates the flow of information through components:



The sector-specific impact models utilize climate scenario variables as input and convert them into sector-specific financial and operational metrics. The metrics are inputted into machine learning-based credit risk models, which then calculate each borrower's probability of default (PD) and the loss-given default (LGD). The Probability of Default (PD) and Loss Given Default (LGD) estimate the anticipated loss and risk-weighted assets at the portfolio level, offering a comprehensive perspective on credit risk related to climate change.

Here's an example of how the energy sector impact model could translate climate factors into financial drivers:



This example illustrates the effects of carbon pricing and the transition to renewable energy on the financial aspects of energy companies, including their revenue, operating costs, and asset values. Credit risk models utilize machine learning and employ climate-adjusted financial metrics to calculate the probability of default (PD) and loss-given default (LGD) for individual borrowers in the energy sector.

Financial institutions can utilize this modeling framework to enhance their understanding of climate-related credit risk exposure and effectively manage and mitigate these risks. The framework allows for analysis across various sectors and aggregates results at the portfolio level.

5. Use Cases

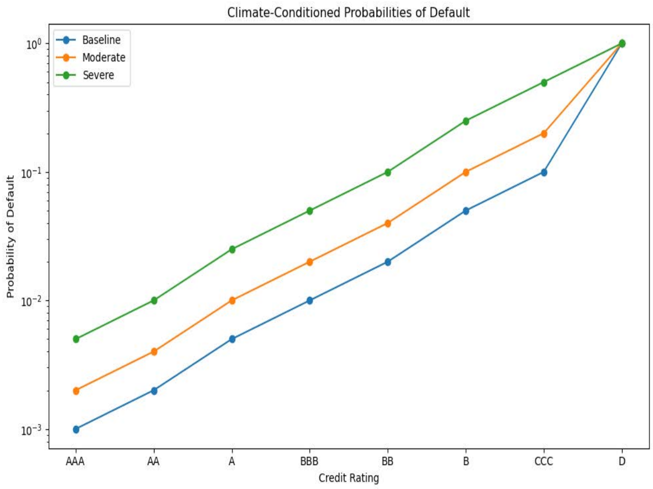
5.1. Model outputs: Climate-conditioned probabilities of default and credit rating transitions

The credit risk models that utilize machine learning techniques produce multiple significant outputs that offer valuable insights into the potential consequences of climate change on credit risk. Climate-conditioned probabilities of default (PDs) and credit rating transitions are two of the most significant outcomes.

Climate-conditioned probability distributions estimate the probability of a borrower failing to meet their obligations under various climate scenarios. Financial institutions can evaluate the additional influence of climate risk on the creditworthiness of borrowers by contrasting these probability distributions (PDs) with the baseline PDs that are not adjusted for climate factors. As an illustration, a borrower who initially has a baseline probability of default (PD) of 1% could experience an increase in their PD to 1.5% in a severe climate risk scenario. This signifies an elevated risk of default caused by climate-related factors.

Credit rating transitions illustrate the anticipated changes in borrowers' credit ratings in response to various climate scenarios. The model offers a predictive assessment of potential deterioration in credit quality caused by climate risk by estimating the likelihood of a borrower moving from one credit rating to another (e.g., from 'A' to 'BBB'). This information can assist financial institutions in predicting and controlling credit risk associated with climate change in their portfolios.

Here's an example of how climate-conditioned PDs and credit rating transitions could be visualized:



5.2. Applications for stress testing, portfolio management, and risk appetite setting

The results of the climate credit risk models have various significant applications, such as stress testing, portfolio management, and determining risk appetite.

Stress testing involves using climate-conditioned probability distributions (PDs) and credit rating transitions to evaluate the potential effects of various climate scenarios on a financial institution's credit portfolio. Using these results with the institution's existing portfolio composition, stress tests can calculate the anticipated losses and risk-weighted assets across different climate risk scenarios. This data assists institutions in assessing their ability to withstand credit risks associated with climate change and pinpoint possible weaknesses.

Portfolio management: The model's results can guide portfolio management choices by identifying borrowers and sectors most vulnerable to climate risk. Financial institutions can utilize this information to realign their portfolios, modify lending criteria, or formulate focused risk mitigation strategies. For instance, an organization may opt to decrease its involvement in sectors or borrowers with high levels of risk or demand extra collateral or covenants to handle credit risk associated with climate change.

The climate credit risk model outputs can be used to develop and implement risk appetite frameworks that specifically consider climate risk. Financial institutions can establish risk appetite statements and limits by assessing the potential impact of climate scenarios on credit risk. This allows them to maintain their exposure to climate-related credit risk at acceptable levels. This aids in harmonizing the institution's comprehensive risk profile with its strategic goals and the expectations of its stakeholders.

5.3. Visualizations of model results across different scenarios

It is essential to visually represent model outcomes under various climate scenarios to effectively communicate the potential consequences of climate risk to stakeholders and facilitate decision-making. Here are several instances of how the outcomes of a model could be displayed visually

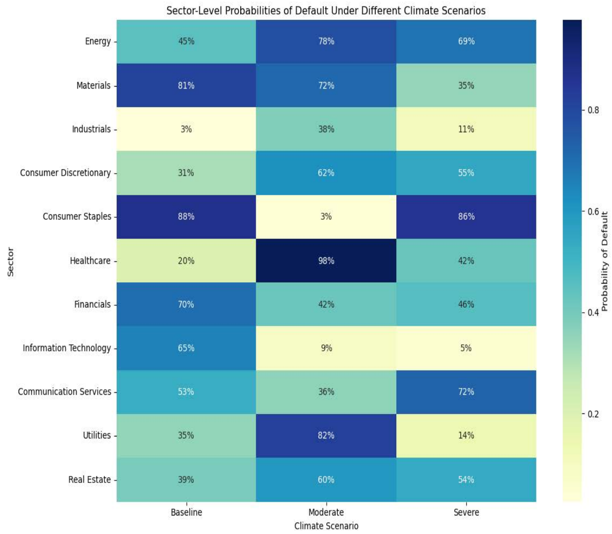


Figure 1: Heatmap of sector-level PDs under different climate scenarios.

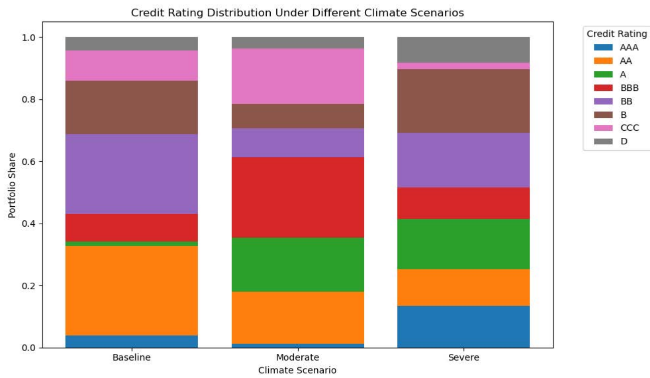


Figure 2: Stacked bar chart showing the distribution of credit ratings under different climate scenarios.

These visualizations provide clear and concise representations of the potential impacts of climate risk on credit portfolios, making it easier for stakeholders to understand and act upon the insights generated by the climate credit risk models.

6. Model Validation and Limitations

6.1. Statistical performance measures for model validation

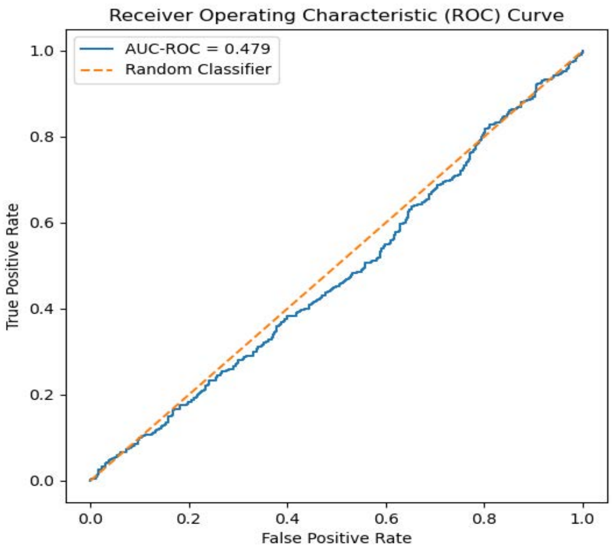
Validating the performance of climate credit risk models is essential to ensure their reliability and accuracy. Several statistical measures can be used to assess the predictive power and robustness of these models[10-12]:

1. **Area Under the Receiver Operating Characteristic Curve (AUC-ROC):** This measure evaluates the model's ability to discriminate between defaulting and non-defaulting borrowers. A higher AUC-ROC indicates better model performance, with a value of 0.5 corresponding to a random classifier and 1 representing a perfect classifier.
2. **Accuracy Ratio (AR):** The AR is another measure of the model's discriminatory power, calculated as the ratio of the area between the perfect and random classifiers to the area between the model's ROC curve and the random classifier. Like AUC-ROC, higher AR values indicate better model performance.
3. **Brier Score:** The Brier Score measures the calibration of the model's predicted default probabilities. It calculates the mean squared difference between the predicted probabilities

and the actual binary outcomes (default/non-default). Lower Brier Scores indicate better calibration.

4. **Kolmogorov-Smirnov (KS) Statistic:** The KS statistic measures the maximum difference between the cumulative distribution functions of the model's predicted probabilities for defaulting and non-defaulting borrowers. A higher KS statistic indicates better model discrimination.

Here's an example of how these performance measures could be calculated and visualized:



6.2. Challenges related to climate model uncertainty and limitations of historical data

Although climate credit risk models are sophisticated, it is essential to recognize and tackle several challenges and limitations.

Climate model uncertainty: The climate scenarios utilized as inputs in the credit risk models are derived from intricate climate models inherently prone to uncertainty. Variations in climate model assumptions, parameters, and structures can result in a spectrum of possible future climate scenarios. Utilizing multiple climate models and scenarios is crucial to account for uncertainty and evaluate how credit risk estimates are affected by various climate assumptions.

Historical data limitations: Climate credit risk models depend on historical data to understand the connections between climate factors and credit outcomes. Nevertheless, the historical documentation might not comprehensively depict the possible consequences of forthcoming climate change if the intensity and frequency of climate occurrences surpass previous observations. This constraint can be partially mitigated by incorporating prospective climate scenarios to complement past data, but it still poses an inherent difficulty in modeling unprecedented climate hazards.

There are gaps and inconsistencies in climate-related data, which means the data may not be available or of good quality in specific sectors, regions, and periods. Insufficient data, discrepancies, and absence of uniformity can impede the progress and verification of climate credit risk models. It is essential to make significant efforts to enhance climate risk disclosure, share data, and establish standardized practices to tackle these challenges effectively.

6.3. Approaches for ongoing model monitoring and re-validation

To effectively address the changing nature of climate risks and the inherent uncertainties in climate credit risk modeling, it is crucial to establish solid procedures for continuously monitoring and re-validating models.

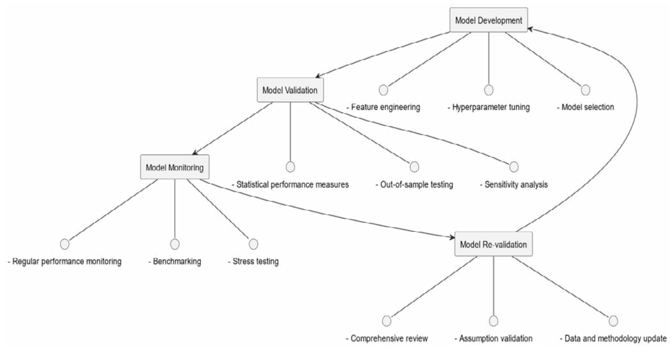
Regular performance monitoring: Model performance should be continuously monitored using the statistical measures discussed in Section 6.1. Any deterioration in model performance or significant deviations from expected outcomes should trigger further investigation and potential model recalibration.

Benchmark against external models: Comparing the model's outputs with those of external climate credit risk models or industry benchmarks can help identify potential issues or areas for improvement. Regularly participating in industry-wide model comparison exercises can provide valuable insights into model performance and best practices.

Sensitivity analysis and stress testing: Conducting sensitivity analyses and stress tests can help assess the model's robustness to changes in input parameters, assumptions, and climate scenarios. By systematically varying these factors and evaluating the impact on model outputs, potential weaknesses or instabilities can be identified and addressed.

Periodic model re-validation: Climate credit risk models should undergo periodic re-validation to ensure their ongoing relevance and accuracy. This process should comprehensively review the model's assumptions, input data, methodologies, and performance. The re-validation frequency should be commensurate with the pace of change in climate risks and the model's materiality.

The following diagram illustrates the continuous cycle of model development, validation, monitoring, and re-validation:



7. Conclusion

Machine learning-based climate credit risk models provide substantial advantages for financial institutions aiming to evaluate and control the potential consequences of climate change on their loan and lease portfolios. These models can use sophisticated algorithms and extensive datasets to capture intricate and non-linear connections between climate factors and credit outcomes. As a result, they offer more precise and detailed insights compared to conventional methods. Financial institutions can effectively anticipate and address climate-related risks by integrating future climate projections and conducting impact assessments for specific sectors. This approach also facilitates stress testing, portfolio management, and the establishment of risk appetite. Nevertheless, the creation and execution of these models are not exempt from difficulties, such as the uncertainty of climate models, constraints imposed by historical data, and the necessity for continuous model validation and monitoring. Given the ongoing evolution of climate risks and the availability of new data and modeling techniques, financial institutions must allocate resources toward research and development to improve and strengthen their ability to assess credit risks associated with climate change. This encompasses the investigation of novel machine learning architectures, integrating alternative data sources, and cooperation with climate scientists and industry partners to construct more resilient and all-encompassing models. Financial institutions prioritizing climate credit risk modeling can effectively manage their risks and contribute significantly to the transition toward a more sustainable and resilient global economy.

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