Chapter 11

A Macroeconomic Perspective on Türkiye's Climate Crisis Risk: Decision Tree Analysis

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Abstract

Green Swan is a risk concept used to describe unpredictable, sudden, and systemic economic crises caused by climate change. Awareness of Green Swan risks began with the 2015 Paris Climate Agreement and was conceptually framed by a 2020 report from the Bank for International Settlements (BIS) and the Banque de France. Green Swan risks are not only environmental but also have systemic impacts that trigger economic and social vulnerability. A review of the literature reveals that no empirical studies specific to Türkiye, which analyze such risks on an annual basis and model them using machine learning, have been encountered. This study aims to model Türkiye's climate-related risk levels using environmental, climatic, and economic indicators, based on ND-GAIN and CO_2 emissions data from 1995 to 2022. A total of 13 variables were used to classify annual risk levels through the Classification and Regression Tree (CART) algorithm. Risks were evaluated across four levels: uncertain, low, medium, and high. The model's accuracy was measured at 82.14%. The findings indicate that GDP growth rate, labor force participation rate, and temperature anomalies serve as key determinants in determining risk levels. While offering a novel national-level contribution to the Green Swan literature, this study proposes a feasible and policy-relevant analytical method for policymakers to detect climate-induced economic vulnerabilities at an early stage.

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INTRODUCTION

The concept of Green Swan is used to define climate-induced economic risks that may result in sudden, unpredictable, and systemic impacts. This concept was introduced to the literature through a report published in 2020 by the Bank for International Settlements (BIS) and the Banque de France. These risks, which can have devastating effects not only on the environment but also on economic and financial systems, point to climate shocks that traditional financial risk analyses are inadequate to foresee. The first global awareness of Green Swan risks began with the 2015 Paris Climate Agreement, which initiated international policy-level discussions on the macroeconomic vulnerabilities associated with climate change.

Green Swan risks emerge in diverse forms not only on a global scale but also at the national level and therefore require interdisciplinary and data-driven methodologies for proper assessment by decision-makers. The macroeconomic effects of climate change are felt more acutely in countries with fragile economies, posing a significant threat to sustainable development policies. Due to its geographical location and economic structure, Türkiye is among the countries vulnerable to such risks.

However, a review of the existing literature reveals that no studies specifically analyzing Green Swan risks in Türkiye on an annual basis and examining them through machine learning-based models have been encountered. Existing international studies are largely confined to scenario-based assessments. Most international studies on climate-related financial risks focus predominantly on scenario-based assessments of transition and physical climate risks, while quantitative, machine-learning-based approaches remain relatively limited (Bolton et al., 2020; McKinsey Global Institute, 2020; IMF, 2024). One of the few studies addressing Green Swan risks in the context of Türkiye is that of Açıkgöz and Gökmen (2022). This study discusses the potential for climate-induced financial instability in Türkiye and Annex II countries within a conceptual scenario analysis framework, based on transition and physical risk scenarios developed by international organizations such as the NGFS.

In this context, the main objective of the study is to determine Türkiye's climate-related risk levels on an annual basis and to analyze the environmental, economic, and climatic indicators influencing these risks using the machine learning-based Classification and Regression Tree (CART) method, thus generating findings that can serve as early warnings against Green Swan risks and contribute to the literature both methodologically and practically.

In the study, a machine learning-based classification model was developed using ND-GAIN and CO_2 emissions data from 1995 to 2022, along with 13 climatic, environmental, and economic variables. Accordingly, the subsequent sections of the study present the materials and methods, findings, and finally, the conclusion and policy recommendations.

METHODS AND FINDINGS

Methods

CART Algorithm

The Classification and Regression Tree (CART) algorithm is a supervised machine learning method utilized for both classification and regression analyses. CART operates by partitioning the dataset into increasingly homogeneous subgroups with respect to the target variable. At each splitting step, the algorithm selects the variable and threshold that result in the greatest reduction of impurity—measured by the Gini index in classification problems. This process continues until a predefined stopping criterion, such as the minimum number of observations at a node or the maximum tree depth, is met.

In this study, the CART algorithm was employed to classify Türkiye's annual climate-related risk levels based on climatic, environmental, and economic indicators. The reasons for preferring the algorithm include its high interpretability, ability to model nonlinear relationships, and suitability for small to medium-sized datasets. Furthermore, the decision tree outputs generate transparent and intuitive decision rules that can be easily understood by policymakers, making it a particularly valuable tool for climate-based early warning systems.

Findings

In this study, annual climate-related risk levels were initially determined by evaluating the ND-GAIN Index and CO_2 emission data for the period 1995–2022. The risk levels were classified into four-category risk level classification for each year: uncertain (0), low (1), medium (2), and high (3). The reason of using the ND-GAIN Index is that it is a global indicator that jointly assesses countries' levels of climate vulnerability and adaptive capacity. CO_2 emissions, along with other environmental and economic indicators, were included in the model as variables directly associated with climate risk. All indicators used in the study were obtained from the databases of the Notre Dame Global Adaptation Initiative (ND-GAIN), Our World in Data, and the World Bank. The common years across all variables were identified, and the dataset was temporally harmonized to cover the 1995–2022 period.

The model incorporates 13 variables representing environmental, economic, and climatic factors which are Winter Temperature Anomaly, Summer Temperature Anomaly, Spring Temperature Anomaly, Autumn Temperature Anomaly, Ratio of Foreign Trade to Gross Domestic Product, Renewable Energy Consumption, Labor Force Participation Rate, Gross Domestic Product Growth Rate, Forest Land Ratio, Agricultural Land Ratio, Per Capita Energy Consumption, Per Capita Electricity Consumption, and Access to Clean Fuels.

Subsequently, a machine learning-based decision tree model was developed to identify the main indicators influencing these risk levels. In this context, the Classification and Regression Trees (CART) algorithm was employed. The model was constructed using 13 environmental, climatic, and economic indicators.

All data processing, modeling, and analysis procedures were conducted in the R Studio environment. The classification was implemented using the rpart package, and the model achieved an accuracy of 82.14%. Additionally, the relative importance of each variable in determining climate-related risk levels was evaluated.

RESULTS

In line with the classification model developed in the study, Türkiye's climate-related risk levels for the period 1995–2022 were visualized over time, and the structure of the variables influencing the risk levels was revealed through the decision tree. Additionally, variable importance ranking was analyzed to identify which indicators contributed most significantly to the model. The graphs presented in *Figure 1* provides a comprehensive representation of both the temporal distribution and the model's decision rules and variable weights.

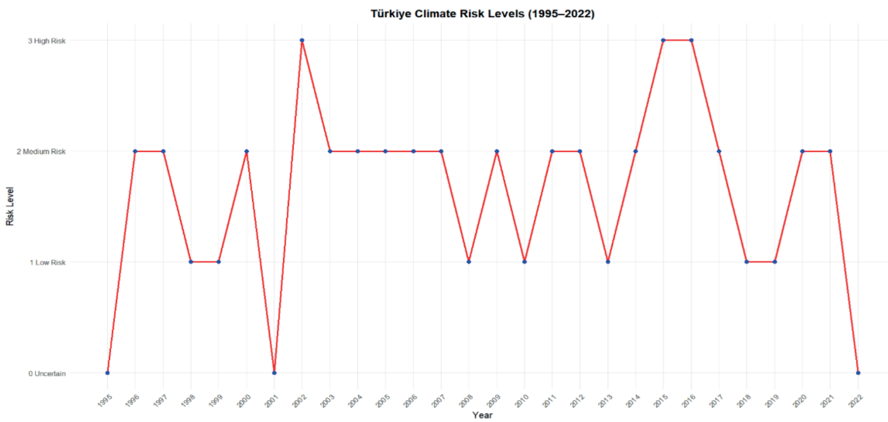

Figure 1. Changes in Turkey's Climatic Risk Levels by Year (1995–2022)

Based on the findings of this study, Türkiye's climate-related risk levels between 1995 and 2022 were classified and visualized in *Figure 1*. The annual data were categorized into four classes based on the ND-GAIN Index and per capita CO_2 emissions: 0 – Uncertain, 1 – Low Risk, 2 – Medium Risk, and 3 – High Risk.

As it can be seen in *Figure 1*, the most frequent category was "medium risk," representing 46% of the total observations. This result suggests that, during the analyzed period, Türkiye's climate vulnerability was predominantly at a moderate level.

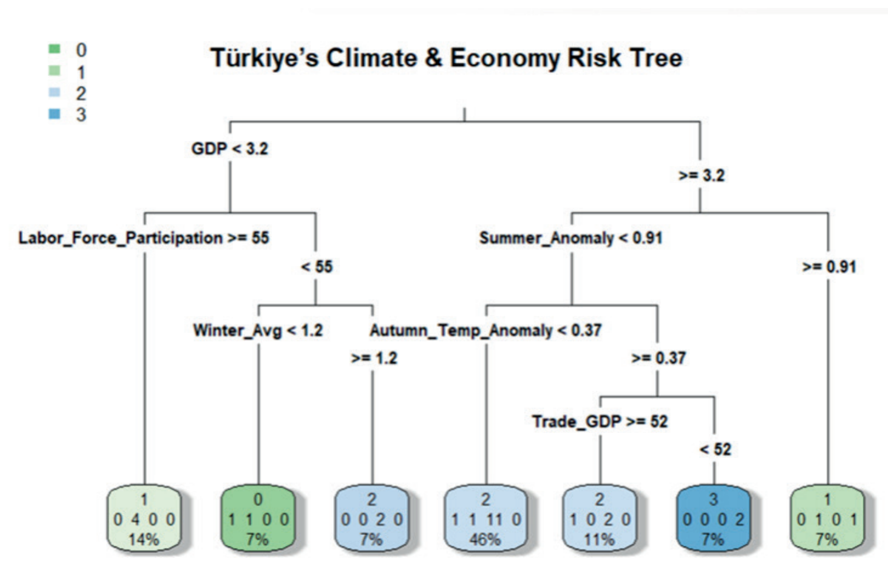

Figure 2. Classification of risk levels using the decision tree model

The decision tree model created for the classification process visualizes the variables and threshold values that are effective in determining the climate-related risk level for each year. This model clearly identifies the key threshold values and determining variables that influenced Türkiye's climate-related risk levels between 1995 and 2022. In the decision tree presented in *Figure 2*, the variable that performs the initial split at the root node is the Gross Domestic Product (GDP) growth rate. Years with a GDP growth rate below 3.2 and those with a rate of 3.2 or above are directed to different branches. This indicates that macroeconomic performance plays a leading role in determining climate-related risk levels.

For years in which the Gross Domestic Product (GDP) growth rate was below 3.2, the second variable influencing the split was the labor force participation rate (Labor_Force_Participation). When this rate exceeded 55, those years were mostly classified as low risk (1).

For years with a labor force participation rate below 55, the determining variable in the decision mechanism was the winter temperature anomaly. For example:

- If the winter temperature anomaly (Winter_Avg) was below 1.2, the year was classified as uncertain risk (0).
- If the winter temperature anomaly (Winter_Avg) exceeded 1.2, the year was classified as medium risk (2).

For years in which the GDP growth rate was ≥ 3.2, the split was made based on the summer temperature anomaly (Summer_Anomaly).

- When the summer temperature anomaly was below 0.91, further splits were influenced by the autumn temperature anomaly and the trade-to-GDP ratio (Trade_GDP). In particular, when the trade-to-GDP ratio was below 52, the year was classified as high risk (3). If the Summer_Anomaly was 0.91 or above, the year was directly classified as low risk (1).

This model clearly demonstrates which variables are dominant under different socioeconomic and climatic conditions, as well as the thresholds at which the risk level increases. The largest leaf of the decision tree represents the medium risk level, encompassing 46% of the dataset.

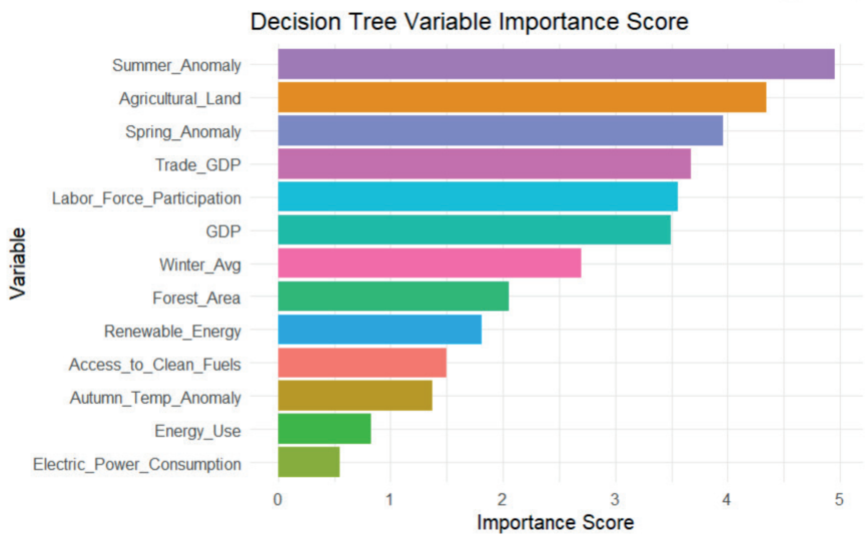

Figure 3. Importance level of variables according to the decision tree model

Figure 3 presents the relative contributions of the variables used in the decision tree model to the classification process. The values displayed on the "Importance Score" axis indicate which variables were more influential in the model's decision-making mechanism.

The highest importance score belongs to the Summer Temperature Anomaly (Summer_Anomaly) variable, indicating that climate-related risk levels in Türkiye are significantly affected by temperature deviations during the summer season.

The second most important variable is Agricultural Land Ratio (Agricultural_Land). Its high score suggests that land use and agricultural activities play a determining role in climate vulnerability.

These are followed by Spring Temperature Anomaly (Spring_Anomaly), Trade-to-GDP Ratio (Trade_GDP), and Labor Force Participation Rate (Labor_Force_Participation). In particular, the labor force participation rate served as a critical splitting variable, as it appeared at an early branching point in the decision tree structure.

On the other hand, variables such as Electric Power Consumption, Energy Use, and Autumn Temperature Anomaly (Autumn_Temp_Anomaly) had relatively limited contributions to the model. The low importance scores of these variables indicate that they were less influential in the classification decisions.

This analysis is significant in demonstrating how environmental and economic variables can have differing levels of influence when jointly evaluated in determining climate-related risk levels. The findings provide a data-driven perspective for policymakers on which areas should be prioritized.

DISCUSSION AND CONCLUSION

In this study, Türkiye's annual climate-related risk levels for the period 1995–2022 were categorized into four groups and classified using the Classification and Regression Tree (CART) model, based on environmental, climatic, and economic indicators. The findings indicate that variables such as summer temperature anomaly, agricultural land ratio, and spring temperature anomaly stand out in determining risk levels. The model's classification accuracy of 82.14% supports both the explanatory power of the selected variables and the overall reliability of the model.

The analysis of the risk classes can be summarized as follows: The low-risk level was observed during periods characterized by a combination of low GDP growth and high labor force participation rates. This finding aligns with the study by Achuo, Nchofoung, Zanfack, and Epoge (2023), which highlights the positive impact of labor force participation on environmental sustainability.

In the medium-risk category, periods characterized by low summer and autumn temperature anomalies, but high GDP growth rates stand out. This finding supports the McKinsey Global Institute (2020) report, which emphasizes the non-linear effects of climate change and the vulnerabilities that arise when systemic thresholds are exceeded.

In the high-risk category, a low share of foreign trade in GDP corresponds with the observation made in the IMF (2024) report, which highlights the limited capacity of trade volume to offset production and consumption losses in the face of climate shocks.

The model results reveal that Green Swan risks should be evaluated not only through environmental indicators but also in conjunction with economic structures and socioeconomic factors. In this regard, the decision tree model developed in the study emerges as a transparent, interpretable, and data-driven early warning system for forecasting climate-related risks specific to Türkiye.

In conclusion, this study aims to contribute to Green Swan literature at the national level while also providing a valuable foundation for policymakers to develop foresight-based intervention strategies. Future research is recommended to compare different machine learning algorithms, conduct regional-level analyses, and expand the model through long-term scenario assessments. This model can be utilized as a practical early warning tool by national agencies involved in environmental and economic planning.

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