Assessing The Nonlinear Effects of Climate Shocks on Macroeconomic Stability in ASEAN: An Interpretable Machine Learning Approach for Sustainable Finance

A Thesis

Submitted to the Master's Study Program of Finance in Sustainable Finance at the Faculty of Economics and Business in partial fulfillment of the requirements for the degree of

Master of Finance (M.Fin)

by:

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UNIVERSITAS ISLAM INTERNASIONAL INDONESIA

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ABSTRACT

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This study analyzes the effects of climate shocks (Temperature, Floods, Storms, Droughts) on the macroeconomic stability (GDP growth, inflation and industrial growth) of eight ASEAN economies for the period 2000–2024. It seeks to estimate the impact of climate shocks, uncovering nonlinear and threshold relationships, and to measure the climate and macroeconomic variables' relative importance. The methodology used is a hybrid approach that involves both panel econometric analysis (Ordinary Least Squares (OLS)) and machine learning (Random Forest (RF)), which includes both linear and nonlinear dynamics such as PDPs and SHAP-Like analysis by using data based on World Bank, EM-DAT, and Berkeley Earth data sources. According to the results, climate shocks have significant impact on macroeconomic stability, having higher impact on growth of GDP and industrial growth than on inflation. Temperature is the most important climate variable and floods, droughts and storms have negative impacts on economic activity by disrupting infrastructure and production. The impacts are also nonlinear and threshold, meaning that economic damages increase beyond a certain threshold of climate change. These impacts are muted by macro-economic variables like government consumption, exchange rate and capital formation. The study emphasizes the need for putting climate risk on the agenda of the macroeconomic policy and the contribution of sustainable finance measures to sustainable finance approaches, including green bonds and Environmental, Social and Governance (ESG) investment strategies.

Keywords: *Climate Shocks, Macroeconomic Stability, Random Forest, Nonlinear Effects, Sustainable Finance*

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ABBREVIATION DIRECTORY

ADB	:	Asian Development Bank
AI	:	Artificial Intelligence
ASEAN	:	Association of Southeast Asian Nations
BIS	:	Bank for International Settlements
EM-DAT	:	Emergency Events Database
ESG	:	Environmental, Social, and Governance
GDP	:	Gross Domestic Product
GHG	:	Greenhouse Gas
IMF	:	International Monetary Fund
IPCC	:	Intergovernmental Panel on Climate Change
ML	:	Machine Learning
NGFS	:	Network for Greening the Financial System
OECD	:	Organisation for Economic Co-operation and Development
OLS	:	Ordinary Least Squares
PDP	:	Partial Dependence Plot
RF	:	Random Forest
RMSE	:	Root Mean Squared Error
R^2	:	Coefficient of Determination
SHAP	:	Shapley Additive Explanations
SDGs	:	Sustainable Development Goals
UN	:	United Nations

CHAPTER I
INTRODUCTION

1.1 Background of the Study

Climate change is now recognized as a key risk for the global economic and financial system. Over the last two decades, climate shocks such as increasing temperatures, floods, storms and droughts have been intensifying, especially in developing and emerging market economies (Intergovernmental Panel on Climate Change [IPCC], 2021). These climate shocks are no longer perceived as purely environmental risks, but are increasingly recognized as systemic risks impacting macroeconomic stability, financial markets and economic growth (International Monetary Fund [IMF], 2022).

Macroeconomic impacts of climate shocks on macro-economic indicators (like GDP growth, inflation and industrial production) occur via a number of channels. Increased temperatures can reduce productivity, crop yields and energy use and consequently economic output (Burke et al., 2015; Kahn et al., 2021). Likewise, climate shocks like floods and storms can cause infrastructure destruction, disruptions to the production value chain, and strain government budgets, resulting in both short-term economic impacts and long-term growth staints (World Bank, 2020). Droughts, though not as abrupt, can have impacts on food and commodity prices, agricultural incomes and food security, and thus macroeconomic performance (Lesk et al., 2016).

Looking at the impacts of climate shocks in the developing world, especially in the Association of Southeast Asian Nations (ASEAN), the economic effects are highlighted. Geographic location, reliance on climate-sensitive industries and varying levels of economic resilience make the economies of the ASEAN region, including those of the Philippines, Indonesia, Viet Nam, Thailand, Malaysia, Cambodia, Myanmar, and Lao PDR, vulnerable to climate shocks (Asian Development Bank [ADB], 2021). Such events are frequently experienced in these countries and can impact economic growth and production, exacerbate social inequalities and place public financial pressures. This means that the effects of climate shocks on macroeconomic stability in these economies is a very important issue to policy and financial actors.

In recent years, sustainable finance has become a concept to integrate climate change risks into financial policy and practice. Sustainable finance is about capital mobilization with a view towards achieving long-term environmental sustainability with economic and financial stability (United Nations Environment Programme Finance Initiative [UNEP FI], 2020). In this strategy, climate risks are increasingly mainstreamed in investment decisions, risk management and policy. Empirical studies to document the effect of climate shocks on economic performance and economic stability are required to better embed climate risks in sustainable finance frameworks.

There is a growing impetus in this area, but empirical research is hampered by a number of limitations. One, many of the studies employ traditional econometric methods, which assume that climate impacts economic outcomes are linear. However, recent studies have revealed that climate shocks can have nonlinear effects on economic growth: threshold effects and sensitivity to different intensities of shocks (Burke et al., 2015; Auffhammer, 2018). For instance, while a small rise in temperature may have little impact on the economy, an extreme fluctuation in temperature could cause significant economic losses. Similarly, the impact of climate disasters on the economy could vary depending on the disaster's intensity, frequency and the robustness of the economy.

Secondly, the relationships between the macroeconomic variables and the climate variables, which are subject of the model, are not fully captured in the conventional econometric modelling. The combination of climate shocks can be overlapping and can also influence structural economic factors like investment, government spending, exchange rates (Kahn et al., 2021; IMF, 2022) and more. This leads to complex phenomena which are difficult to model using linear models. This has resulted in the need to develop more complicated approaches to modelling nonlinearities, interactions, and high dimensionality in climate-economy analysis (Athey & Imbens, 2019).

Machine learning techniques, in particular ensemble models such as Random Forest are promising in this respect. Random Forest models do not require stringent functional form assumption and can be used to model complex relationship and interaction, which is especially important when analyzing the interaction between climate and economy (Athey & Imbens, 2019). Furthermore, with the recent progress made in interpretability tools, like Partial Dependence Plots (PDP) and SHAP (Shapley Additive Explanations), economists can better understand the output of machine learning models and connect model performance with interpretability.

Drawing on these advances, this research seeks to understand the effects of climate shocks on macroeconomic stability measures in a select group of ASEAN economies through a mix of baseline econometric models and interpretable machine learning approaches. The inclusion of Random Forest models with PDP and SHAP analysis will help to detect nonlinear and threshold effects of climate variables, as well as the importance of various predictors.

Importantly, the findings from this study impact on the field of sustainable finance. The study identifies the climate risks that could impact the macroeconomic stability, and provides insights for investment, policy and financial institutions to consider climate risk in financial decision making. This information is essential to inform climate adaptation policies, risk management and for a resilient and sustainable economic development in the climate sensitive regions.

1.2 Problem Statement

Climate change is an economic and financial challenge, particularly for the emerging economies, which are more susceptible to climate change. The macroeconomic impact of climate shocks is well documented but the impacts of climate shocks on indicators of macroeconomic stability, such as gross domestic product (GDP) growth, inflation, and industrial output have not received as much attention, especially in the context of the ASEAN region (Kahn et al., 2021; World Bank, 2020).

Empirically, climate factors have been found to impact the economy in various ways, such as through their effects on productivity and investment and supply chain (Burke et al., 2015; Dell et al., 2012). But the existing studies are mostly based on linear econometric models, which place stringent assumptions on how climate shocks affect economic outcomes. These methods do not consider the nonlinear, threshold and asymmetric effects that are typical in climate-economic relationships (Auffhammer, 2018).

This is also a key issue in the case of climate shocks, as the impacts of such shocks are not always proportional to changes in climate variables. For instance, an increase in temperature may affect economic activity in a limited fashion until a certain threshold is reached, after which the impact of the temperature increase on the economic performance may become disproportionate. Similarly, the impact of climate disasters (including floods and storms) on economic activity can be linked to the intensity, frequency and interactions with other vulnerabilities. As such, relying solely on linear models may lead to a misrepresentation of the estimates and hence to poor policy and economic choices (Athey & Imbens, 2019; Molnar, 2022).

Another important gap is the lack of studies on the use of interpretable machine learning models in macroeconomic climate studies. Although machine learning techniques have gained popularity in financial and economic forecasting, their use in climate-macroeconomic research is still in its infancy, especially in developing countries. In addition, machine learning models have also been historically "black-box" which has been a limitation in policy-relevant studies. However, more recent methods in the realm of model interpretability, such as Partial Dependence Plots (PDP) and SHAP-based methods, offer a means to overcome these problems by providing clear and economically relevant interpretations of these models (Molnar, 2022).

Finally, there is a lack of empirical literature focused on the links between climate shocks, macroeconomic stability and sustainable finance in an integrated approach. Sustainable finance is about the incorporation of environmental risk factors into financial aspects including investment portfolio, risk assessment and regulation (UNEP FI, 2020). However, understanding the relationship between climate risk and macroeconomic stability is missing, which is a constraint to implementing sustainable finance approaches. This absence of empirical analysis can make financial institutions and policy makers less able to realistically assess the financial value of climate risks and provide adequate risk management plans.

Research should be done in the ASEAN region. Indonesia, the Philippines, Viet Nam, Thailand, Malaysia, Cambodia, Myanmar and Lao PDR are regularly hit by extreme floods, storms and temperature shocks, and are among the world's most climate-vulnerable economies (ADB, 2021). The structural transformation and higher level of financial globalization in these economies is also raising their vulnerability to environmental and economic shocks. Yet, there is little empirical evidence on nonlinear influences of climate shocks on macroeconomic stability in ASEAN.

With this in mind, this paper seeks to address this gap by assessing the impact of climate shocks on macroeconomics stability of selected ASEAN countries using integrated econometric and machine learning technique. The study aims to go beyond the conventional linear approach of assessing the effects of climate shocks by applying Random Forest and interpretability methods to characterize the non-linear effect of climate shocks, identify threshold effects and prioritize the relevance of climate and macroeconomic parameters.

This approach helps to fill the knowledge gaps on the climate-economy connection and inform sustainable finance approaches. In sum, bridging these gaps will be essential for economic resilience, climate risk management and sustainable economic growth in vulnerable economies, such as those in climate change.

1.3 Research Questions

Based on the gaps identified in the existing literature, this study is guided by the following research questions:

1. How do climate shocks affect macroeconomic stability indicators (GDP growth, inflation, and industrial growth) in selected ASEAN economies?

2. Do climate shocks exhibit nonlinear and threshold effects on macroeconomic outcomes in the selected ASEAN economies?
3. Which climate and macroeconomic variables are the most important predictors of macroeconomic performance in these economies?

1.4 Research Objectives

To address the research questions outlined above, the study is guided by the following objectives:

1. To estimate the impact of climate shocks on macroeconomic stability indicators using baseline econometric models.
2. To identify nonlinear and threshold effects of climate shocks on macroeconomic outcomes using interpretable machine learning techniques.
3. To determine the relative importance of climate and macroeconomic variables in explaining macroeconomic performance through feature importance analysis.

The research questions and objectives are tightly linked to provide an integrated analytical approach. The first research question is linked to the baseline econometric models used to determine the direct impacts of climate shocks on macroeconomic measures. The second research question relates to the detection of non-linear and threshold effects, which are tackled using Random Forest models and Partial Dependence Plots. The third research question is related to feature importance and SHAP interpretation, which refers to the importance of the variables as indicators of macroeconomic performance.

The analysis of climate shocks on macroeconomic stability offers a basis for understanding the implications of environmental risks on financial markets. Nonlinear effects and feature importance provide insights for investors, policymakers and financial institutions to assess and account for climate risks in their decision-making, thereby facilitating the building of climate-proof and sustainable financial systems.

1.5 Significance and Contributions of the Study

This study contributes to the literature in the areas of climate economics, macroeconomics and sustainable finance, and traditional econometric and cutting-edge machine learning techniques. In doing so, this helps fill important gaps in the literature and offers a comprehensive empirical approach to gauge the relationship between climate and macroeconomic stability in developing countries.

1.5.1 Theoretical Contribution

From a theoretical perspective, this research contributes to the climate-economy literature by incorporating nonlinearities and threshold effects in the empirical analysis. Conventional economic theories, such as neoclassical economic growth and the climate damage function theory, recognize the possible effects of environmental shocks on economic growth via productivity, capital and adaptation (Nordhaus, 2017). But empirical studies are usually done under linear assumptions.

This research builds on the increasing evidence for the presence of nonlinearities between climate and economic variables, and hence supports theoretical studies that find the impacts of climate change are non-linear and non-proportional. Indeed, the effects of climate shocks on the economy might be non-proportional, with greater effects after a threshold. These nonlinearities improve the understanding of the effect of climate change on economic variables, and are informative for the construction of more dynamic models. The research is also insightful to theory by bridging climate economics and sustainable finance theory, in showcasing the systemic impacts of climate risks on financial stability. Theories of sustainable finance are increasingly recognizing the systemic of environmental risks, and their inclusion in economic and financial systems. The study's connection of the impact of climate shocks to macroeconomic instability gives us a more comprehensive view of the environment-economy-finance nexus.

1.5.2 Empirical Contribution

In terms of the empirical contribution, this research offers new empirical evidence on the effects of climate shocks on measures of macroeconomic stability in eight selected ASEAN economies Indonesia, the Philippines, Viet Nam, Thailand, Malaysia, Cambodia, Myanmar and Lao PDR from 2000-2024. Our country sample covers a set of emerging markets with diverse economic, institutional and climate risks. We create a new data set which combines the World Development Indicators (WDI) of the World Bank, EM-DAT disaster data and Berkeley Earth temperature data to develop a panel data set of macroeconomic stability and climate shocks. This allows us to conduct a high-quality study.

Significantly, the study contributes to the empirical literature by including several aspects of macroeconomic stability (GDP growth, inflation and industrial growth). This study uses multiple dependent variables, rather than a single dependent variable as is found in the literature, which allows a more comprehensive understanding of the impact of climate shocks on various parts of the economy. The findings give region-specific information, which is relevant for ASEAN economies that are the world's most vulnerable to climate change.

1.5.3 Methodological Contribution

The second contribution of this study is to methodology. This study adopts a combined modelling approach, which uses baseline econometric models and cutting-edge machine learning models to address shortcomings of conventional models. With linear models used to estimate the direct impact of climate shocks on macroeconomic variables, the study provides an interpretable baseline modelling framework using Ordinary Least Squares (OLS). But given the limitations of linear models, the study also employs Random Forest models to capture the nonlinearities and interactions in the data, without imposing rigorous assumptions about the functional forms of the relationships.

Moreover, the study also uses interpretable machine learning techniques, such as Partial Dependence Plots (PDP), and similar to SHAP methods, to improve the interpretability of the machine learning. This method overcomes the problem that machine learning models are black boxes, and can be used to visualize and explain the model predictions, and the effects of the variables on the macroeconomic variables. This approach addresses the issue that machine learning models are black boxes and using machine learning in empirical economic research. Additionally, this paper applies cross-validation methods to assess the accuracy and stability of machine learning models and stability tests for the feature importance to check the results. The combination of machine learning models' prediction power, interpretability and stability, improve the study of climate macroeconomics.

1.5.4 Sustainable Finance Contribution

The study also contributes to the growing literature on sustainable finance by highlighting the importance of incorporating climate-related risks into economic and financial decision-making. Sustainable finance emphasizes the integration of environmental, social, and governance (ESG) factors into financial activities, including investment decisions, risk management, and financial regulation (IMF, 2022; UNEP FI, 2020). By providing empirical evidence on the relationship between climate shocks and macroeconomic stability, this study offers insights into how climate-related risks can influence broader economic conditions that are relevant to the financial system. The identification of key climate variables and their nonlinear effects enhances understanding of the complex transmission of climate risks, thereby providing useful information for financial institutions, investors, and policymakers in assessing and managing climate-related financial risks. Although this study does not directly examine financial markets or ESG outcomes, its findings have important implications for climate risk pricing, the development of green and sustainable financial instruments such as green bonds, ESG-oriented investment strategies, and climate-related financial disclosures. More broadly, the findings support the integration of climate risk considerations into macroeconomic and financial decision-making, thereby contributing to the transition toward more resilient and sustainable financial systems.

1.5.5 Policy Contribution

Finally, the study gives policy recommendations for ASEAN policymakers. The analysis on particular climate shocks that have the greatest effect on macroeconomic stability offers policy advice on how to manage climate risks. The non-linear and threshold response is significant for policy as it may help policy makers identify critical thresholds at which the impacts may rise. This can help guide the allocation of resources to climate adaptation and resilience policies such as infrastructure investment, risk reduction and climate-proofing in agriculture. The study also highlights the need to consider climate risks in macroeconomic policies, such as fiscal and monetary policies. The findings of this study which links climate shocks to various macroeconomic variables can inform policy that can enhance economic stability and growth in the face of climate change.

1.5.6 Overall Contribution

This work explores the links between climate shocks and macroeconomic stability in a specific spatial, temporal and analytical scope. The region of interest is eight member states of the Association of South East Asian Nations (ASEAN) - Indonesia, the Philippines, Viet Nam, Thailand, Malaysia, Cambodia, Myanmar and Lao PDR. The countries are chosen for their climate vulnerability (to flooding, storm, droughts and rising temperature), economic complexity and participation in the regional and global markets. This selection would enable us to examine a mix of low- and middle-income Southeast Asian economies for a comprehensive evaluation of the vulnerability to climate impacts. The time period is 2000-2024, which is a period of increasing climate impacts and considerable changes in the economic structures. This is adequate for identifying patterns, trends and for non-linearity of climate impacts on the macroeconomic performance. It also coincides with the improvement in data quality and coverage of the data sources.

As for data sources, three main sources are used to develop a panel data set. The World Bank's World Development Indicators (WDI) are used to obtain data on the following macroeconomic variables: GDP growth, inflation, growth of industrial production, government consumption expenditures, exchange rates (annual average), gross capital formation and population growth. Natural disasters (flood, storm and drought) are from the EM-DAT International Disaster Database, which offers consistent disaster measures. We obtain temperature variables from Berkeley Earth, which provides a consistent measure of temperature. Data sources like these enable a broad analysis of the climate-macroeconomy nexus. The focus of the study is determined by the variables selected. The dependent variables capture some of the main aspects of macroeconomic stability: gross domestic product (GDP) growth to measure economic growth; inflation to measure price stability; and industrial growth to measure structural and productive capacity. Independent variables represent climate shocks (measured in terms of temperature, floods, storms and droughts) to capture moderate and extreme weather events. Other variables are used to control for other macroeconomic and structural variables (government spending, exchange rate volatility, investment and population growth).

Both base models and machine learning models are used in the study. Simple linear models (Ordinary Least Squares or OLS) are used to find the initial association between climate shocks and the variables of interest. The OLS models are complemented with Random Forest models, which can account for non-linear effects, threshold effects and interaction effects. Partial Dependence Plots and a SHAP-like method are used to gain insights into the marginal effects and importance of the predictors. The current study attempts to be complete, but is not without limitations. First, it is a country-level study, ignoring sub-country differences in climate change impacts and economic effects. Second, the study uses annual data, which might not capture shorter-term variability and high-frequency effects of climate events. Third, the study considers specific climate impacts and does not consider all other possible environmental impacts such as sea-level rise or air pollution that could have adverse effects on the economy. Fourth, while the study theoretically considers sustainable finance aspects, it does not explicitly model financial market variables, but rather the macroeconomic variables that are the basis for financial analysis.

However, the study design allows us to focus and rigorously address the climate - macroeconomic relationship in the ASEAN economies. The study offers valuable insights into the impacts of climate events on macroeconomic stability and a framework for future studies of climate - financial and sustainable finance - links using high quality data, clear definitions of variables and sophisticated techniques.

1.6 Structure of the Thesis

The thesis consists of 5 chapters each of which is related to the aim and objectives of the study and provides an exhaustive analysis on how climate shocks affect the macroeconomic stability of the ASEAN region as well as its implications for sustainable finance.

Chapter 1 Introduction offers a general introduction to the study, with a particular focus on the background, as climate change is becoming an ever more important macroeconomic and financial risk. It gives reason of the problem, research questions and research objectives and explains the importance of the study and specifies the scope as well as structure of the thesis.

The literature review, presented in Chapter 2, covers both the theory and empirical findings regarding climate change and the macroeconomic stability and sustainable finance. This chapter summarizes some of the most influential theories (neoclassical growth theory, climate damage function theory and sustainable finance theory), and empirical evidence of climate shocks' impact on growth, inflation and industry productivity. It also addresses how machine learning can be applied in economic research and the research gaps this study aims to address.

The research design and analysis are discussed in Chapter 3 Methodology. It provides a theoretical and conceptual framework for climate shocks and climate effects on macroeconomic performance and sustainable finance. The chapter details the process of data collection, definition of variables and selection of samples, and specification of the econometric and machine learning models. It also discusses the processes of model fitting, validation and interpretation, including the Random Forest, cross-validation, feature importance, Partial Dependence Plots, and SHAP-like approaches.

The results and discussion are discussed in Chapter 4. This includes descriptive statistics and correlations, and the baseline econometric models. It then reviews the performance of machine learning models and contrasts them to the traditional approaches. It features a thorough explanation of feature importance, non-linearity and threshold effects using Partial Dependence Plots and SHAP-like explanations. The results are compared with the literature and theoretical predictions, focusing on the implications for sustainable finance and economic policy in ASEAN countries.

Chapter 5 Conclusion and Policy Implications offer a summary of the findings from the study and its theoretical, empirical and policy implications. It delves into the implications for sustainable finance including climate risk, investment and regulation. It also considers the scope of the study and suggests areas for further research such as the use of our framework for financial markets and detailed data.

CHAPTER II
LITERATURE REVIEW

2.1 Theoretical Foundations

Climate shocks and macroeconomic stability are multifaceted and complex phenomena, and the analysis of their interaction requires a strong theory that draws on the various strands of economic growth theory, environmental economics and sustainable finance theory. Based on neoclassical growth theory, the climate damage function theory, the Environmental Kuznets Curve (EKC), and sustainable finance theory, this research aims to create a comprehensive approach to analyzing the effects of climate shocks on macroeconomic performance and financial stability.

Growth studies have been provided with a very basic framework by the neoclassical growth theory, which was developed by Solow (1956). In this model production depends on capital, labor and technological progress, and technological progress is a large exogenous source of long-term growth. The effects of climate shocks can be simulated as an exogenous shock to the productivity of capital and inputs. For instance, higher temperatures may reduce labor productivity, particularly in outdoor or physical labor-intensive sectors, such as agriculture and industry (Dell et al., 2012). Similarly, severe weather such as flooding and storms can cause damage to infrastructure, loss of production, and destruction of physical capital, thus lowering the amount of capital available for production. This may lead to lowered productivity, investment, and economic instability, and affect the long-term growth.

Beyond productivity and capital formation, climate shocks can also impact technological change and allocation of resources in the production processes. Adverse impacts of climate shocks could be larger in less developed economies, where institutional and adaptive capabilities may be less robust. This is particularly relevant in the ASEAN region which many economies are heavily dependent on climate-sensitive activities, and also vulnerable to extreme weather events. Hence, the neoclassical growth model provides a convenient framework to examine climate shocks as a possible constraint on economic growth, particularly in areas which are most climate-susceptible.

In this spirit, the theory of climate harm operates, as expressed in what is known as integrated assessment models (IAMs) by Nordhaus 1991, 2017. In this way, the effects of climate change are frequently linked to temperature change, leading to economic activity loss with rising temperatures. One of the important consequences of this theory is the non-linear and frequently convex association between the temperature and the economic losses. Lower temperature rises have relatively harmless impacts, but higher rises could have much more serious impacts. Nonlinearity is key to understand the potential thresholds and tipping points, in which the level of damage rises significantly with the climate change level.

The empirical evidence of non-linear effects of temperature on economic growth has increased in developing and emerging markets. As an example, Burke et al. (2015) demonstrate that the overall trend is that output tends to peak at a certain temperature and sharply drops when temperatures go higher than that. This evidence is consistent with climate damage functions and implies the use of flexible modelling strategies, which consider these non-linear effects. In this respect, the use of machine-learning techniques, for example by random forest models, are of particular interest because they can find nonlinear relationships without imposing restrictions on the functional form of the relationship.

The theory of Environmental Kuznets Curve (EKC) also contributes to the theoretical discussion as it establishes the relationship between economic growth and environmental degradation. Under the EKC hypothesis as economies increase in size, environmental degradation increases initially, but eventually decreases as the economy becomes more efficient and advanced, and develops more efficient, less polluting technologies (Grossman & Krueger 1995). Although the focus of EKC is largely on environmental quality, there are consequences for the relationship between climate change and economic growth. In particular, it has to be assumed that the resilience of an economy to climate risks will be influenced by economic development, such that more developed economies may have more capacity to adapt to climate change.

However, the usefulness of the EKC towards climate change is disputed. According to some research, the global nature of climate change makes it difficult for countries to achieve their goals of reducing vulnerability to climate change by implementing national policies (Stern, 2018). In addition, the majority of the ASEAN countries are at a relatively early stage of development where environmental pressures and climate vulnerability still have significant impacts, and may not be able to benefit from the adaptive capacity suggested by the EKC theory (ADB, 2021; IPCC, 2022). It is therefore relevant to examine the relation between economic growth and climate vulnerability in order to assess macroeconomic impacts of climate events in these countries (Dell et al., 2012; Burke et al., 2015).

The concept of sustainable finance theory is crucial to connect the economic theories with the impact of climate risks. Sustainable finance aims to integrate environmental, social and governance (ESG) considerations into financial markets, in this respect the climate risks and the need for sustainable economic growth (UNEP FI, 2020). In this context, climate change is identified as a significant source of financial risk, impacting asset prices, investment strategies and financial stability. Some climate risks are commonly categorized as physical risks (from direct impact of climate shocks) and transition risks (from economic adaptation to the transition to a low-carbon world) (IMF, 2022).

In this research we mainly focus on physical risks, which are captured by the impact of climate shocks (temperature rise, floods, storms, droughts) on indicators of macroeconomic stability. The analysis offers insights into macroeconomic channels of transmission of climate risks to the financial system. This is important in the context of sustainable finance because macroeconomic instability can have several consequences on financial markets, including higher risk premiums and investment decisions, and volatility. Therefore, it is important to have a grasp of the principal climate drivers of macroeconomic stability to help inform and direct risk assessment and management, as well as investment decisions, in the context of climate change.

Both these theories provide a full and comprehensive picture of the impact of climate shocks on macroeconomic stability. The neoclassical growth model captures the impacts of climate shocks on productivity and investment, the climate damage function theory recognizes the non-linear effects of climate change, the EKC theory sheds light on the impact of economic growth on climate vulnerability and the theory of sustainable finance explores the connection between climate risk and financial stability and finance. By integrating these perspectives, this research takes an integrated approach that acknowledges the interdependencies between environmental, economic and financial systems. Such an integrated approach argues for the application of econometric and machine learning methods for empirical analysis to provide a more accurate and comprehensive evaluation of the relationship between climate and the ASEAN economies.

2.2 Climate Change and Economic Growth

The empirical evidence on the impacts of climate change on economic growth is growing in size, and the importance of climate factors such as temperature and extreme climate events on economic outcomes is gaining increasing recognition. The early research in this area focused on the effect of extended climatic trends; however, short-term climatic variability and extreme events have been emphasized more recently. This is partly because the world is increasingly realizing that climate events have longer-term and short-term impacts on the economy, particularly in developing and emerging economies (Dell et al, 2012; Burke et al, 2015).

One of the major research streams is on the impact of temperature on productivity. Dell et al. (2012) shows for a panel of countries that higher temperatures are negatively associated with economic growth, primarily because of reduced agricultural and manufacturing productivity, and reduced human efficiency. They find that a 1°C rise in temperature results in a significant decline in growth rates in poor economies, but has a weak or even positive impact in rich economies. This differential effect highlights the importance of structural factors (income, adaptability) on the economic impact of climate change.

In a more detailed study, Burke et al. (2015) provide compelling evidence of a more complex relationship between temperature and economic growth: they find that economic productivity peaks at an annual temperature of approximately 13°C and declines sharply above and below this value. Their figures illustrate the adverse impacts of both hot and cold conditions on economic productivity, and that the adverse impacts are larger in hotter areas. The nonlinearity identified is in line with the predictions of climate damage functions and highlights the need to consider threshold effects in empirical studies.

These ideas have been further developed in recent research incorporating future climate change projections and examining long-term growth impacts. Kahn et al. (2021) utilize a panel dataset of numerous countries to estimate the significant effect of unabated climate change on global GDP by the end of the century, and greater impact on developing countries. The emphasis is placed in this study on the long-term consequences of climate change on economic growth, as short-term climate shocks may have long-term impacts through capital destruction and decreases in productivity and investment.

In addition to temperature, extreme weather has also been proved to have a significant effect on economic fluctuations by floods, storm, and droughts. The impact on the economy may be by way of damage to infrastructure, displacement of people and disruption to trade. For instance, the effects of tropical cyclones on national income can be significant, and the impacts can persist over a number of years (Hsiang and Jina 2014). Similarly, the World Bank (2020) states that climate disasters in developing countries may cause economic impacts and slow economic development.

In particular, it has been demonstrated that floods have significant short-term impacts on economic growth, especially for vulnerable economies with weak infrastructure. They can damage crops, disrupt supply chains and result in increased public expenditure on reconstruction that can affect supply and demand in the economy. Storms, depending on their frequency and intensity, can have different impacts, from short term to long term. While less short term, droughts can also have significant impacts on agriculture and food security, which in turn can impact inflation and growth rates (Lesk et al., 2016).

There is a great deal of literature on the impacts of climate change on economic growth, but a number of caveats exist. First, most studies employ linear econometric models, which may not accurately represent the relationships between climate and the economy. Some studies have implemented quadratic terms to account for nonlinear effects, but these are limited by functional forms imposed. Second, research has not taken into account the interaction effects among multiple climate variables and macroeconomic indicators, which can be important in determining economic growth. Third, there is less empirical evidence for specific regions, such as ASEAN, in particular studies that consider multiple climate shocks and macroeconomic parameters in a comprehensive framework.

This work aims at complementing and contributing to the literature from this perspective, by implementing a more flexible and holistic approach. By combining Random Forest models with tools like Partial Dependence Plots and SHAP-like analysis, the study can also uncover more intricate relationships and interactions that might not be revealed using traditional econometric techniques. This is especially relevant for the analysis of the effects of temperature and extreme weather events on economic growth, which are likely to have nonlinear and non-constant effects.

Moreover, the analysis of the ASEAN economies provides an opportunity to provide ASEAN-specific conclusions on the relationship between climate and growth. These economies are highly climate-exposed and have a wide range of economic structures which can give insights into the effects of climate shocks on economic growth by country and by time. For research, these findings are useful and for policy and sustainable finance, it helps to know the major climate risks that should be tackled in the long-term, for economic stability and resilience.

To sum up, the literature suggests that the climate change impact on economic growth is significant and complex, and will likely be nonlinear, dependent on multiple factors, and have long-term effects. By overcoming the shortcomings of previous research and adopting sophisticated analytical approaches, this research adds to our knowledge of the complex relationship between climate change and economic growth in the ASEAN economies.

2.3 Climate Shocks and Macroeconomic Stability

In addition to influencing economic growth, climate shocks also play an important role in influencing other aspects of macroeconomic stability such as consumer prices, industrial output and economic stability. In general, macroeconomic stability means a sustained level of growth, low and stable inflation and a balanced growth of the economic sectors. However, climate shocks such as increased temperatures, flooding, storms and drought can impact on these indicators in a variety of ways and can interact with one another. Therefore, the effects of climate shocks on macroeconomic stability are an important consideration in economic policies and financial decisions, particularly in climate sensitive regions such as ASEAN.

A key pathway climate shocks impact macroeconomic stability is via supply shocks. However, severe weather events can have devastating impacts on infrastructure, production and industrial activity, leading to a fall in aggregate supply. Such shocks can have simultaneous impacts on different parts of the economy, with spillovers from the primary affected sector. For example, flooding and storms affect the transportation system and manufacturing facilities and can result in temporary or permanent shutdown of industrial production (Hsiang & Jina, 2014). This can result in massive losses of output and employment in areas where industry and agriculture are major factors, thereby undermining economic security.

The potential impacts of climate shocks on inflation are also significant, largely through effects on food and energy prices. Crop production may be impacted by floods and droughts, inducing supply shocks and affecting food prices, a large portion of price indices in developing countries. Similarly, extreme temperatures can also increase the need for air conditioning or heating, and thus contribute to higher energy costs and fuel inflation (Burke et al., 2015). The effects of these can be greater in developing countries, where the prices of food and energy are a larger percentage of the household budget. This makes climate shocks prone to causing cost-push inflation that can confuse and complicate monetary policy, and can have a negative shock impact on the economy.

Climate shocks also can impact macroeconomic stability through the demand and fiscal channels. Governments can increase public funding for relief, reconstruction and adaptation to mitigate the impacts of climate disasters. Such spending is critical, and can be costly to public budgets, especially in low fiscal space countries (World Bank, 2020). Increased government spending may lead to increased government debts and deficits, which could have long-term consequences on macro-economic stability. At the same time, climate shocks can impact on the household's income and expenditure, particularly in sectors which are climate-sensitive, and therefore on aggregate demand.

Another important focus of macroeconomic stability is climate shocks' impacts on industrial development. Infrastructure, energy and labor productivity shocks are often important for the industry sectors, and climate shocks can affect these. Floods and storms, for instance, can damage industrial infrastructure, and break supply chains; hot temperatures reduce productivity and drive-up costs. This may lead to a decline in industrial output and investment and slow structural transition and diversification in developing economies (World Bank, 2020; Asian Development Bank [ADB], 2021). The economic contribution of industrialization and job creation can have a major impact on economic stability when there are shocks to these areas (ADB, 2021).

An important feature of the climate shock-macroeconomic stability nexus is its non-linear and highly context-specific nature. The economic impacts of climate shocks may vary depending on the intensity and frequency of the shocks, and the state of the economy. For example, small climate shocks may affect economic activity to a small extent, but large shocks may have larger effects. Similarly, the resilience of an economy to climate risk and its ability to adapt to future shifts in climate is related to factors like institutional design, infrastructure strength and financial capacity (World Bank, 2020; IMF, 2022). The variability indicates that the effects of climate shocks differ from country to country and from year to year, suggesting the need to explore analytical frameworks that reflect this (Athey & Imbens, 2019; Molnar, 2022).

Recent empirical research has started to examine these effects, highlighting the need to take into account a range of macroeconomic indicators. Kahn et al. (2021) show that climate change can have long-lasting negative impacts on economic growth, as well as contributing to increased volatility of macroeconomic indicators. In other areas, climate shocks have been found to have inflationary consequences and worsen macroeconomic imbalances, particularly in low-income countries with low climate resilience (IMF, 2022). However, much of past research is fragmented with emphasis on specific measures, rather than on macroeconomic stability as a whole.

Here, the current study takes a broad-based approach as it considers the impact of climate shocks on GDP growth, inflation and industrial growth. This all-encompassing perspective allows a more comprehensive grasp of the effects of climate shocks on different economic aspects and the interplay between these effects on economic stability. Furthermore, both econometric and machine learning approach can be used to identify direct and nonlinear interaction of climate variables, and their significance.

The impact of these effects on sustainable financing can be traced. Climate shocks that lead to macroeconomic instabilities may raise financial risks due to their effects on asset values, returns and credit. For example, high inflation and macroeconomic uncertainty may lead to higher interest rates and higher risk premiums, and industrial disruption may affect corporate returns and investment decisions. It is crucial to understand the macroeconomic impacts of climate shocks in this context to incorporate climate risk into financial models, investment portfolios and regulatory regimes (TCFD, 2017; NGFS, 2020).

Overall, the findings indicate that climate shocks are important for macroeconomic stability and affect the two main variables of economic growth, inflation, and industrial activity in different ways. The complexity and non-linearity of these linkages, however, demand more complex approaches to capture the dynamics of these linkages. This research helps address these challenges to gain a more comprehensive view of the climate-macroeconomic link, with implications for policy and sustainable finance in the ASEAN region.

2.4 Climate Change and Inflation

The effects of climate change on inflation are important, particularly for emerging and climate-vulnerable countries, where food and energy products are prominent items of consumption. The impacts on long-term growth are largely productivity and investment impacts of climate change; the impacts on inflation are largely cost-push, supply chain and expectations impacts. An emerging empirical literature demonstrates that climate shocks (e.g. extreme temperatures, floods, storms, droughts) can impact prices in the long-term and can make macroeconomic and monetary policy (IMF) more complex (IMF, 2022; World Bank, 2020).

One of the key channels of climate change on inflation is via food prices. Agriculture is extremely vulnerable to climate change, and extreme temperatures adversely affect crop harvests. Drought reduces water supply and crop productivity, floods kill crops and delay planting, for instance. They result in a drop in food supply, leading to price rises and are generally very quickly pushed into the consumer price indices. In poorer and lower income countries, where food spends a bigger share of the income, these events may affect more broadly the inflation (Lesk et al., 2016). Evidence suggests that extreme events result in proportionally high rises in food prices, which then get passed through to inflation, especially in low- and middle-income countries.

Temperate changes also play an important role for inflation. High temperatures can adversely affect agricultural production and productivity, increasing production cost. At the same time, rising temperatures increase the need for cooling which increases electricity and fuel prices. These supply and demand effects can lead to inflationary pressures that can flow through the economy, in addition to agriculture (Burke et al., 2015). In addition, temperature shocks can impact the transport and logistics sector, causing increased transportation expenses and thus price volatility.

In addition, extreme temperatures (such as flooding and storms) can compound inflationary pressures via infrastructure and supply chain disruptions. Flooding may lead to loss of infrastructure and storage facilities, higher transport costs and restrictions on transport. Storms can impact manufacturing and limit the availability of critical goods. An interruption in the supply chain can lead to both a temporary shortage of supply and temporarily higher prices. In some cases, the effects can be long-lived if it takes time to rebuild or if there are multiple shocks (Hsiang & Jina, 2014). This is especially relevant to the ASEAN countries, as their infrastructure is not equally strong and vulnerable to climate shocks in their value chains.

Expectations and the monetary channel are also ways climate shocks can affect inflation. Hence, the nature of climate shocks (whether they are regular or not) could affect expectations about future output and prices, affecting household and firm inflation expectations. This could impact the wage determination and price determination processes and drive-up inflation if expectations are high. This could also be a new challenge for central banks, as effects on prices from supply side shocks may be less well met by central bank action (IMF, 2022). In such cases, the inflation effect resulting from climate changes can be short-term or long-term.

The evidence is slowly revealing the nonlinear and conditionality effects of climate shocks on inflation. Inflation caused by climate shocks can be more - or less - persistent depending on the intensity and frequency of shocks, and the type of the economy (Faccia et al., 2021; Kotz et al., 2024). For instance, more diversified economies with a more diverse production structure and infrastructure are likely to have the capacity to adapt to climate shocks, that can lower the inflationary effects. Economies that are more reliant on agriculture and/or have limited adaptation capacity, in contrast, may be more exposed to the inflationary impacts. More recent research has also indicated that there may be non-linear responses, such that inflationary impacts of extreme events are greater than impacts of normal climate variability (Kotz et al., 2024; Faccia et al., 2021).

However, there is a need for more studies. Prior to now, there has been a large number of studies on the impact of individual climate variables or shocks, but not yet on the impact of multiple climate variables. In addition, linear econometric models limit our capacity to capture non-linear relationships and threshold effects that may exist between climate shocks and inflation. Furthermore, the Association of Southeast Asian Nations (ASEAN) region, which is especially susceptible to climate change, might have different inflation dynamics from the western economies, and there is limited empirical evidence for the ASEAN region.

In this context, the present research contributes to this knowledge base by examining the impact of a number of climate shocks (temperature, floods, storms and droughts) on inflation within a consolidated framework. The use of Random Forest models, in addition to conventional econometric techniques, allows for the analysis of non-linear and interaction effects that may be missed using other approaches. Interpretability metrics like Partial Dependence Plots and SHAP-like explanations also provide opportunities for an in-depth study of the effects of each climate variable on inflation.

The results of this study are significant for the field of monetary policy and sustainable finance. From a policy point of view, awareness of the climate shock and its impact on inflation can assist in shaping the monetary policy in a more appropriate manner with consideration of climate risks. Climate-induced inflation is a risk which can affect investment, prices and financial stability from a sustainable finance point of view. The research can help include climate considerations in economic and financial policies and decisions by providing empirical evidence of these links.

Overall, the research indicates that climate change is increasingly having an impact on inflation, particularly in emerging economies. The complexity of the effects suggests that more advanced techniques that can capture a wide range of climate-economic interactions are needed. To tackle these challenges, the present study takes a hybrid approach of both econometric and machine learning techniques to understand the relationship between climate and inflation in the ASEAN region.

2.5 Climate Change and Industrial Growth

Industrial growth is an essential component of economic development, of structural transformation of the emerging markets and it may be strongly affected by the impacts of climate change. Industrial growth is a key indicator of productive capacity and potential for long-term growth (Rodrik, 2013; Szirmai, 2012) and is important for macroeconomic stability. However, climate shocks like rising temperatures, floods, storms and droughts may affect industrial activity in different ways: production, investment, productivity, or disrupt supply chains (Dell et al., 2012; Auffhammer, 2018; IPCC, 2022).

The most apparent effect of climate change on industrial development is direct damage to infrastructure and industrial facilities. In the case of flooding and storms, factories, equipment, infrastructure, and even power supply may be damaged, causing the immediate drop of production in the industrial sector. For instance, storms may impact physical assets and electric facilities while floods wash out industrial areas, harm machinery and hinder production. This not only leads to immediate declines in production but also takes time and resources for recovery and rebuilding, thereby impacting medium-term industrial growth (Hsiang & Jina, 2014; World Bank, 2020).

In addition to effects on industrial production, climate shocks may also affect industrial growth through supply chain disruptions. Modern industries have complex and interconnected supply chains, which are vulnerable to climate change. Transportation infrastructure can be impacted by storms and flooding, which can cause delays in shipments of inputs, increase transport costs, and interfere with production workflows and productivity. These impacts can be cascaded in the economy, worsening the impact on industrial production and in interconnected economies. The growing geographical dispersion of production networks also exacerbates these risks, with climate shocks in one part of the world impacting production in other parts (Kahn et al., 2021).

Industrial productivity is also greatly affected by the changes in temperature. Increased temperatures may result in reduced productivity, particularly in manufacturing processes that require correct heat conditions. Elevated temperatures can result in fatigue, decreased productivity and health issues, ultimately reducing productivity per worker. Rising temperatures also have a negative impact on machinery performance and increase the need for cooling, increasing operational costs. In tropical and subtropical regions, including the ASEAN economies, this could have a more profound effect since temperatures are already hot (Dell et al., 2012; Burke et al., 2015).

Indirect impact of droughts on industrial growth can occur due to the effect on water supply, which is an important input for industrial production (IPCC, 2022; World Bank, 2021). Water-intensive industries like food processing, textiles and power generation can face production bottlenecks and higher costs due to water scarcity (Dell et al., 2012; FAO, 2023). Besides, droughts can also negatively affect agriculture activities and consequently the provision of raw materials for agri-based industries, and therefore the industrial activities. Such cross-sectoral effects underline the potential of climate shocks to have wide-ranging effects on the economy (IPCC, 2022).

Another key pathway by which climate change affects industrial growth is by impacting investment and capital. Climate shocks increase uncertainty and risk, and can result in lower levels of private investment in the industry (World Bank, 2020; OECD, 2021). Uncertainty over the future impacts of climate change, as well as infrastructure reliability and political instability, can lead to delay or reduced investment in projects by businesses. It's also likely that the government will have to shift resources to recovery and reconstruction, which could eat into productive funds. This can be a potential barrier to structural transformation and industrial growth in developing nations (World Bank, 2020; Asian Development Bank [ADB], 2021).

Finally, the effects of climate shocks on industrial growth are also non-linear and dependent on specific circumstances. Small climate shocks can have little impact on industrial production while larger shocks can lead to large and lasting impacts. The recovery and resilience of an economy to these shocks will be driven by a range of factors such as the resilience of infrastructure and institutions, and access to capital (IPCC, 2022; IMF, 2022). The ability of economies to adjust to climate shocks could also be crucial in mitigating negative impacts, and less resilient economies could experience more and longer impacts on industrial activity (IPCC, 2022).

There is growing evidence of the adverse effects of climate change on industrial production. For example, Dell et al. (2012) show that temperature has a negative impact on industrial production in less developed countries, while Burke et al. (2015) note the overall productivity impact of temperature. The effects of extreme climate events on industrial performance and climate change economic impacts have also been studied, particularly where there is low climate change adaptation capacity (Hsiang & Jina, 2014; Kahn et al., 2021). But much of this research has examined aggregate economic performance, with less emphasis on industrial growth as an aspect of macroeconomic stability.

In addition, as with the studies of economic growth and inflation, many of these studies are based on linear models which may not be suitable for capturing the nonlinear interaction between climate and industrial activity. Little is known about the interactions between different climate variables, and their combined impacts on industrial development. This indicates a need for modelling methods that are more flexible in nature, to address non-linear effects and relationships between variables.

In this regard, the current research adds to this body of research by examining the effects of multiple climate shocks on industrial growth in an integrated framework. The use of econometric and machine learning techniques allows this study to tackle linear and non-linear effects and threshold effects. The use of Random Forest models based on Partial Dependence Plots and a SHAP-like analysis allows a detailed examination of the effects of different climate variables on industrial performance and how they vary at different levels of exposure.

The results of this analysis are relevant for sustainable finance. Industries are crucial to investments, and the development of industries can influence company profits, financial risk, and investment outcomes. As such, knowledge of the climate risks faced by industrial sectors is critical for sustainable and resilient investment decisions for investors and financial institutions. The research provides insights for designing climate-resilient investment strategies and financial products from the assessment of key drivers in the industrial growth climate.

To sum up, the evidence confirms that climate changes pose risk to industry's economic growth, particularly in developing economies. These effects are expected to be more nonlinear in nature and there is a need for new analysis methods to better understand the effects of climate on the growth of industry. The present research overcomes these challenges by including several climate variables, flexible modeling approaches and provides a comprehensive perspective on the development of the industry links with climate change and sustainable finance.

2.6 Nonlinear Effects and Threshold Behavior in Climate Economics

An important conclusion drawn from theory and from recent empirical research is that the impacts of climate variables on economic activities are, in fact, highly non-linear and may have threshold effects. Linear equations are easy to use, but can obscure important aspects of the climate-economy relationship, such as tipping points and the non-symmetric effects and interactions of climate shocks. It is important to understand and to capture these characteristics accurately in order to estimate the macroeconomic impacts of climate change as well as for policy and sustainable finance applications.

Theoretical underpinning of the nonlinearity of the relationships between climate and economy is well understood: this is the case in climate damage functions where the increase in damages is nonlinear in the temperature. In most of these cases, output reactions to changes in temperature are specified as being convex, meaning that the marginal damages grow as the temperature rises (Nordhaus, 2017). This convexity is due to several reasons such as physiological constraints of labor productivity related to heat stress, relationship of crop yield to temperature and precipitation inputs and increasing risk of extreme events as the climatic conditions shift away from historical conditions. In addition to the mechanisms, beyond a certain point, more changes of climate could lead to more effects on the economy.

These theoretical findings are backed up by empirical evidence. Burke et al. (2015) show that the productivity of an economy has an inverted U shape as temperature increases, with the maximum productivity at an "optimal" temperature and a rapid drop-off above it. More sectoral research confirms this finding, showing a non-linear relationship between temperature and rainfall and crop yields and workforce productivity (Auffhammer, 2018). More importantly, average temperatures in tropical and developing countries are nearer to physiological and crop productivity limits, thereby increasing the nonlinear impacts. In this region, threshold effects are likely to be strong, such as in ASEAN.

The other source of nonlinearity is extreme weather events. Floods, storms and droughts can cause economic impacts due to both the frequency and the intensity of the event, as well as how close it occurs to the economic activity. While low-intensity events can be dealt with relatively minorly, high-intensity events or series of events can overwhelm society's ability to adapt, leading to long-term damage (Hsiang & Jina, 2014). Similarly, the effect of multiple shocks (such as drought followed by flood) may be compounding and may have non-linear and path dependent impacts, making linear modeling difficult.

Lastly, there could be thresholds in macroeconomic channels. Climate shocks can, for instance, have a small impact on both inflation and output up to a certain threshold, after which supply bottlenecks take over and inflationary pressures build up. Similarly, as risk increases, investments can become increasingly sensitive, but at low risks, they may be less sensitive to climate risk. Expectations, risk premiums and financial constraints and threshold effects are closely related and will require a joint modelisation of climate and macroeconomic developments.

Such nonlinearities are increasingly being known but many empirical papers continue to model nonlinearities by using a quadratic or cubic specification. The models are more flexible than linear ones but still, there are restrictions, or assumptions, about the form of the relationship types that may not be accurate. These constraints can lead to misspecified systems and biased estimates in systems where multiple interacting variables whose exact relationships are known.

As a means of addressing these issues, there has been a growing trend towards using machine learning approaches for modelling climate-economic relationships. Random Forests, for example, can model complex nonlinearities and interactions without assumptions of the functional form of the relationship (Athey & Imbens, 2019). Random Forest models are able to model complex functions and detect structural shifts in the relationships between variables by dividing the data into multiple decision trees and combining their predictions.

Flexibility of machine learning models comes with interpretability problems, however. Recent advances have offered tools to quantify the contribution of variables while keeping the values of other ones fixed, such as Partial Dependence Plots (PDP) and SHAP (Shapley Additive Explanations) values (Molnar, 2022). For example, PDPs can be used to see whether there are nonlinear effects and threshold responses by visualizing the relationship between predicted values and one variable. Similarly, SHAP values provide a decomposition of the model's predictions into the effect of each feature, giving an understanding of feature interactions and importance.

For this research, Random Forest models, in combination with PDP and SHAP-like methods, provide a solid tool for detecting a nonlinear relationship between climate and macroeconomics. These methods enable identification of threshold effects in temperature and extreme weather events and also enable identification of asymmetries in the impact on various macroeconomic indicators (Friedman, 2001; Lundberg & Lee, 2017). For example, GDP growth may increase in a gradual fashion at low temperatures, but then begin to fall rapidly at higher temperatures (Burke et al., 2015). Similarly, the impact of flooding on the manufacturing production may differ depending on the level of infrastructure resilience leading to different responses and outcomes in countries (IPCC, 2022).

The existence of nonlinear and threshold effects is of relevance for sustainable finance. Costly capital is allocated based on models to assess climate change risks. The absence of nonlinearities in these models could lead them to fail to adequately reflect the risk of large losses and price warps. This research can also be used to explain nonlinear impacts, thereby improving the understanding of risks, and to inform financial strategies to address climate-related risks (Battiston et al., 2021; NGFS, 2020). For instance, thresholds can help policy makers and investors recognize what critical thresholds may be present where economic and financial risks may rapidly become more severe.

So far literature indicates that the climate-economy system is in general inherently nonlinear and has threshold effects. These dynamics require models that are flexible and transparent and go beyond the linear (Burke et al., 2015; Carleton & Hsiang, 2016; IPCC, 2022). This study's use of machine learning and economic theory to examine empirical evidence on climate impacts, and its ability to better understand the implications of climate shocks on macroeconomic stability in the ASEAN countries, contribute to the empirical literature on climate impacts (Athey & Imbens, 2019; Lundberg & Lee, 2017).

2.7 Machine Learning in Macroeconomic and Climate Analysis

As the nature of climate-economy dynamics becomes more complex, researchers have become interested in the use of machine learning methods in macroeconomic and climate studies. The traditional methods of inference and hypothesis testing based on econometric techniques are helpful but have strong assumptions about the functional form and the linear and independent nature of the variables. This can limit their ability to capture the nonlinear, high dimensional and interactional characteristics of climate shocks and macroeconomic effects. Machine learning methods have thus become more popular as ways to model complex systems and offer greater flexibility and accuracy in modeling nonlinearities and interaction effects (Athey & Imbens, 2019).

Machine learning is a group of algorithms that is used to discover patterns and structure from high dimensional data. In macroeconomic and climate analysis, supervised learning algorithms are of particular interest as they can be used to model the relationship between a set of predictor variables and a response variable. Ensemble methods such as Random Forest are gaining popularity for their stability, flexibility of adding nonlinear relationships and their ability to prevent overfitting (Breiman, 2001). The RF models are constructed by generating several decision trees from random samples of the data set and averaging the predictions of these trees to eliminate variance and increase the accuracy of prediction (Breiman, 2001).

The use of machine learning techniques in macroeconomics has grown significantly in recent years, especially in forecasting, risk management and policy evaluation. Missions have revealed that machine learning models are able to outperform traditional econometric models, especially in situations where there is a large amount of data and interactions (Mullainathan and Spiess, 2017). At the regional level, machine learning has been used in the field of climate economics to investigate the impact of climate and extreme climate events on the economy, as well as to calculate the climate risk and vulnerability (Kahn et al., 2021). Such uses show the capacity of machine learning to offer fresh insights into the climate-economy interaction.

The advantage of machine learning models is that they can learn the nonlinearities and interactions without having to write the functional form (Athey & Imbens, 2019). This is crucial in modelling climate shocks, in which the impact of temperature and extreme weather events may vary as a function of other factors, such as economic structure, institutional efficiency and geography (Carleton & Hsiang, 2016). This could be the situation when the impact of a flood on industrial production is dependent on infrastructure resilience, or when the impact of temperature on productivity is different in different sectors of the economy and between income groups. These interactions can be automatically captured by machine learning models, and be included in the prediction of these models, providing a better understanding of the dynamics (Athey & Imbens, 2019).

But there have been worries regarding interpretability and transparency in the use of machine learning in economics. Although most of the traditional econometric models can be interpreted as having explicit parameter estimates, many machine learning models can be seen as “black boxes” where it is difficult to understand the process that results in the prediction. This is a significant issue in policy work, where knowledge of how things change and how they come about is important (Varian, 2019).

The problem is overcome by the field of interpretable machine learning, which has developed various techniques for making machine learning models more interpretable. In particular, PDP (Partial Dependence Plots) and SHAP (Shapley Additive Explanations) are widely used in practice. The PDPs are used to identify non-linearity and thresholds effects when other variables are held constant, and enable researchers to capture the relationship between a single predictor variable and the response variable (Friedman, 2001). SHAP values, on the other hand, offer a theoretically sound, consistent measurement of feature importance through decomposing model predictions in terms of the contributions of individual features (Molnar, 2022).

The interpretability tools are particularly valuable for the climate-macroeconomic research. They enable researchers to move beyond the focus on predicting the impacts of climate change to better grasp the mechanisms driving economic impacts. For instance, PDPs can illustrate changes in GDP growth across various temperature or extreme events, and SHAP can help to identify the effects of temperature and macroeconomic factors on GDP. These methods establish a connection between predictive accuracy and interpretability, thus connecting machine learning and economic analysis.

One of the most important parts of machine learning models is model validation and robustness. To assess the performance of the models on unseen data and prevent overfitting, methods such as cross-validation are often used (Athey & Imbens, 2019). For panel data, cross-validation will help to avoid overfitting on the sample data (Hastie et al., 2021; James et al., 2021). Likewise, measures of robustness like looking at feature importances or examining the stability of model variants with multiple random initializations also provide confidence in the results (Molnar, 2022).

Machine learning offers numerous advantages, but it should be noted that it does not replace traditional econometric techniques. The construction of relationships and the derivation of interpretable estimates of average effects is essential in the setup of econometric models. Machine learning models, in turn, add to the analysis by enabling the consideration of non-linearities, interactions and heterogeneity that are not captured by linear models (Athey & Imbens, 2019; Mullainathan & Spiess, 2017). Complementary application of these models gives a comprehensive perspective of economic processes.

The Ordinary Least Squares (OLS) and Random Forest models are adopted in our research to achieve a balanced model that makes the best of both worlds. The OLS models are able to reflect simple relations between climate shocks and macroeconomic variables, whereas the Random Forest models offer insights into nonlinearities and interactions. Another advantage of applying PDP and SHAP-like analysis is the interpretability it brings, which makes possible a more detailed analysis of the influence of individual variables (Friedman, 2001; Lundberg & Lee, 2017).

With machine learning, there are important implications for sustainable finance. The key to successful financial institutions adapting to environmental risks is reliable climate risk models that can be integrated into investment and risk management practices (Battiston et al., 2021; NGFS, 2020). The estimates of climate risks can be improved by incorporating non-linearities and other complexities in economic outcomes in machine learning models. These models can provide more insight into the effects of climate change and contribute to a more sustainable financial system by informing financial decision-making (IMF, 2022).

To sum up, the increasing use of machine learning in macroeconomic and climate analysis appears to be a trend in using data for economic research. Machine learning approaches are promising for capturing the complex and nonlinear dynamics between climate and the economy by offering a good balance between flexibility, accuracy and interpretability (Athey & Imbens, 2019; Mullainathan & Spiess, 2017). This research adds to this body of work by using interpretable machine learning models to study the effects of climate shocks on macroeconomic stability in the ASEAN region, thus advancing both methodological and empirical knowledge.

2.8 Climate Risk and Sustainable Finance

Sustainable finance, which integrates environmental, social and governance (ESG) principles into financial practices, is a rapidly changing field as climate change is now acknowledged as a systemic risk. In this context, climate risk has become a key consideration, affecting asset valuations, investment decisions, and financial resilience. There is therefore a need to be aware of the potential for climate shocks to lead to macroeconomic instability, in order to foster sustainable finance and risk management (UNEP FI, 2020; IMF, 2022).

Financial risks due to climate change can be broken down into physical risks and transition risks. Physical risks are associated with the physical impacts of climate change (e.g. extreme events like floods, storms and droughts; and slow onset events, like rising temperatures). These risks can result in physical asset damage, loss of productivity and lost output. Transition risks arise from the transition to a lower-carbon economy and could include policy, technology and customer preferences shifts that could impact asset prices and businesses (Network for Greening the Financial System [NGFS], 2021).

The bulk of our research focuses on the effects of physical climate risks on macroeconomy. The physical risks are reinforced in emerging economies as a result of the possible lack of infrastructure, institutional systems and financial systems. The hazards of recurrent flooding, high intensity storm events and high temperatures are significant concerns for economic development and stability in ASEAN nations. The impact of these events is often catastrophic on economic activity, productivity and macroeconomic volatility, resulting in mistrust of investors and financial markets.

Climate risks are transmitted from the physical world to the financial sector through the macro economy. Climate shocks may, for example, affect GDP growth, inflation, and industrial production, which may affect corporate profits, government budgets and household incomes. For example, lower GDP growth in the face of climate change events may have a negative effect on corporate profits and credit risk, which in turn can affect credit markets and banks. Similarly, inflation due to climate change can hurt the incomes of consumers, and affect interest rates and the prices of financial assets. The climate impacts on industry can impact supply chains and investment and thus financial risks. The impacts of climate on industry can impact supply chains and investment and thus financial risks.

These impacts are crucial for pricing climate risk in financial markets. Climate risk mispricing could lead to misallocation of resources as investors are using models to estimate the risk and return of various investments. Relying on linear relationships and/or the small size of climate shocks may result in underestimation of tail risks of extreme losses and in systemic financial risks. Thus, including reliable and holistic measures of climate risk in macroeconomic analysis is crucial in enhancing financial decision-making.

The financial sustainability approach is also based on financial instruments and policies to address climate risk. Financial instruments that seek to mobilize financing for sustainable projects include green bonds, sustainability linked loans, and climate funds. However, these instruments would need an understanding of the economic impacts of climate change. For instance, understanding which segments and regions are most vulnerable to climate risks can guide project investments to boost climate resilience, such as green infrastructure investments and investments in renewable energy generation.

Climate risk is also a part of financial regulation and supervision. There is growing inclusion of climate in stress testing, risk management, and disclosure regulations and rules by regulators and central banks (NGFS, 2021). The climate stress tests, for example, assess how financial institutions would fare under various climate conditions and climate scenarios, including physical and transition risks. The impact of climate shocks on the economy is a crucial aspect of these tests, as this is part of the financial sector's transmission channels.

The incorporation of climate risk into financial systems also calls for more forward-looking and data-driven approaches. The historical data might not be enough to make a risk analysis of climate risk. Machine learning is a potential solution to this as it can be used to uncover relationships that are complex and nonlinear, as well as identify new risks. Leveraging these techniques in climate risk assessments can help financial institutions better predict and manage climate risks.

For ASEAN economies, sustainable finance is particularly pertinent. These economies are highly vulnerable to climate risks, and are also at the forefront of economic growth and financial development. These considerations call for the development of a climate-resilient, sustainable financial system that balances these aspects. Knowledge about the macroeconomic impact of climate events is thus essential in informing the policy and investments in the region.

This study contributes to the existing sustainable finance literature by studying the effects of climate shocks on measures of macroeconomic stability for the ASEAN region. The research offers practical insights for the assessment of climate risks, financial regulation and investment decisions, by determining climate variables that influence economic growth and analyzing the non-linear effects of climate shocks. The interpretability of the machine learning models used in the analysis also contributes to the actionability of the findings, enabling policy makers and financial practitioners to manage and respond to climate risk.

In summary, incorporating climate risk into sustainable finance is essential for the development of resilient and sustainable economies. The research's emphasis on the climate shocks – macroeconomic indicators link allows for improved climate risk assessments and financial measures that align with environmental and economic objectives in the longer term.

2.9 Research Gap

Although the existing literature on the economic impacts of climate change is extensive and growing, there are still key gaps in the knowledge of the effects of climate shocks on macroeconomic stability, especially in emerging and climate-vulnerable economies such as ASEAN. Filling these gaps is essential to strengthen research and policy-driven analyses and to incorporate climate risks into sustainable finance strategies.

A major limitation of the existing literature is that the impact of climate on the economy continues to be modelled using linear econometric models. Though they play an important role in giving an initial picture, these models require strong assumptions regarding the functional form of the relationship between climate and indicators of economic activity, and do not capture the threshold and asymmetric effects. Recent research also shows that the impact of climate shocks (e.g., temperature) can be highly non-linear, and economic outcomes can differ at varying levels of exposure (Burke et al., 2015; Auffhammer, 2018). Many studies, however, approximate these nonlinearities by fitting a quadratic or polynomic function, that may not be a true representation of the nature of the relationship studied. It has consequences for the requirement for flexible approaches which can preserve the complexity of the relationship without imposing a functional form on it.

The second limitation is the fact that multiple climate shocks have not been considered as an integrated bundle. Research studies on the effects of climate variables tend to concentrate on one variable at a time, such as temperature or rainfall. But in practice, economies are commonly faced with multiple climate shocks, such as floods, storms, droughts, and temperature fluctuations. These shocks can be interconnected, such that they may have more or less impact than they're worth individually. There is limited research that looks into the combined effects of several climate variables, which further hinders our understanding of how the combined impacts of climate shocks affect macroeconomic stability.

Third, there is a lack of empirical studies that investigate the impact of climate shocks on several dimensions of macroeconomic stability, including GDP growth, inflation, industrial production, etc. Previous studies tend to consider only one outcome variable (often economic growth) while ignoring other important measures of macroeconomic stability. This practice makes it difficult to grasp the complexity of economic impacts of climate change, and can lead to incorrect inferences. A holistic approach that simultaneously accounts for multiple macroeconomic indicators is thus needed to gain a better understanding of the broader climate impacts.

A further crucial aspect is the lack of use of interpretable machine learning methods in climate-macroeconomic analysis. The potential of machine learning in economic analysis is growing, but has not yet been employed to an extent to investigate the impacts of climate shocks, particularly in developing countries. In addition, the lack of interpretability of the machine learning model has constrained its use in the creation of policies. However, recent advances in interpretability methods, including methods based on Partial Dependence Plots and SHAP (SHapley Additive Explanations) provide a way to overcome these drawbacks to make interpretable and meaningful explanations about the models (Molnar, 2022). These techniques are under-used and a chance to increase the accuracy and interpretability of climate-economic analysis.

Moreover, the literature is geographically limited and there is not much literature related to the economies of ASEAN. Aggregate and comparative studies are useful but may not provide enough information to illuminate region-specific vulnerabilities and characteristics. This is particularly relevant to the ASEAN economies that are climate change vulnerable, climate-sensitive industry-dependent and have differing economic and institutional development. The lack of regional analyses makes it difficult to create region-specific policy and financial solutions to address the issues these economies face.

Moreover, there has been a lack of research on the connection between climate shocks, macroeconomic stability, and sustainable finance. There is a considerable body of literature on sustainable finance, or climate risk studies, but it typically focuses on financial markets, asset prices or ESG investments, but does not explicitly link them to macroeconomics. On the other hand, research on climate and macroeconomics seldom includes a financial dimension. This leaves a gap in our understanding of the macroeconomic impacts of climate risk and how this translates into financial risks, and affects investment strategies, risk management and policy.

Finally, there is a requirement for more empirical methods that are rigorous, such as model validation, robustness and stability tests. Existing research studies typically employ only one-model techniques without assessing the stability and robustness of the results. For machine learning models, cross-validation and stability analysis of feature importance is crucial for ensuring that the output is not overfitting or from a sample-specific trend. The lack of application of such methods in current studies undermines the confidence in the empirical findings.

This paper sets out with certain objectives in view, in the background of which the following can be mentioned: First, it uses a dual method which involves both baseline econometric models and Random Forest machine learning, giving the flexibility of both linear and non-linear effects. Second, it integrates several of these climate shocks – temperature, floods, storms and droughts – into one model to assess their impacts on macroeconomic stability. Third, it takes into account a number of macroeconomic condition indicators that reflect economic stability, including GDP growth, inflation and industrial growth. Fourth, it uses interpretable machine learning techniques, like Partial Dependence Plots and SHAP-like analysis, to improve the interpretability and policy usefulness of the findings. Fifth, it offers insights for the ASEAN countries, which are not emphasized in the literature. Lastly, it contains extensive validation and stability analysis for better credibility of results.

These challenges make the study more comprehensive and integrated in terms of the climate-macroeconomic nexus, and offer insights to policy-makers, the academic world and financial institutions that engage in climate and sustainable finance.

2.10 Theoretical and Conceptual Framework

This research is based on a combined theoretical-conceptual framework that describes the impact of climate shocks on macroeconomic stability and, in turn, the implications for sustainable finance. It combines theory with a conceptual model, which provides a consistent structure for the analysis of the data and outlines the links between the variables of interest in this study.

The core of the framework is the occurrence of climate shocks, which are represented in the model by temperature and extreme weather events (flood, storm and drought). These are represented as exogenous disturbances on the economy that cannot be controlled by policy makers and economic actors. As with the theory of climate damage functions, the impacts on the economy from these shocks is expected to be non-linear, with the impacts increasing with increasing frequency and intensity of the shocks (Nordhaus, 2017; Burke et al., 2015). These shocks do not occur in isolation but rather pass on via several channels to impact economic activity at the sector and overall levels.

There are several impacts on macroeconomic performance when climate shocks occur. One such key channel is the productivity channel, which involves heat extremes or extreme weather events reducing the productivity and output of the labor input, particularly in the climate-sensitive sectors like agriculture and manufacturing (Dell et al., 2012). High temperatures can have negative impacts on physical productivity, shorten working hours, and extreme weather events can influence labor supply and labor conditions (Dell et al., 2012).

The other channel is through the capital and infrastructure channel, where climate shocks impact physical capital, like manufacturing facilities, road and rail networks, and power supplies. In particular, floods and storms can cause substantial capital stock destruction, decrease the productive capacity of the economy and drive the need for rebuilding. This can impact both the current and future economic activity.

Climate shocks also have effects via a supply chain and production channel: a shock in transport and logistics networks also impacts on the movement of goods and services. These can cause delays, cost and productivity losses in factories. These shocks can then radiate to other sectors in integrated economies, thereby impacting further the economic output.

Further, the agricultural and resource channel is important, especially in developing countries. Both droughts and floods can impact agricultural productivity, causing variations in food supply and prices. This has implications for rural livelihoods, and can cause macro-economic effects, most importantly in the form of inflation.

The model also accounts for the fiscal/policy channel, in which governments react to climate impacts by raising the level of government spending on relief, reconstruction and adaptation programs. This could be required, but it can place a significant strain on fiscal balances, particularly in tightening budgets. Meanwhile, if there is less activity, there will be less tax collected, exacerbating the situation (World Bank, 2020).

The investment and uncertainty channel is another important pathway, with higher levels of climate risk leading to higher levels of uncertainty for businesses and investors. This has disinvestment impact and restricts capital formation and slows down long-term economic growth. The response to climate risks can impede industrial growth and economic growth, leading businesses to be more conservative about climate risks.

These are the links between climate shocks and macroeconomic stability indicators (the dependent variables in this study). They are economic growth (GDP growth rate), price stability (inflation) and industrial growth (industrial growth rate) respectively. These indicators help to define the dynamics of the economic system's stability.

Besides climate shocks, the model accounts for a number of control variables that affect the macroeconomic indicators. These consist of government consumption, exchange rates, gross capital formation and population. They reflect elements of the structure, policy and population characteristics which could impact economic results and are potentially affected by climate shocks. Taking these variables into consideration will minimize the confounding effect of other variables on the impact of climate variables.

Conceptually, these are considered as the main explanatory variables (climate shocks) and dependent variables (macroeconomic variables), with the control variables being additional explanatory variables in a conceptual model. This study's conceptual framework is as follows:

Climate shocks (temperature, floods, storms, droughts) affect macroeconomic stability indicators (GDP growth, inflation, industrial growth), and macroeconomic stability is also affected by control variables such as government consumption, exchange rates, investment and population.

This comprehensive solution is also related to sustainable finance. Financial markets are affected by climate-induced macroeconomic instability, in terms of investment, prices and risk. Lower GDP growth and greater economic volatility, for example, can lead to increased credit risk and decreased returns on investment, while increased inflation from climate change could have an impact on interest rates and financial markets. Industry disturbances may have negative effects on the business and supply chain, which can lead to financial risks.

The knowledge of such connections is crucial for sustainable finance, as financial institutions, investors and policymakers can anticipate and take climate risks into account. This study does two things: It first lists the most important climate triggers that impact macroeconomic performance, and then examines their non-linear impact, providing insights into climate risk assessment, ESG investing and financial regulation.

In this regards, the integrated theoretical and conceptual approach offers a whole package solution approach to the climate-macroeconomic nexus. It links different pathways of climate impact, shows the nonlinearity of climate impact and establishes causal relationships. The method supports the empirical approach adopted in the study where both econometric and machine learning techniques are applied to capture both linear and nonlinear effects, leading to a more meaningful and relevant analysis of the climate shocks in the ASEAN region.

Figure 1. Theoretical and Conceptual Framework of the Study

Source: WDI, Berkely Earth, EM-DAT (2026)

2.11 Overview of Literature Review

This chapter has reviewed the theoretical and empirical research on the relationship between climate change, macroeconomic stability and sustainable finance that forms the foundation of the analytical framework of the study. The review indicates that climate change is no longer just an environmental issue, but an economic indicator and a financial stability factor, particularly in emerging markets and those at risk of climate change.

A theoretical analysis revealed that there are multiple alternative explanations for the impact of climate shocks on economic performance. The neoclassical growth theory describes the effects of climate shocks on productivity, labor productivity and capital accumulation, and hence, on economic growth. The concept of climate damage function theory emphasizes the non-linear impacts of climate change and suggests that the economic damages from climate change are increasing as the speed of warming increases. The Environmental Kuznets Curve theory provides insights into the relationship and interactions between economic growth and environment, and sustainable finance theory links climate risks with financial markets, highlighting the implications for financial investments, risks and stability. These theories offer a holistic approach to understanding the climate-macroeconomic relationship.

The evidence is also empirical and indicates that climate factors like temperature and extreme weather have important implications for macroeconomic performance. The existing literature on economic growth shows that higher temperatures and climate variability can affect productivity and economic growth, especially in developing countries. The effects of climate shocks on food and energy prices have been identified as drivers of inflation, leading to cost-push inflation and price volatility. Likewise, research on industrial growth suggests that climate shocks can impact productivity, infrastructure and investment, and hence influence industrial growth and structural change.

One important conclusion of these studies is the importance of nonlinearities and threshold effects in the interactions between the climate system and the economy. There is empirical evidence that the effects of climate shocks are not constant, but depend on the exposure to the shocks, with larger effects above certain threshold levels. This is a big change from linear models, and is a reminder of the need for more flexible tools which can model complex interactions and dynamics.

The review further highlights the increasing use of machine learning methods in economic and climate studies. The use of such methods as the Random Forest model provides an excellent way to account for nonlinear effects and complex interactions and has greater predictive power than conventional econometric methods. But recent advances in interpretability, like Partial Dependence Plots and SHAP, enable us to learn from these models and thus make them applicable to policy-oriented research.

Last, but not least, climate risks are recognized as a key consideration in sustainable finance in the academic literature, and integrating environmental issues into financial considerations. Climate risks can impact macroeconomic stability, which in turn impacts financial markets, investment and risk management. However, the existing research literature focuses more on climate economics and sustainable finance in isolation, and encourages more focused research in their integration.

There is still a significant amount of progress to be made, but there are a few things that still need to be addressed. First, the limited use of nonlinear frameworks for analysis, lack of integrated analysis of multiple variables of climate shocks, limited use of interpretability of machine learning techniques, limited number of studies for the ASEAN region, and the lack of integration of climate risks in macroeconomic and financial analysis. These gaps need to be filled to gain better understanding of the relationship between climate, economy and finance.

This study aims to overcome these limitations by employing a combined econometric and machine learning techniques to explore the impact of climate shocks on GDP, inflation and industrial growth in several ASEAN countries. Through the use of nonlinear models, multiple climate indicators, and interpretable machine learning techniques, the study seeks to enhance the accuracy and understanding of the effects of climate on macroeconomy. In addition, the research can be used to inform policy making for sustainable financing and better risk management policies for climate risks, and to design strategies for economic resilience and sustainable development.

The chapter concludes that, in summary, climate shocks are an important determinant of macroeconomic stability and that sophisticated analytical methods are required to appreciate the impact of climate shocks.

Table 1. Summary of Recent Empirical Studies

Study	**Coverage and data**	**Climate and outcome variables**	**Method**	**Main findings**	**Relevance and remaining gap**
Goulet Coulombe (2020)	US macroeconomic time-series data	Multiple macroeconomic predictors; inflation, unemployment, and other macroeconomic outcomes	Macroeconomic Random Forest	Develops an interpretable Random Forest framework capable of capturing time-varying parameters, structural changes, thresholds, and nonlinear macroeconomic relationships.	Provides methodological support for using Random Forest in macroeconomic analysis, but it does not investigate climate shocks or developing economies.
Kahn et al. (2021)	Panel of 174 countries, 1960–2014	Temperature and precipitation deviations; real GDP per capita	Dynamic panel econometric models	Persistent deviations of temperature from historical norms adversely affect long-run economic growth, with effects extending to both richer and poorer economies.	Establishes the macroeconomic importance of climate variability, but focuses mainly on aggregate output and relies on econometric specifications rather than interpretable machine learning.
Faccia, Parker, and Stracca (2021)	Cross-country monthly price and weather data	Extreme temperatures; consumer-price inflation	Panel local projections/econometric analysis	Extreme temperatures influence inflation, although the direction and persistence of the effects differ according to	Directly supports the inflation dimension of the thesis but does not jointly examine growth, industrial activity, and

Study	Coverage and data	Climate and outcome variables	Method	Main findings	Relevance and remaining gap
				climate, season, and level of economic development.	multiple disaster types.
Battiston, Dafermos, and Monasterolo (2021)	Review and synthesis of climate–financial-system research	Physical and transition climate risks; asset values, credit, and financial stability	Financial network and climate-risk framework	Climate risks can affect financial stability through asset repricing, credit losses, interconnected financial exposures, and macroeconomic transmission channels.	Establishes the sustainable-finance relevance of climate shocks, but does not empirically model macroeconomic outcomes using country-level climate data.
Kotz, Levermann, and Wenz (2022)	More than 1,500 subnational regions across the world	Rainfall frequency, intensity, and extremes; regional economic production	Subnational panel econometric analysis	Changes in rainfall patterns, particularly more intense wet days and prolonged dry periods, reduce economic production. Effects also extend beyond agriculture to industrial and service activities.	Demonstrates that climate–economy relationships depend on the distribution and intensity of climate variables, but does not include inflation or interpretable machine-learning models.
Callahan and Mankin (2022)	Country-level historical temperature and economic data	Anthropogenic warming; national GDP	Counterfactual climate attribution and	Historical warming has generated uneven economic damages across countries, with	Highlights cross-country heterogeneity and vulnerability, but focuses on

Study	Coverage and data	Climate and outcome variables	Method	Main findings	Relevance and remaining gap
			econometric modelling	hotter and lower-income economies generally experiencing greater losses.	temperature and aggregate income rather than multiple macroeconomic indicators.
Kotz, Kuik, Lis, and Nickel (2024)	More than 27,000 monthly price observations from 121 countries, 1996–2021	Temperature, heat extremes, and precipitation; food and headline inflation	Global panel econometric analysis with nonlinear response functions	Higher temperatures and heat extremes increase food and headline inflation, with stronger effects in hotter regions and seasons. The responses are nonlinear and may persist for several months.	Strongly supports the inflation and nonlinearity components of the thesis, but does not analyse GDP growth, industrial growth, or disaster counts within one framework.
Kotz, Wenz, Levermann et al. (2024)	Approximately 1,600 subnational regions using around 40 years of economic and climate data	Temperature, precipitation, and weather variability; regional income	Subnational panel modelling and climate projections	Past emissions have committed the global economy to substantial income losses by mid-century. Damages are persistent and unevenly distributed, with particularly severe consequences in vulnerable regions.	Provides recent evidence on persistent and heterogeneous macroeconomic damages but focuses on regional income rather than inflation and industrial growth.

Study	Coverage and data	Climate and outcome variables	Method	Main findings	Relevance and remaining gap
Bilal and Känzig (2024)	Global and national macroeconomic and temperature data	Global and local temperature shocks; GDP, consumption, and investment	Structural time-series/local-projection approach	Global temperature shocks generate large and persistent macroeconomic losses, partly because global temperature captures interconnected climate events and international spillovers that local temperature measures may omit.	Highlights the importance of broad climate transmission and persistent macroeconomic effects, but does not examine individual ASEAN countries or use machine-learning interpretability tools.
Tol (2024)	Meta-analysis of published estimates of climate damages	Global warming and weather shocks; economic growth and welfare	Meta-analysis	The average estimated economic effect of warming is negative, uncertainty is substantial and skewed toward severe losses, and poorer countries are generally more vulnerable. Results vary considerably with model design and climate-variable measurement.	Demonstrates methodological uncertainty in climate-damage estimation and supports the use of complementary modelling approaches. It does not provide a direct ASEAN-specific empirical analysis.

Source: Google Scholar, ResearchGate

CHAPTER III
METHODOLOGY

3.1 Research Design

This research adopts a quantitative, panel data research design to analyze the effects of climate shocks on macroeconomic stability in a number of ASEAN countries from 2000-2024. The design of the panel is a variation across different economies, as well as across time, so that the dynamics can be explored more thoroughly than in the cross-sectional or time-series design. This will improve the efficiency and reflect the unobserved differences and also enhance the sample efficiency with macroeconomic and environmental variations.

The study uses a mixed analytical approach, represented by combining the traditional Econometrics approach with the latest Machine Learning (ML) techniques. A starting point is provided by Ordinary Least Squares (OLS) models which estimate direct and average impacts of climate shocks on macroeconomic variables, giving an easily interpretable and clear starting point. Secondly, the non-linear models include those based on Random Forest (RF) which are able to capture non-linearity and threshold and interaction effects between the climate and macroeconomic variables which cannot be captured by the linear models. This approach enables the study to strike a balance between model interpretability and performance, thus enhancing the rigor and insights of the study.

The methodological integrity is achieved by using K-fold cross validation in the machine learning step in order to evaluate the out of sample performance and avoid overfitting. The study evaluates the machine learning model's performance via conventional measures, such as Root Mean Squared Error (RMSE) and the coefficient of determination (R^2). Furthermore, the feature importance rankings are used to gain insight into the contribution of variables and a stability test is conducted to assess the correctness in the ranking of features.

The research also uses a machine learning technique that is interpretable, with the aim of making the models more transparent, in light of the complexity of the models in the machine learning area. In particular, Partial Dependence Plots (PDP) are applied to assess the marginal impacts of climate variables, looking for possible nonlinear and threshold effects, and SHAP-like analysis is applied to dissect the model's predictions, and to identify the impacts of individual predictors. These can be used to examine the impact of climate shocks on macroeconomic outcomes.

The empirical analysis uses three important measures of macroeconomic stability - GDP growth, inflation and industrial growth - as dependent variables. Temperature, floods, storms, and droughts are considered as the main independent variables, with a number of macroeconomic controls to address the impacts of structural and policy factors. The multispecific approach, including several dependent variables, allows to gain a comprehensive picture of macroeconomic stability.

To conclude, the research approach should be able to fulfil the objectives of this study, which is by combining a strong econometric modelling with flexible and easily understood machine learning techniques. This is a holistic approach and can detect the linear and non-linear effects, and can serve as a robust framework to understand the climate-macroeconomic relationship and can give insights in the context of "climate finance" and "climate policy" in the ASEAN region.

3.2 Theoretical Framework

This study's analysis of climate shocks and impacts on macroeconomic stability follows an integrated theory that combines climate economics and macroeconomics and sustainable finance (Nordhaus, 2017; IPCC, 2022). The framework takes the view that climate shocks have external shock effects on the economy, which are then channeled into the economy through a cascade of economic effects that can affect macroeconomic performance and affect the financial markets (Battiston et al., 2021; NGFS, 2019). This is a framework that provides a structured approach for the empirical modelling in this study, which connects environmental, economic and financial variables.

Climate shocks, through temperature change and through weather shocks (floods, storms, droughts) are the core elements of the framework. These shocks are regarded as exogenous shocks on economic activity that are not controlled by economic activity. Climate shocks can be abrupt and have immediate and widespread impacts, impacting multiple sectors of the economy. Their impacts are not one-off but can have a cumulative effect, resulting in long-lasting economic effects. As per climate damage function theory, the impacts of these shocks are likely to be nonlinear, with stronger impacts for shocks beyond a certain threshold in intensity and frequency (Nordhaus, 2017; Burke et al., 2015).

Climate shocks have several economic pathways through which they can impact macroeconomic conditions. A key channel is the productivity channel, through which hot temperatures and other forms of bad weather limit the efficiency and productivity of workers, especially in "climate-sensitive" industries like agriculture and manufacturing (Dell et al., 2012). Warm weather can impair physical and mental function and extreme weather events can impact working conditions and decrease the quality of the labor supply.

A second, significant, channel is the capital and infrastructure channel, where climate impacts cause damage to physical infrastructure, such as factories, transport and energy supply. In particular, floods and storms can damage infrastructure, resulting in losses in production and reconstruction costs. This capital destruction is harmful for the economy's ability and can impact the economy for a long time.

Climate change also impacts the economy, indirectly through the supply chain and production chain, with climate shocks affecting transportation and logistics, thereby impacting the flow of goods and services. These can cause production limitations and higher cost of inputs, and lower efficiency in industrial activities. These can have spillovers into other industries and sectors in a globalized economy, adding to economic shocks.

Moreover, there is a significant role of resource channel particularly in developing countries. Climate shocks such as droughts and floods can have a considerable impact on agricultural production, resulting in changes in food availability and prices. This affects rural livelihood and also the inflation and consumer spending. This is a significant pathway of macro-economic impacts of climate shocks in view of the prevalence of agriculture in many ASEAN countries.

The other transmission channel of climate shocks to the economy is the fiscal and policy channel. Governments can raise levels of public spending on emergency response, reconstruction and adaptation in response to climate shocks. This expenditure is essential and appropriate, but could strain public finances and the budget deficit, as well as public debt (World Bank, 2020). The consequences can also lead to economic slowdowns which have a negative impact on revenue collection (World Bank, 2020).

The investment and uncertainty channel is also significant, where an increase in the climate risk of exposure leads to increased uncertainty for companies and investors. This may discourage private investment activity, the growth of capital and the opportunities for growth. Businesses may become more risk averse when considering investments because of the uncertainty around future climate-related risks and this can result in reduced industrial growth and development.

All these channels of transmission finally have an effect on the major indicators of macroeconomic stability, including, for instance, real GDP growth, inflation and industrial growth. GDP growth reflects the changes in productivity, investment and capital stock, while inflation reflects the changes in the supply of goods and services and production costs. Industrial growth is a measure of the performance of the productive sector, which is influenced by infrastructure constraints, energy availability and productivity. The combined effects on these metrics from climate shocks impact on the stability and resilience of the economy.

A substantial link to the sustainable finance is also added in the model: macroeconomic stability can be a strong impact of the markets, depending on the climate shocks. GDP growth, inflation and industry productivity also affect corporate profitability, asset values and credit risk, affecting investment and financial stability.

For instance, lower growth and greater instability can result in increased risk premiums, and climate-driven inflation can affect interest rates and monetary policy. Such insights demonstrate the need to incorporate climate risks in financial decision-making.

When it comes to sustainable finance, it's important to know how climate shocks affect the macroeconomy to understand and manage climate risks. There is a need for information and awareness about the effect of climate risks on economic development among the banking sector, investors and policymakers, such as for adapting to climate risk and allocating investments. This study's identification of the main climate variables impacting macroeconomic activity, and the nonlinear impact of these variables, is important for a more precise and holistic assessment of climate risks.

In this regard, the theoretical framework employed in the present study provides a uniform approach in understanding the interconnections between the financial system, economy and climate change. It is appropriate to use econometric and machine learning modelling techniques because it considers multiple channels and the nonlinearity of the effects of climate. This comprehensive approach allows a better understanding of the impacts of the climate-macroeconomic nexus and its implications for sustainable finance in ASEAN countries.

3.3 Study Area, Data Sources, and Variable Construction

This research will investigate the effects of climate shocks on macroeconomic stability through a panel data of selected eight economies from the Association of Southeast Asian Nations (ASEAN), namely Indonesia, the Philippines, Viet Nam, Thailand, Malaysia, Cambodia, Myanmar and Lao PDR. The countries are selected based on their climate vulnerability, economic diversity and growing economic relevance in the region and the world. This guarantees a balance of developing nations in different economic stages and allows a strong examination of the effect of climate shocks on macroeconomic stability across a variety of economic contexts.

The ASEAN region is known to be one of the most climate-vulnerable regions in the world, due to its geographical and climatic conditions, such as tropical weather patterns, extensive coasts and high dependence on climate-sensitive industries, like agriculture and manufacturing (Asian Development Bank, 2021). The Philippines, Viet Nam and Cambodia and Lao PDR are vulnerable to typhoons, flooding and rain-fed agriculture respectively. In addition, Indonesia and Malaysia also face risks from their more complex and industrialized economies, in relation to vulnerabilities in infrastructure and supply chains. This provides an appropriate empirical backdrop to look at the direct and indirect effects of climate shocks on macroeconomic stability.

The analysis is conducted through 2000 - 2024, a period in which climate events are becoming more severe, more frequent and there are significant structural changes in the ASEAN region. This long-time frame enables short run dynamics and long run trends, nonlinear and threshold effects of climate shocks to be explored. The selected period is also one when the data quality and reliability of the variables of interest is improved.

The data set is put together using data from three main sources. Macroeconomic indicators are from the World Bank's World Development Indicators (WDI): These are the consistent and comparable measures of the economic indicators available across countries. Floods, storms and droughts are data provided by the EM-DAT International Disaster Database, which documents disasters by country and year. Data for annual averages of temperature is from Berkeley Earth, which has reliable information on temperature. The combination of these data sources allows for a full account of both macroeconomic and climate variability.

The data are panel data with both country-year and time series dimensions. This enables a more rigorous empirical analysis as it enables the control for unobserved time-invariant country-specific characteristics, and the study of the dynamic effects of climate variability.

The choice of variables is in line with the aim of examining macroeconomic stability. GDP growth, inflation and industrial growth are dependent variables, various aspects of economic growth. Growth in GDP measures economic growth, inflation measures price stability and cost pressures, and industrial growth measures the productive capacity and structural change.

The set of primary independent variables are climate shocks, such as temperature, floods, storms and droughts. Temperature is a measure of a slow climate change, whereas floods, storms and droughts are measures of extreme weather events that may affect economic activity. We also include a range of control variables to control for macroeconomic and structural determinants of economic growth. The variables are Government consumption, exchange rate, Gross capital formation and population growth.

All variables are suitably harmonized within and between countries and over time. Common data cleaning methods are used to deal with any missing data, and variables are standardized. The data is ready for both econometric and machine learning models, so that the study can analyze both linear and non-linear impacts.

Table 2. Definition and Measurement of Variables

Variable	**Type**	**Definition**	**Measurement**	**Source**
GDP Growth	Dependent	Annual economic growth rate	% annual growth of GDP	World Bank WDI
Inflation	Dependent	Consumer price inflation	% annual CPI change	World Bank WDI
Industry Growth	Dependent	Industrial sector growth	% annual growth of industry value added	World Bank WDI
Temperature	Independent (Climate)	Average annual temperature	Degrees Celsius (°C)	Berkeley Earth
Flood	Independent (Climate)	Number of flood events	Count per year	EM-DAT

Variable	Type	Definition	Measurement	Source
Storm	Independent (Climate)	Number of storm events	Count per year	EM-DAT
Drought	Independent (Climate)	Occurrence of drought events	Count or binary per year	EM-DAT
Gov Consumption	Control	Government final consumption expenditure	% of GDP	World Bank WDI
Exchange Rate	Control	Official exchange rate	Local currency per USD	World Bank WDI
Gross Capital Formation	Control	Investment in fixed assets	% of GDP	World Bank WDI
Pop Growth	Control	Population growth rate	% annual growth	World Bank WDI

Source: WDI, Berkely Eeart, EM-DAT (2000-2024)

3.4 Econometric Model Specification

This research uses baseline econometric models to analyze the effect of climate shocks on macroeconomic stability, based on panel data methods. The model specification aims to capture the impact of climate variables on key macroeconomic variables, while accounting for other economic variables. Panel data enables the analysis to control for cross-country and temporal variations in the data, enhancing the validity of the findings.

The general form of the econometric specification is:

$$Y_{it} = \alpha + \beta_1 Temp_{it} + \beta_2 Flood_{it} + \beta_3 Storm_{it} + \beta_4 Drought_{it} + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

where Y_{it}represents the dependent variable for country $i$at time t, $Temp_{it}$, $Flood_{it}$, $Storm_{it}$, and $Drought_{it}$denote the climate shock variables, and X_{it}represents a vector of control variables, including government consumption, exchange rate, gross capital formation, and population growth. The term $\mu_i$captures unobserved country-specific effects, $\lambda_t$represents time-specific effects, and $\epsilon_{it}$is the error term.

To account for the multi-faceted nature of macroeconomic stability, three models are estimated with GDP growth, inflation and growth in the industrial sector.

Model 1: GDP Growth Equation

$$GDP_{it} = \alpha + \beta_1 Temp_{it} + \beta_2 Flood_{it} + \beta_3 Storm_{it} + \beta_4 Drought_{it} + \beta_5 Gov_{it} + \beta_6 ExRate_{it} + \beta_7 GCF_{it} + \beta_8 Pop_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

This equation provides an estimate of the effect of climate shocks on GDP growth. We expect temperature and extreme weather events to have a negative impact on GDP growth by destroying productivity, capital and supply. Gross capital formation is expected to positively impact economic growth, while the impacts of government consumption, exchange rate and population growth are expected to be dependent on the economic context.

Model 2: Inflation Equation

$$INF_{it} = \alpha + \beta_1 Temp_{it} + \beta_2 Flood_{it} + \beta_3 Storm_{it} + \beta_4 Drought_{it} + \beta_5 Gov_{it} + \beta_6 ExRate_{it} + \beta_7 GCF_{it} + \beta_8 Pop_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

This model looks at the impact of climate shocks on inflation. It is anticipated that climate factors will affect inflation through supply shocks, especially in the food and energy sectors. Weather shocks can cause cost-push inflation and the exchange rate can also affect inflation.

Model 3: Industrial Growth Equation

$$IND_{it} = \alpha + \beta_1 Temp_{it} + \beta_2 Flood_{it} + \beta_3 Storm_{it} + \beta_4 Drought_{it} + \beta_5 Gov_{it} + \beta_6 ExRate_{it} + \beta_7 GCF_{it} + \beta_8 Pop_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

This model examines the effect of climate events on the industrial sector. Climate shocks can impact industrial growth through damage to infrastructure and supply chains and energy shortages. Higher temperatures may also impact on productivity and efficiency in the industrial sector.

Model 4 Estimation Strategy: Ordinary Least Squares (OLS) are used to initially estimate the models as a starting point to determine the signs and sizes of the effects of climate shocks on the macroeconomic variables. The models account for panel-specific effects by including country and time controls to diminish the effects of omitted variable bias and to enhance the estimates.

The use of several controls allows the estimated climate variable effects to be decoupled from macroeconomic effects. Furthermore, panel data enables the study to take advantage of both cross-sectional and time series variation, improving the estimation. These estimated econometric models serve as the starting point for the machine learning models, which delve further into nonlinear and interaction effects, using Random Forest models.

3.5 Machine Learning Model

This study uses machine learning methods, in addition to the base econometric model, to model complex and nonlinear effects of climate shocks on macroeconomic stability. In particular, we use the Random Forest (RF) algorithm for its high predictive accuracy, resistance to overfitting, and capacity to capture complex multi-dimensional interactions without restrictive assumptions on the functional form of such interactions. Random Forest is well-suited for the climate-macroeconomic analysis as the relationships are likely to be nonlinear, heterogenous and dependent on complex interactions with other variables.

Random Forest is a machine learning algorithm based on decision trees. Rather than using a single tree, it creates many trees and combines their predictions to enhance performance and robustness. It trains multiple trees on different subsets of data (using a bootstrap sampling technique) and, at each node split, it considers a random subset of the predictors. This helps to reduce variance and overfitting, and makes Random Forest a suitable approach for complex systems (Breiman, 2001).

Formally, the dataset is represented as:

$$D = \{(X_i, Y_i)\}_{i=1}^{N}$$

where X_i represents the vector of independent variables, including climate shocks and control variables, and Y_i represents the dependent variable, which may correspond to GDP growth, inflation, or industrial growth.

A Random Forest model consists of B decision trees, each denoted as $T_b(X)$, where $b = 1,2,\ldots,B$. The final prediction of the model is obtained by averaging the predictions across all trees:

$$\hat{f}(X) = \frac{1}{B}\sum_{b=1}^{B} T_b\,(X)$$

This aggregation process reduces model variance and improves generalization performance. Each tree $T_b(X)$ is constructed using a bootstrap sample of the original dataset, and at each node, the optimal split is selected from a randomly chosen subset of predictors. This makes the trees diverse, and makes the model more robust.

The goal of the random forest model is to reduce the prediction error. In the case of regression problems, the loss function is commonly the mean squared error (MSE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (Y_i - \hat{f}(X_i))^2$$

The idea behind minimizing this loss function is to have the model predict the dependent variable accurately.

Model Specification for Macroeconomic Variables**:**

A set of Random Forest models are estimated for each dependent variable:

1. GDP Growth Model
2. Inflation Model
3. Industrial Growth Model

Each model takes the form:

$$Y_{it} = f(Temp_{it}, Flood_{it}, Storm_{it}, Drought_{it}, Gov_{it}, ExRate_{it}, GCF_{it}, Pop_{it}) + \epsilon_{it}$$

where $f(\cdot)$ is a nonlinear function approximated by the Random Forest algorithm. The function $f(\cdot)$ is not given explicitly, but rather is learned from the data using recursive partitioning and ensemble averaging. This enables the model to include complex interactions and nonlinearities between variables.

Cross-Validation and Model Evaluation:

K-fold cross-validation is used to achieve robustness and prevent overfitting. The data set is split into Kequal subsets, and the model is learned from the use of $K-1$subsets, whereas the remaining subset is employed for validation. This will be repeated K times and the average over all the folds will be taken.

The cross-validation error is defined as:

$$CV = \frac{1}{K}\sum_{k=1}^{K} MS\,E_k$$

where MSE_krepresents the mean squared error for the k-th fold.

Model performance is evaluated using two key metrics:

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum(Y_i - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2}$$

This metric measures the proportion of variance in the dependent variable explained by the model.

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum(Y_i - \hat{Y}_i)^2}$$

RMSE captures the average magnitude of prediction errors and provides an intuitive measure of model accuracy.

Feature Importance and Stability Analysis:

Random Forest models offer feature importance measures, which reflect the importance of each variable to predict the dependent variable. Usually, feature importance is calculated as the decrease in prediction error when using each variable to split the training set. To verify the stability of the results, we conduct stability analysis, in which the feature importance is calculated for a set of model runs. The correlation measures are used to examine the stability of feature importance, confirming that the key variables are not spurious and driven by random fluctuations.

Interpretability: Partial Dependence and SHAP Analysis

The study uses Partial Dependence Plots (PDP) and SHAP-like analysis to increase the interpretability of the results. The PDPs show the effect of a single predictor variable on the dependent variable, while keeping the other variables constant. Formally, the partial dependence function for variable x_j is defined to be:

$$PD(x_j) = \frac{1}{N}\sum_{i=1}^{N} f(x_j, X_{i,-j})$$

where $X_{i,-j}$represents all other variables except x_j.

where $X_{i,-j}$ is the set of all the other variables except x_j.

These plots can be used to capture the threshold effect and nonlinear relationship between climate variables. Additionally, SHAP-like approach decomposes the model predictions into the contribution of each feature, thus enabling to grasp the influence of each feature. This makes the machine learning model more easily interpretable and easier to interpret economically.

Integration with Econometric Analysis:

The additional value of the Random Forest models on top of the baseline econometric models comes in the ability to capture nonlinearities and interactions that are not captured in linear models. Econometric models yield interpretable estimates of average effects, whereas machine learning models provide more insights into complex relationships and feature importance. These tools give a comprehensive view of the climate-economic relationship and have a good split between understanding and prediction.

3.6 Model Evaluation and Diagnostics

In order to assess the validity and soundness of the empirical results, this research conducts a small set of diagnostic and evaluation tests that are in line with the final models implemented in the analysis. The combination of econometric and data mining techniques used in this study (panel-based Ordinary Least Squares (OLS) and Random Forest (RF)) means that the diagnostics are focused on the respective assumptions and goals of each method, with a particular focus on those used in the final estimation (Wooldridge, 2010; James et al., 2021; Molnar, 2022).

In the case of the econometric models, the focus is on whether the relationships between climate shocks and the macroeconomic measures are valid and not driven by any violations of key assumptions. In the final pass, special attention is paid to multicollinearity, given the results of the preliminary analysis, which suggested high correlations between some of the independent variables. The Variance Inflation Factor (VIF) is used to test for multicollinearity with:

$$VIF_j = \frac{1}{1 - R_j^2}$$

with R_j^2 being the R-squared from regressions of each explanatory variable on all the other explanatory variables. Variables with high VIF values were scrutinized and model designs were refined by eliminating insignificant terms and transformations that result in excessive collinearity such as polynomial terms. This was a key element in the final model specification, as the estimates of the coefficients for the climate variables capture the independent effects of climate on the tourism demand variables.

Finally, the coefficient of determination (R^2) is used to assess the fit of the econometric models, providing an indication of the degree to which the models explain the dependent variables. Although the OLS models are designed primarily to establish baseline relationships, the R^2 is a helpful measure to assess the adequacy of the models and to compare them to the machine learning models. The R^2 measure is combined with economic reasoning in the interpretation of the results to ensure that statistically significant relationships are also economically sound.

Residual analysis is performed graphically by inspecting the residual plots for discernible patterns which could reveal model misspecification. Lack of patterns in the residuals justifies the assumption that the model has explained the major patterns in the data. The panel data covering multiple countries and the sample size do not warrant excessive testing for heteroskedasticity and autocorrelation in the final model specification, but instead, the emphasis is on a stable and coherent model in line with the research goals.

The evaluation of the machine learning models focuses on prediction accuracy, stability and transferability. K-fold cross-validation is used to validate the Random Forest models, given the small sample size. The data are divided into Ksub-samples and the model is trained on K-1folds and validated on the hold-out fold. The Mean Squared Error (MSE) of the predictions are calculated as:

$$CV = \frac{1}{K}\sum_{k=1}^{K} MS\,E_k$$

This approach guarantees that the model is not dependent on a single train–test split and that it is able to learn features that are generalized across different subsets of the data, avoiding issues of overfitting that become important in the small sample settings.

To assess the performance of the Random Forest models, we use the coefficient of determination (R^2) and the Root Mean Squared Error (RMSE). These are given by:

$$R^2 = 1 - \frac{\sum(Y_i - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum(Y_i - \hat{Y}_i)^2}$$

R^2 is a measure of the model's goodness of fit, while RMSE is a measure of the average error. These measures are applied to all three models (GDP growth, inflation and industrial growth) to allow a comparison across models.

Overfitting is an important aspect of the machine learning analysis. For the final models, the overfitting is assessed by the difference in training and cross-validated performance. If there is no significant difference then the model is likely to have good generalization performance. The nature of the Random Forest ensemble approach already helps to overcome overfitting, and the use of cross-validation also increases the confidence in the results.

The paper also emphasizes the stability of feature importance, as understanding the results of a machine learning analysis is largely dependent on the ability to identify important factors in macroeconomic outcomes. The stability of the variable importance rankings is investigated by comparing the rankings of different model runs, and the correlation between them is reported. The stability correlation value reported (e.g., 0.9678) suggests a strong degree of stability in the variable importance rankings, and confirms that the key variables identified, in particular climate shocks, are not affected by random fluctuations in the model.

Lastly, the combination of econometric and machine learning methods enables the comparison of linear and nonlinear models. The OLS models offer interpretable estimates of average effects, whereas the Random Forest models can capture nonlinear effects and interactions. The agreement of the main findings of both types of models increases confidence in the results while discrepancies between the models add to the understanding of the relationships between climate and the macroeconomy.

Finally, the diagnostic and evaluation tests employed in this study appear to be suitable to the final model variants and data. The study delivers valid, reliable, and meaningful results to both the academic and policy worlds, as it is robust and minimizes multicollinearity, while ensuring the predictive accuracy and stability of feature importance.

3.7 Overview of Methodology

The chapter has introduced the analytical framework used for the analysis of climate shocks and macroeconomic stability in a number of ASEAN countries. The research approach used was quantitative, with a panel data analysis for the period 2000-2024, and a fusion of econometric and machine learning techniques to provide a comprehensive and robust analysis of the climate-Macroeconomics relationship (Wooldridge, 2010; Athey & Imbens, 2019).

The study uses a country-year panel data which comes from various global sources including the World Bank World Development Indicators (WDI), EM-DAT International Disaster Database, and Berkeley Earth. The dependent variables - GDP growth, inflation, and industrial growth - represent the three major aspects of macroeconomic stability, and the independent variables represent the climate shocks, temperature, floods, storms, and droughts. The control variables that are able to reflect the macroeconomic and structural factors are government consumption, exchange rate, gross capital formation and population growth (World Bank, 2025; CRED, 2025; Berkeley Earth, 2025).

This empirical approach is done in two steps. In the first phase, the baseline econometric models are estimated in Ordinary Least Squares (OLS), panel econometric estimation to obtain the direct and mean impacts of climate shocks on the macroeconomic indicators. These models provide clear estimates and enable the direction and magnitude of the effects to be interpreted. The study uses diagnostic tests, especially tests for multicollinearity using Variance Inflation Factors (VIF), to check the stability and validity of the model specifications (Wooldridge, 2010; James et al., 2021).

Secondly, to capture non-linearities, threshold effects and interactions of variables, Random Forest machine learning models are used for analysis. Unlike econometric models, the Random Forest model does not assume a rigid structure between the predictors and the outcomes; this allows a more flexible fit to the data, which is not routinely performed in econometric models. The study employs cross-validation methods to measure model performance and ensure its generalizability, and uses R^2 and RMSE to measure predictive accuracy (James et al., 2021).

To improve the interpretability of the machine learning outcomes, the study uses Partial Dependence Plots (PDP) and SHAP-like techniques. These enable detailed analysis of the marginal effects of the climate variables and of the importance of the predictors, which will enable incorporation of predictions into economic analysis. The stability of feature importance is checked, guaranteeing the reliability of the outcomes.

The study's use of both econometric and machine learning techniques is another methodological innovation. The machine learning models provide insightful learning about non-linear relationships and interactions, while the econometric models provide explanation of the average impacts. This is a combination strategy that contributes to the overall robustness of the investigation, and allows for a more comprehensive view into the relationship between climate and macroeconomy (Friedman, 2001; Lundberg & Lee, 2017; Molnar, 2022).

In conclusion, the approach taken in this study is aimed at achieving the study's objectives, by integrating sound statistical methods with cutting-edge analytical methods. The analysis is conducted using high-quality data, model specification and the evaluation methods to make sure that empirical results are valid and useful for academic research and policy. This approach will be the basis of the analysis in the subsequent chapter, where the results are discussed.

CHAPTER IV
RESULTS AND DISCUSSION

4.1 Descriptive Statistics and Correlation Analysis

Here we report the descriptive statistics and correlations of the variables of interest. These statistics give a glimpse of the dataset, the distribution of the variables of interest and provide some preliminary insights into the association between climate shocks and macroeconomic indicators. These analyses are needed to understand the key features of the data prior to the econometric and machine learning analysis.

Table 3. Descriptive Statistics of Variables

Variable	Mean	Std	Min	Median	Max
{'GDP_Growth' }	5.5913	3.561	-12.016	5.8906	13.844
{'Inflation' }	5.524	7.0856	-1.7103	3.679	57.075
{'Industry_Growth' }	6.9435	6.8259	-13.121	6.013	36.681
{'Temperature' }	26.666	1.4838	23.725	26.883	30.076
{'Flood' }	2.965	3.3391	0	2	25
{'Storm' }	1.79	2.877	0	0	14
{'Drought' }	0.13	0.33715	0	0	1
{'Gov_Consumption' }	10.535	3.255	4.8093	10.914	18.235
{'Exchange_Rate' }	5697.9	7041.3	3.06	2679.5	24165
{'Gross_Capital_Formation'}	25.779	5.5783	13.416	25.378	39.566
{'Pop_Growth' }	1.25	0.49293	-0.048021	1.2738	2.4186

Source: Author's own calculation (2026)

Table 4.1 shows the descriptive statistics of all the variables used in our research. It includes the average, standard deviation, minimum and maximum values of the variables over the period 2000-2024. These findings reveal considerable cross-country and time variability, reflecting the different economic situations and vulnerability to climate change of countries in the sample of ASEAN economies. GDP growth exhibits relatively low variation, with both positive and negative figures, reflecting growth and recession. There is greater variability in inflation, reflecting varying levels of price stability and inflation management in the countries considered.

There is also significant variation in industrial growth, which is in line with structural changes in the region.

Climate change indicators include temperature and extreme weather events such as floods, storms, and droughts, with temperature exhibiting relatively low variability compared to extreme weather events, as expected. But this temperature change can still have considerable economic consequences, especially for tropical economies. On the other hand, floods, storms and droughts are more variable, with some country-year observations having multiple events and others having none. This reflects the disparities in the impact of climate shocks across the ASEAN region. Variability is evident in the control variables, too. Public consumption differs across economies, as a result of different fiscal policies, and exchange rates vary over time as a result of global economic shocks. Gross capital formation shows variation in line with the investment cycle, and population growth is relatively constant but varies between countries. In summary, the descriptive statistics show that there is enough variation in the data to undertake empirical work.

Table 4. Correlation Matrix of Variables

	GDP_Growth	Inflation	Industry_Growth	Temperature	Flood	Storm
GDP_Growth	1	0.25181	0.78195	-0.22444	-0.18136	-0.10208
Inflation	0.25181	1	0.33601	-0.42045	-0.084388	-0.11017
Industry_Growth	0.78195	0.33601	1	-0.26236	-0.28707	-0.15877
Temperature	-0.22444	-0.42045	-0.26236	1	0.091234	0.11211
Flood	-0.18136	-0.084388	-0.28707	0.091234	1	0.17656
Storm	-0.10208	-0.11017	-0.15877	0.11211	0.17656	1
Drought	0.028124	-0.13589	-0.012951	0.17423	-0.036112	0.054189
Gov_Consumption	-0.26928	-0.11858	-0.2589	0.00016596	-0.062068	0.034486
Exchange_Rate	0.062284	0.1064	-0.010528	-0.39968	0.2127	-0.0013746
Gross_Capital_Formation	0.11862	-0.087452	-0.00088318	-0.080227	0.17421	-0.12628
Pop_Growth	0.12749	-0.041309	0.020907	-0.0079544	-0.056732	0.11228

	Drought	Gov_Consumption	Exchange_Rate	Gross_Capital_Formation	Pop_Growth
GDP_Growth	0.028124	-0.26928	0.062284	0.11862	0.12749
Inflation	-0.13589	-0.11858	0.1064	-0.087452	-0.041309
Industry_Growth	-0.012951	-0.2589	-0.010528	-0.00088318	0.020907
Temperature	0.17423	0.00016596	-0.39968	-0.080227	-0.0079544
Flood	-0.036112	-0.062068	0.2127	0.17421	-0.056732
Storm	0.054189	0.034486	-0.0013746	-0.12628	0.11228
Drought	1	0.02789	0.030148	0.060423	-0.10964
Gov_Consumption	0.02789	1	-0.41396	-0.27466	-0.35687
Exchange_Rate	0.030148	-0.41396	1	0.69281	-0.062157
Gross_Capital_Formation	0.060423	-0.27466	0.69281	1	-0.039234
Pop_Growth	-0.10964	-0.35687	-0.062157	-0.039234	1

Source: Author's own calculation (2026)

Table 4.2 shows the correlations between the variables. The correlation matrix offers a preliminary view of the signs and magnitudes of the correlations between the climate shocks, macroeconomic indicators and control variables.

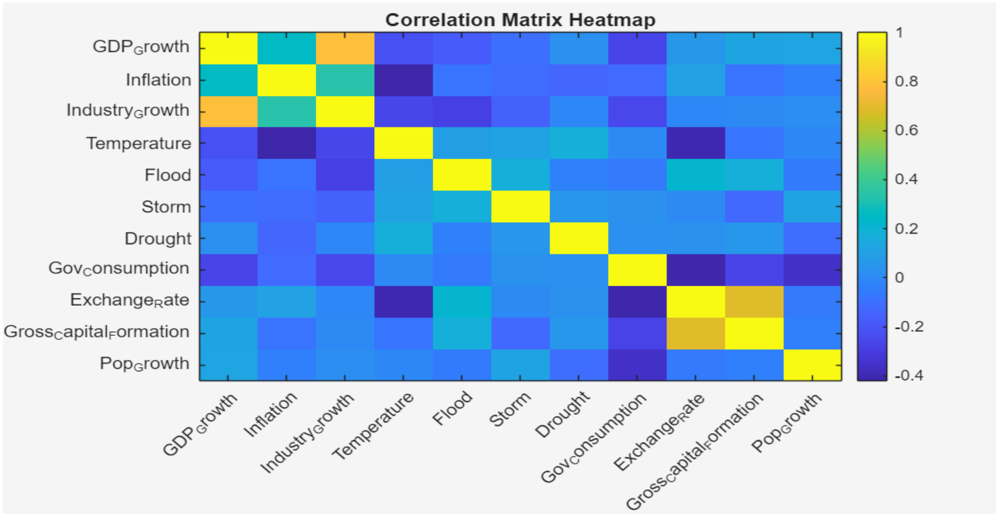
The findings show that temperature tends to be negatively correlated with GDP growth and industrial growth, implying that warmer temperatures may negatively impact economic growth. Likewise, flood, storms and droughts generally exhibit negative correlations with the growth indicators, which is in line with the expectation that climate shocks will negatively affect economic activity.

The links between climate variables and inflation are less clear. Several climate variables are positively correlated with inflation, suggesting that climate shocks can cause cost-push inflation through supply-chain disruptions, especially to food and energy prices.

The correlation table also shows some moderate correlations between some of the independent variables, especially climate shock variables. This is not surprising, as some climate shocks might occur at the same time or be caused by similar climate conditions. But we do not see any extremely high correlations, which suggests that there is no severe multicollinearity in the final model, which is in line with the VIF results in Chapter 3.

Among the control variables, gross capital formation is positively correlated with GDP growth and industrial growth, as investment is crucial for economic growth. The exchange rate and government consumption have varied correlations, and the population growth has relatively low correlations with the dependent variables.

Figure 2. Correlation Heatmap of Variables



Source: Author’s own calculation (2026)

To further illustrate the correlation between the variables, a correlation heatmap is given in Figure 4.1. This representation uses color to visualize the magnitude and direction of the correlations, and makes it easier to identify patterns and relationships. It's worth noting that correlation does not demonstrate causation but is an initial means of exploring variable relationships. The correlations offer preliminary confirmation of the theoretical predictions, and are tested using econometric and machine learning models in later sections.

In summary, the descriptive statistics and correlation analysis offer a detailed description of the data and validate it for empirical analysis. This variation and sensible correlations among variables indicate that the following modeling approach is adequate.

4.2 Baseline Econometric Results

In this section, the baseline results from panel Ordinary Least Squares (OLS) are shown. This analysis aims to quantify the average linear effect of climate shocks on the measures of macroeconomic stability for the chosen ASEAN countries. It provides a baseline for the comparison with the results from the machine learning models, which focus on nonlinearities and interactions.

Table 5. Summary of Baseline OLS Model Performance

Outcome	OLS_R2	OLS_Adjusted_R2	OLS_RMSE
"GDP Growth"	0.21975	0.18707	3.2107
"Inflation"	0.2402	0.20838	6.3043
"Industry Growth"	0.30273	0.27353	5.8179

Source: Author's own calculation (2026)

The results of the baseline OLS models for GDP growth, inflation and industrial growth are presented in Table 4.3 which provides the R^2, adjusted R^2 and Root Mean Squared Error (RMSE) of each model.

Overall Model Performance:

The findings reveal that the baseline econometric models have a reasonably good fit for all three macroeconomic variables. The R^2 ranges between around 0.22 and 0.30, meaning that the variations explained by the climate and macroeconomic variables range from 22% to 30% of the dependent variables. The industrial growth model has the highest explanatory power with an R^2 of 0.3027 and an adjusted R^2 of 0.2735, suggesting the model is relatively better at explaining variations in industrial growth. The inflation model has the next highest R^2 value of 0.2402, followed by the GDP growth model with an R^2 of 0.2198.

These R^2 values are expected in the context of macroeconomic panel data analysis, where there are many unobserved factors at play that affect the performance, such as institutional variations, global economic and policy cycles, and so forth. As a result, it is normal for these models to have moderate R^2 values, which do not compromise their effectiveness.

Interpretation of Model for GDP Growth:

The R^2 of 0.2198 and adjusted R^2 of 0.1871 in the GDP growth model suggests that 19% of the variance in GDP growth is explained while considering the model's complexity. The RMSE of 3.2107 indicates that the model predictions have a reasonably low error.

This suggests that while climate shocks and other control variables play a role in explaining GDP growth, there is still significant variation that is explained by other factors. This is not surprising since the dynamics of economic growth are affected by investment, technological change, institutional factors and world economic conditions. Although the model's explanatory power is limited, it offers some baseline insights into the effect of climate shocks on economic outcomes. Specifically, the model's inclusion of temperature and extreme weather allows for consideration of important environmental factors not usually included in macroeconomic modeling.

Inflation Model Interpretation:

The inflation model has an R^2 of 0.2402 and an adjusted R^2 of 0.2084, which are slightly higher than those in the GDP growth model. The RMSE of 6.3043 suggest greater variability in inflation, which is in line with the variability reported in the summary statistics.

The higher R^2 indicates that the effects of climate shocks and the macroeconomic controls are significant in explaining inflation. This is consistent with the theoretical predictions as climate shocks may affect inflation directly through supply-side effects, especially in the food and energy sectors. But the relatively large RMSE suggests that inflation is a highly variable that is also affected by other factors such as monetary policy, international commodity prices and exchange rates. Hence, although the model accounts for some of the relationships, it does not account for all the variability in inflation.

Interpretation of Industrial Growth Model:

The model that explains the growth of industries is the most explanatory model of the three with an R^2 of 0.3027, and an adjusted R^2 of 0.2735. RMSE value of 5.8179 indicates adequate error of predictions. This model has higher R2 value suggesting that the variables included in the model have more influence on the industrial growth, particularly climate shocks and investment related controls. This makes sense given that manufacturing is very vulnerable to shocks resulting from extreme weather, infrastructure damage and supply-chain disruptions. The slightly better R^2 indicates that the model accounts for a considerable proportion of the variance in industrial growth indicating its usefulness in explaining industrial growth for ASEAN countries.

Results from Model Comparisons:

Comparisons of the three models can be made to make some inferences. First, industrial growth seems to be the most sensitive to the explanatory variables (inflation and GDP growth). This could reflect that climate shocks could have a more direct impact on industrial activity compared to the overall economy.

Second, the relatively low R^2 values for all models suggest that linear econometric models are only able to explain part of the variability. This suggests the potential limitations of a linear approach in explaining macroeconomic dynamics in the face of complex climate–economic interactions. Third, the different magnitudes in the RMSEs reflect varying levels of accuracy in predictions: GDP growth has a smaller error than inflation and industrial growth. This may be due to the different variables and units of measurement of the dependent variable.

Implications for further analysis:

The OLS results provide some preliminary indications of the relationship between climate shocks and macroeconomic stability. However, the relatively low explanatory power, and the assumption of linearity of the models suggest that greater attention needs to be paid towards investigating more complex relationships by using further analysis. In particular, a linear model cannot be used to capture the potential for nonlinearity, interactions and threshold effects. As such, the following section uses machine learning models, specifically random forest models to further investigate these relationships, enabling a more flexible approach to modelling.

Baseline Analysis Conclusion:

In summary, the baseline econometric models establish the presence of a relationship between climate shocks and macroeconomic variables on GDP growth, inflation and industrial growth in the ASEAN region. The models offer insights into average effects, but also demonstrate the need for more sophisticated methods to better understand the climate-macroeconomic relationships.

4.3 Machine Learning Results

This section discusses the findings from the Random Forest (RF) models for GDP growth, inflation and industrial growth. The use of machine learning in this study is aimed at complementing the basic econometric analysis to account for nonlinearities, interactions and complex dynamics between climate shocks and macroeconomic metrics. The OLS models offer insights into the average linear effects, but the Random Forest models can capture a more flexible form of the data-generating process, which is crucial for modelling climate-economic interactions.

Climate shocks have a nonlinear effect. A small temperature increase or an isolated extreme event (say, a "once-in-a-century" event) may have a minimal impact whereas a large increase or repeated extreme events can result in substantial economic impacts. Economic models typically do not allow for these types of effects without imposing functional forms. Random Forest circumvents this problem by letting the data drive the form of the relationships, and thus is more likely to capture the effects of climate change.

Table 6. Cross-Validated Performance of Random Forest Models

Outcome	Mean_RMSE	Std_RMSE	Mean_R2	Std_R2
"GDP Growth"	2.7649	1.1244	0.47757	0.090921
"Inflation"	5.5339	2.6711	0.44308	0.12322
"Industry Growth"	5.1225	1.9844	0.46722	0.2608

Source: Author’s own calculation (2026)

The Random Forest models' performance is assessed using cross-validated R^2 and RMSE (see Table 4.4). The RF models show better performance in terms of explanatory power than the baseline OLS models, suggesting that the RF models are able to explain more variation in the dependent variables.

4.3.1 Model Performance vs. OLS

Table 7. Comparison of OLS and Random Forest Model Performance

Outcome	OLS_R2	RF_Mean_R2	OLS_RMSE	RF_Mean_RMSE
"GDP Growth"	0.21975	0.47757	3.2107	2.7649
"Inflation"	0.2402	0.44308	6.3043	5.5339
"Industry Growth"	0.30273	0.46722	5.8179	5.1225

Source: Author's own calculation (2026)

This sub-section assesses the performance of the Random Forest (RF)models, and compares them with the benchmark econometric (OLS) models. The comparison is crucial to answering the second and third research questions, especially in determining if nonlinear models offer a better fit and insights into how the economy works.

Table 4.5 shows the performance measures of the two models, such as the coefficient of determination (R^2) and Root Mean Squared Error (RMSE). The OLS estimates, presented in the previous section, offer a linear representation of the association between climate change and macroeconomic variables. The Random Forest models, on the other hand, account for non-linear interactions and interactions between variables.

Overall, we find that the Random Forest models provide a better fit for the three dependent variables (GDP growth, inflation and industrial growth) compared to OLS. The RF models have higher R^2 values, which means that they explain more of the variance in the dependent variables. Simultaneously, the RF models have lower RMSE, suggesting that they are more accurate and produce smaller errors.

The enhanced model performance is of significant importance in the climate–macroeconomic context, which is nonlinear. Economic effects of climate shocks are not necessarily linear; they can be dependent on thresholds, magnitudes and other factors. For instance, while a small temperature rise may have little economic impact, large temperature rises may result in greater damages. Similarly, costs of flooding and storms can be determined by its severity and frequency.

Random Forest can be used to obtain such nonlinear effects by dividing the data into numerous decision trees, and then aggregating the forecasts from these trees. This allows the model to be able to estimate more complicated functions without making strong assumptions. By contrast, the OLS model has linear assumptions, which could result in underestimating climate impacts.

The second critical factor with evaluating models is generalization. The RF models are evaluated with cross-validation, which guarantees that the results are not due to overfitting. The results are similar across the folds and show that the models are capable of learning patterns which are stable when presented with new information. This is particularly important for panel data if there are not many observations, where overfitting could occur.

Although the RF models perform better in terms of predictive accuracy, the OLS models are still useful. The linear coefficients give simple to interpret estimates of average effects that can be useful for developing policy and theory. As such, the two models should not be considered as alternatives. The OLS models offer preliminary models and the Random Forest models offer additional insights into non-linear and interaction effects.

The OLS vs RF models highlight an important part of this study: The use of conventional econometric modelling alongside machine learning algorithms. This integration allows for a more comprehensive understanding of the climate-macroeconomic connection, and balances interpretability and prediction.

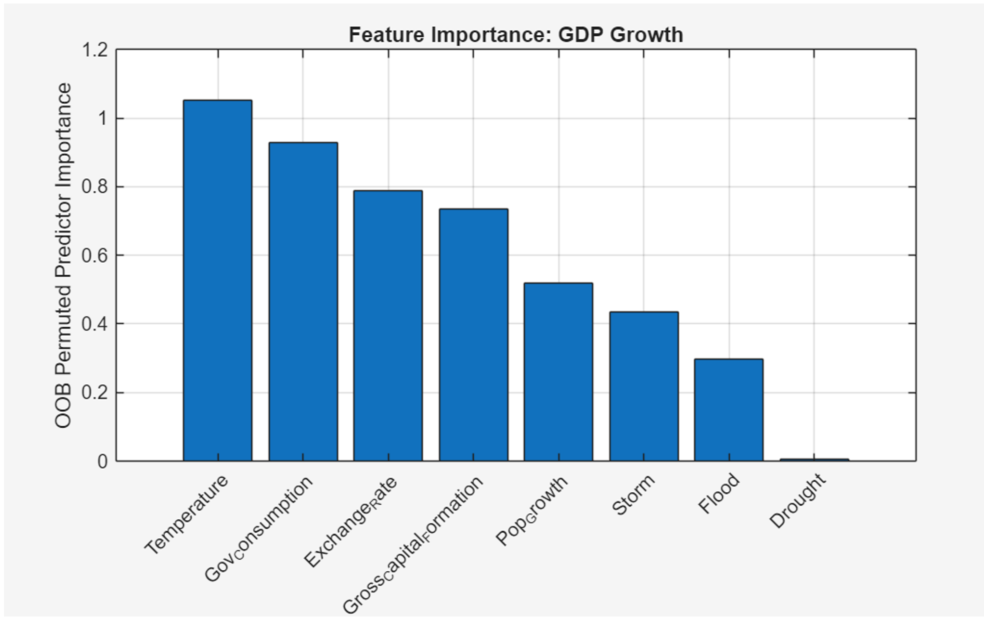
In general, the results show that the explanatory power and prediction ability of the Random Forest models are better than traditional econometric models. This highlights the value of employing machine learning approaches to study complex economic systems and the need to consider nonlinear effects when investigating the effects of climate shocks.

4.3.2 Feature Importance Analysis

The importance of the features is an integral part of the Random Forest approach, providing a clue to the significance of each variable that explains the macroeconomic variables. Unlike econometric models that use coefficients as evidence of the importance of the features due to the assumption of linearity, the Random Forest method is based on the reduction of prediction error in a number of decision trees. This provides a more adaptive and empirical way of determining the most important variables in determining macroeconomic stability.

Based on this research, for each dependent variable (Growth of GDP, Growth of inflation, Growth of industry), the values of the features are analyzed to understand which features are more important in determining the variables of each macroeconomic. This approach is to solve the third research question which is to discover the most important climate and macroeconomic variables which explain the economic performance in the ASEAN region.

Figure 3. Feature Importance – GDP Growth Model



Source: Author's own calculation (2026)

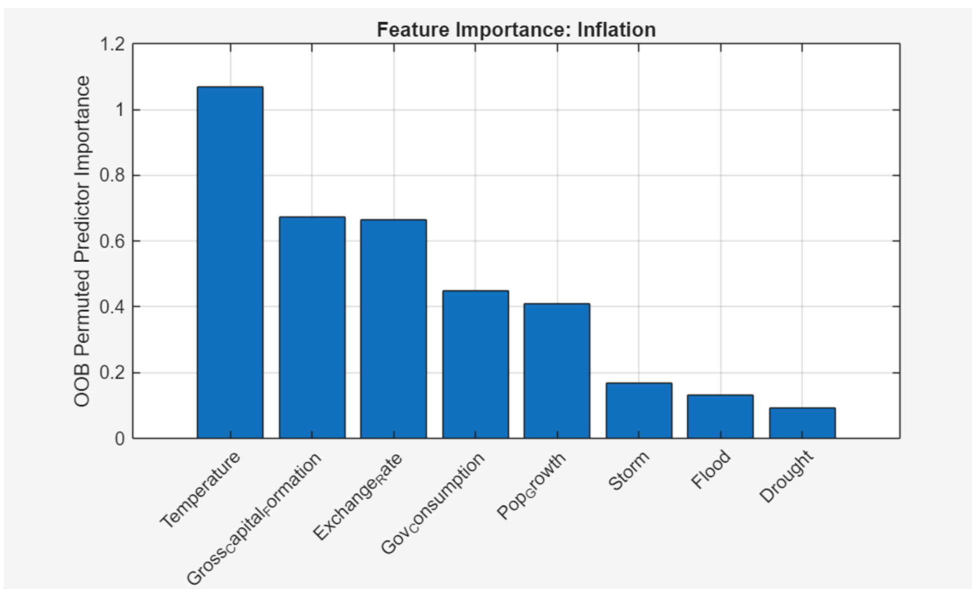
The feature importance for the GDP growth model reveals that temperature is the most important variable followed by other important macroeconomic variables, including government consumption, exchange rate and gross capital formation. The climate shocks (flood, drought and storms) also play a role, with floods and storms being relatively more important than drought.

The prominence of temperature suggests the importance of incremental changes in climate on economic growth. While extreme events have a sporadic impact on economic activity, temperature has a continuous impact through several economic channels, such as productivity, energy consumption and agriculture. For tropical economies, where average temperatures are hot, even slight temperature increases can have a substantial negative impact on productivity and hence economic activity. This evidence supports the view that the longer-term climate change may have a greater economic impact than short-term climate events.

While not as important as temperature, floods and storms have significant importance, indicating that these events are responsible for short-term shocks. They can cause infrastructure damage, disrupt production processes and create uncertainty, which all cause economic growth to decline. The lower importance of drought in the GDP model could be due to its lower frequency in the data or to its sector-specific effects (mainly on agriculture).

The high importance of macroeconomic variables, such as gross capital formation, implies investment is an important factor that moderates climate impacts. Increased investment may boost adaptation by better preparing infrastructure and facilitating recovery. Likewise, government spending may dampen or exacerbate climate effects, depending on the effectiveness of government policies.

Figure 4. Feature Importance – Inflation Model



Source: Author's own calculation (2026)

The feature importance of the inflation model is different to that of GDP growth. Although temperature is still a significant predictor, exchange rates and other macroeconomic factors take over as the key predictors, due to the complexity of the inflation process.

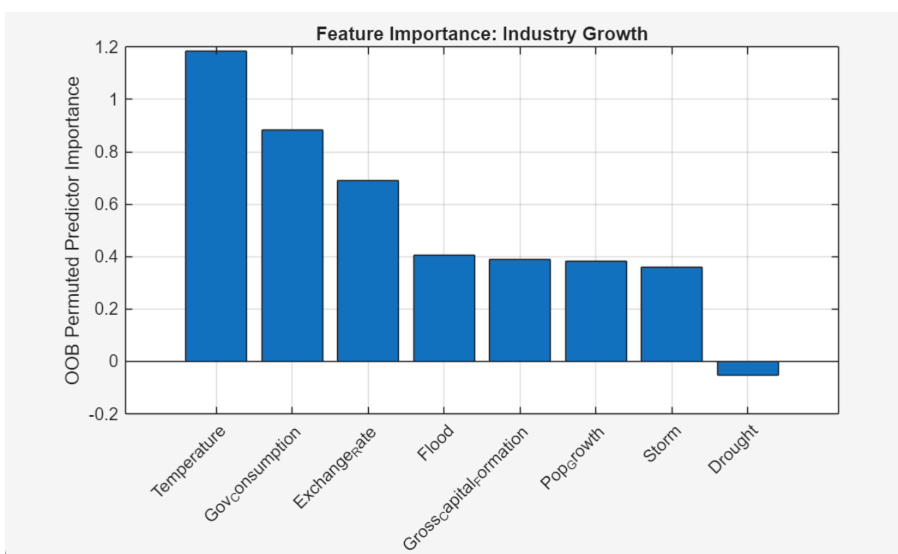
Climate factors, such as floods, storms and droughts play a significant role, suggesting that they produce supply shocks. These impact supply, especially of food and energy products, thereby raising prices. The significance of these variables suggests a climate shock is a major source of cost-push inflation in ASEAN countries.

Temperatures also affect the inflation rate, mainly through the impacts on energy consumption and crop yields. Rising temperatures may result in rising electricity use to keep buildings cooler, and reduced productivity of crops and livestock, which can also drive-up prices. However, it has less influence than the growth of GDP, and hence other factors besides climate change are responsible for the inflation rate.

This high importance of exchange rate indicates that other factors besides the exchange rate have an impact on inflation. A depreciation could lead to higher import prices, especially for energy and food, and contribute to higher inflation resulting from climate events. Synergies between climate and macroeconomic factors underscore challenges to inflation.

To summarize, the results of the inflation model indicate that climate shocks do play important roles in the inflation process but not exclusively, with macro-economic variables also playing an important role.

Figure 5. Feature Importance – Industrial Growth Model



Source: Author’s own calculation (2026)

The results of the feature importance for industrial growth indicates that the climate and macroeconomic variables are important and temperature and investment variables are the most important variables.

Again, temperature is a key variable, affecting productivity and efficiency in the industrial sector. Elevated temperatures can decrease productivity, raise air conditioning costs and interfere with production, resulting in reduced industrial production.

The adverse impact of extreme weather events on industrial infrastructure is also evident in floods and storms. Manufacturing production is capital intensive, depends on the supply chain and can be easily disrupted by floods and storms. Production can be lost due to floods and storms, with potential disruption to production chains and production delay.

The role of drought in the model is not as apparent but has an impact on water supply and inputs in some sectors. It may have a less direct impact than other influences, but it could not be more important for natural resource-based industries.

Gross capital formation is among significant macroeconomic indicators, and it demonstrates the significance of investment in enhancing industrial strength and resilience. The more invested, the more infrastructure, technology capacity and adaptation to climate change.

Considering the overall impact of the climate and investment variables, the growth of industries is influenced not only by nature but also by economic variables and thus needs overall policies.

4.3.3 Interpretation of Features Importance

The results from the three models reveal a number of common features. First, temperature is the most important climate factor, as it has a key role in macroeconomic performance. Second, extreme climate events, like floods and storms, play an important role, especially with respect to their impact on short-term economic variables. Third, macroeconomic variables in particular, investment and exchange rate, play a significant role in transmitting climate shocks.

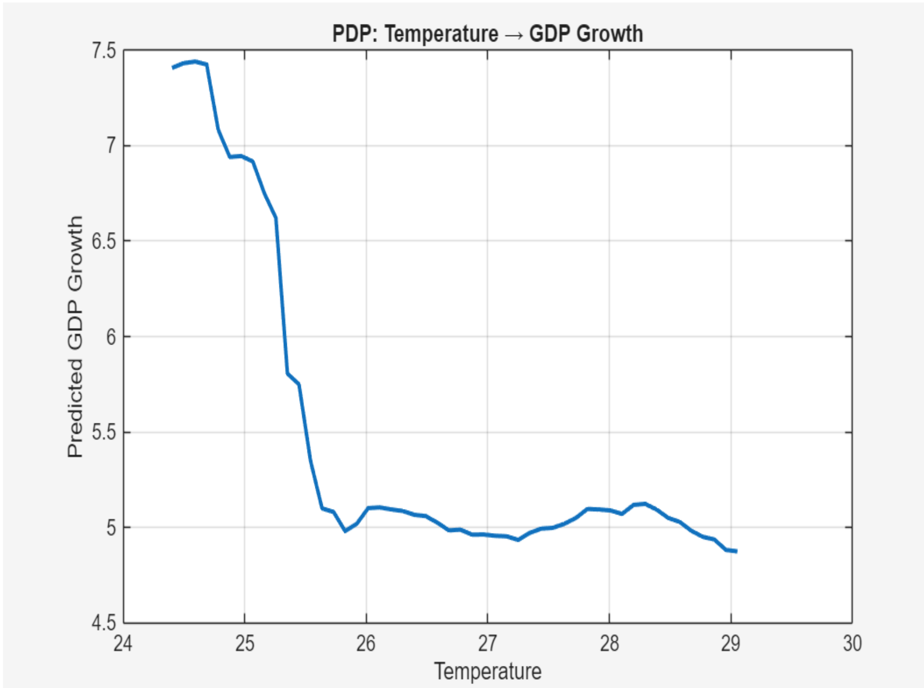
The results offer empirical evidence supporting the theoretical analysis in the previous chapters that stresses the multiple channels through which climate shocks impact the economy. The findings also show that it is crucial to include both climate and economic variables in the analysis.

Furthermore, the feature importance analysis highlights the benefits of using machine learning methods to determine the key drivers, while imposing few constraints. This approach, where variable importance is learned from the data, allows the Random Forest model to give a more detailed view of the climate-macroeconomic relationship.

4.3.4 Partial Dependence Analysis (PDPs)

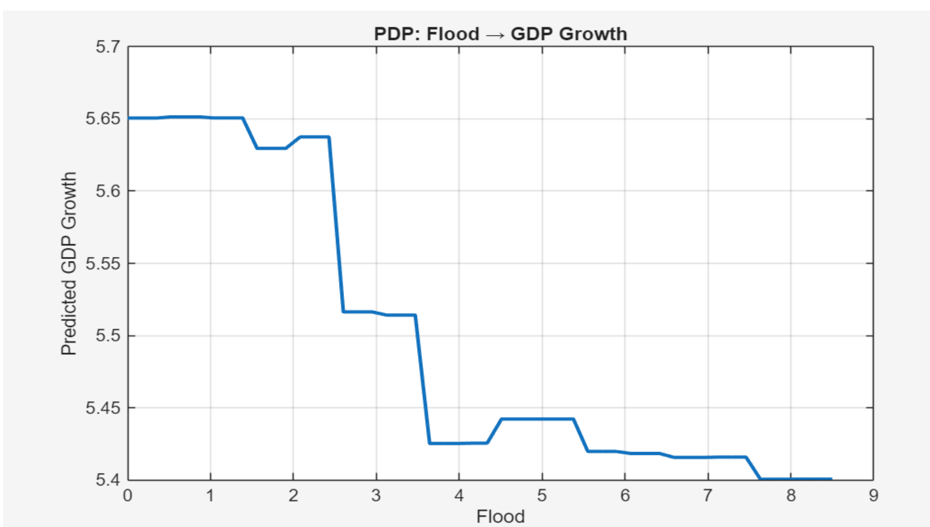
Partial Dependence Plots (PDPs) allow us to analyze the partial effect of each climate variable on macroeconomic factors while controlling for other variables. This allows us to closely examine nonlinearities and threshold effects, which are not captured by linear models. The PDP for GDP growth, inflation and industrial growth are displayed in separate panels to illustrate the differences in the effects of climate shocks on various aspects of macroeconomic policy.

Figure 6. PDP: Temperature → GDP Growth



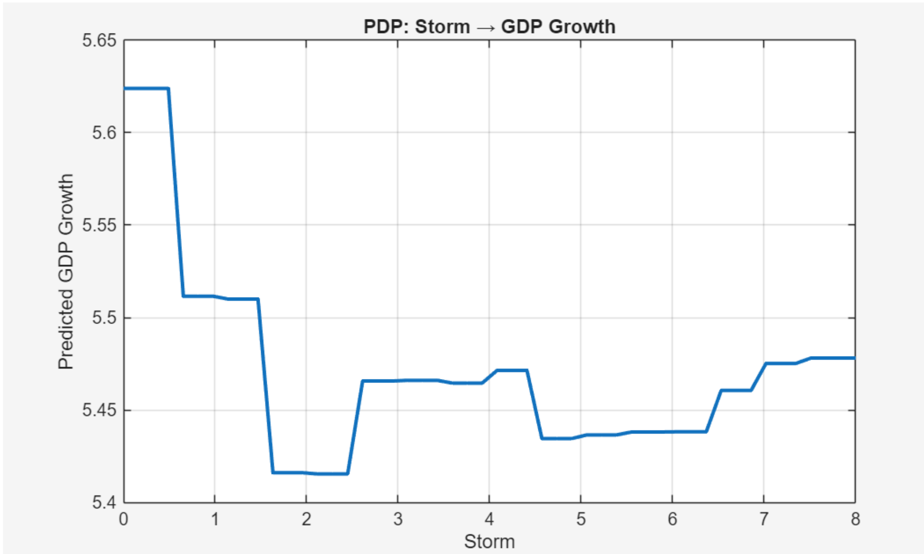
Source: Author's own calculation (2026)

Figure 7. PDP: Flood → GDP Growth



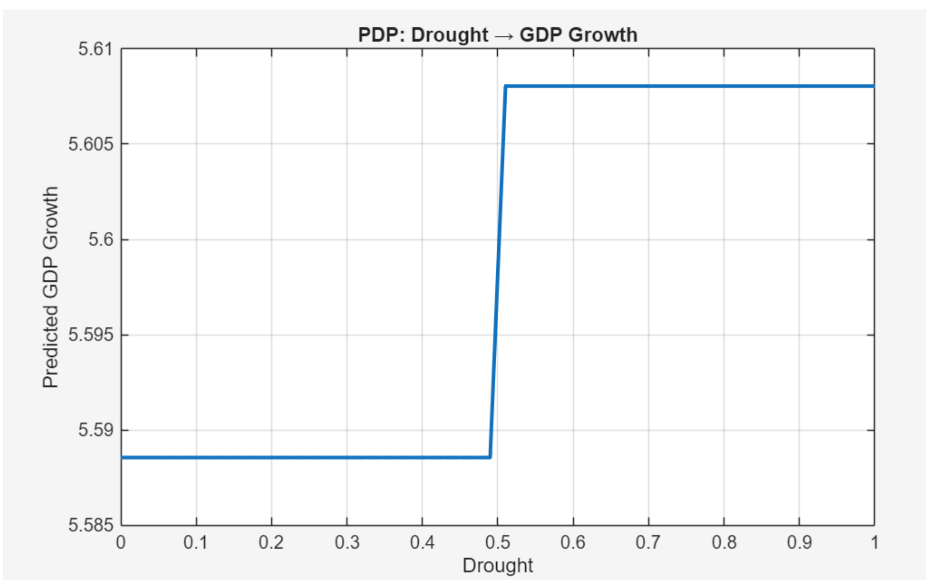
Source: Author's own calculation (2026)

Figure 8. PDP: Storm → GDP Growth



Source: Author's own calculation (2026)

Figure 9. PDP: Drought → GDP Growth



Source: Author's own calculation (2026)

The PDP for temperature (in Figure 4.5) shows a strong nonlinear relationship between GDP growth and temperature. GDP growth is fairly high at low temperatures.

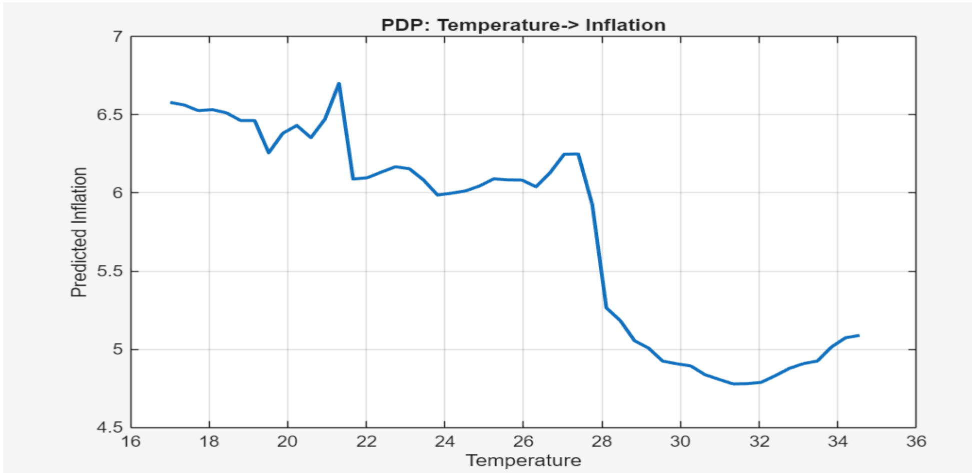
But for higher temperature levels (beyond about 25-26°C), there is a dramatic fall followed by a stabilization at lower levels in the projected GDP growth. This suggests that there is a threshold temperature level, above which marginal damage from temperature rises increases. The sharp drop indicates that the economy is very sensitive to temperature increases beyond the "temperature sweet spot".

The PDP for floods (Figure 4.6) displays a monotonic negative trend with GDP growth. The estimated future GDP growth decreases with increasing frequency of flood events. This is expected due to the economic activities' damages from the floods, such as infrastructure damage, supply chain disruptions, and lost production capacity. The discontinuous curve is due to the discrete nature of measuring flood frequency, but does not affect the overall trend.

The storm PDP in Figure 4.7 shows a nonlinear, and heterogeneous, relationship. The GDP growth rate initially decreases as the number of storms increases, then recovers and fluctuates. This indicates that the effects of storms on the economy are not uniform, with more severe storms and less resilient economies having greater impacts. The effect of less intense storms may be minimal, but more intense and/or frequent storms result in greater impacts.

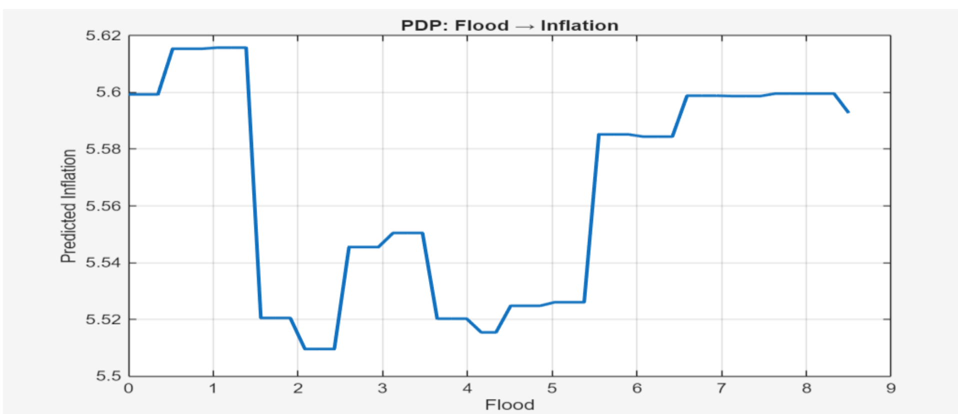
The drought PDP in Figure 4.8 has a step-like shape, due to the binary nature of the drought indicator. Drought occurrence is associated with a step change in GDP growth. But this finding must be taken with a grain of salt. Due to the lack of variability in drought observations and the possibility of spurious effects of other variables, the pattern is likely to reflect specific circumstances, rather than a causal link. So, it's likely the effect of drought is non-linear and context dependent.

Figure 10. PDP: Temperature → Inflation



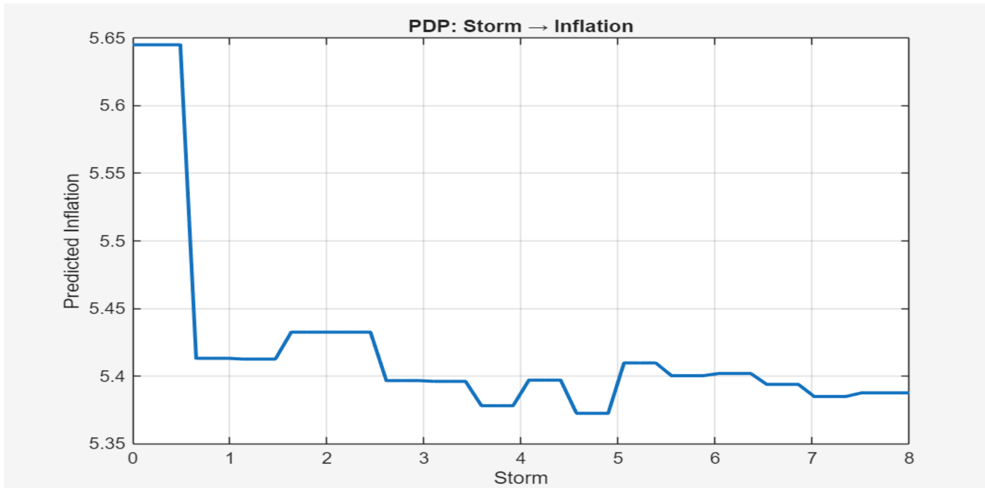
Source: Author's own calculation (2026)

Figure 11. PDP: Flood → Inflation



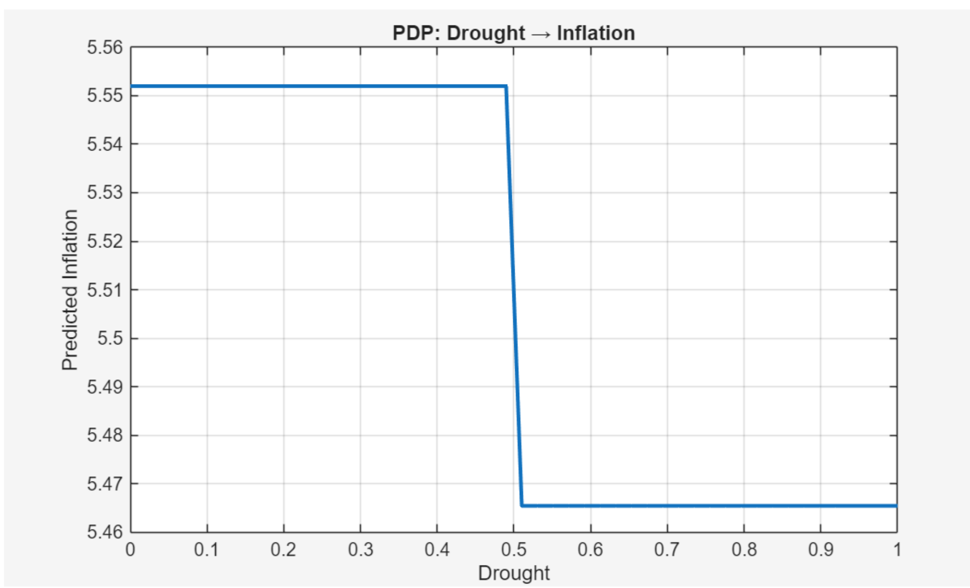
Source: Author's own calculation (2026)

Figure 12. PDP: Storm → Inflation



Source: Author's own calculation (2026)

Figure 13. PDP: Drought → Inflation



Source: Author's own calculation (2026)

The PDP for temperature (Figure 4.9) is nonlinear and nonmonotonic. At lower and moderate levels of temperature, inflation varies within a small range. But at a higher temperature level, there is a substantial decrease in inflation and then stability.

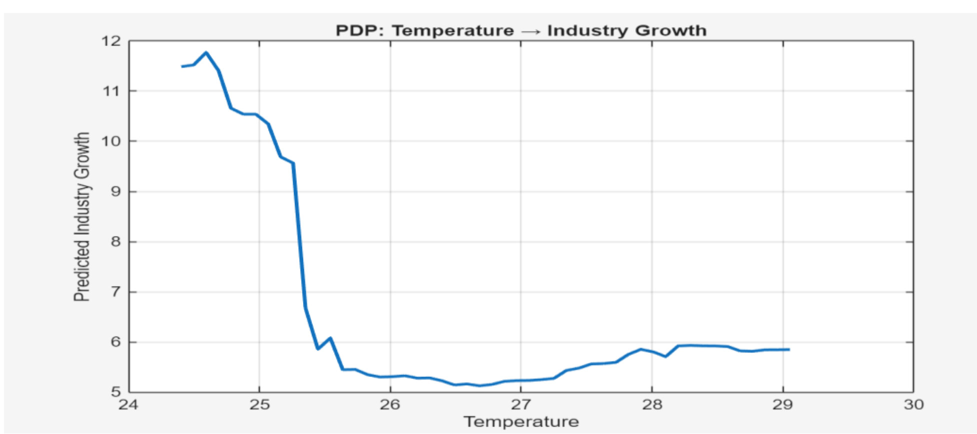
This behavior suggests the presence of two effects, with rising temperatures potentially increasing the costs of production, but also decreasing economic activity and hence demand, and the net effect on inflation.

In Figure 4.10 the flood PDP shows a stepped and rather weak pattern, with small variations in predicted inflation with changes in flood frequency. There is an increase in inflation as flood levels increase but it is not monotonic. This suggests that the effect of floods on inflation is dependent and could differ across countries based on factors such as supply chain strength and policy interventions.

The storm PDP in Figure 4.11 shows a typical downward trend with increased storm frequency leading to slightly lower levels of inflation. This might indicate that storms can cause a demand contraction, in addition to supply shocks, and thus reduce inflation. The relatively flat sections of the curve suggest the impact is not across all levels.

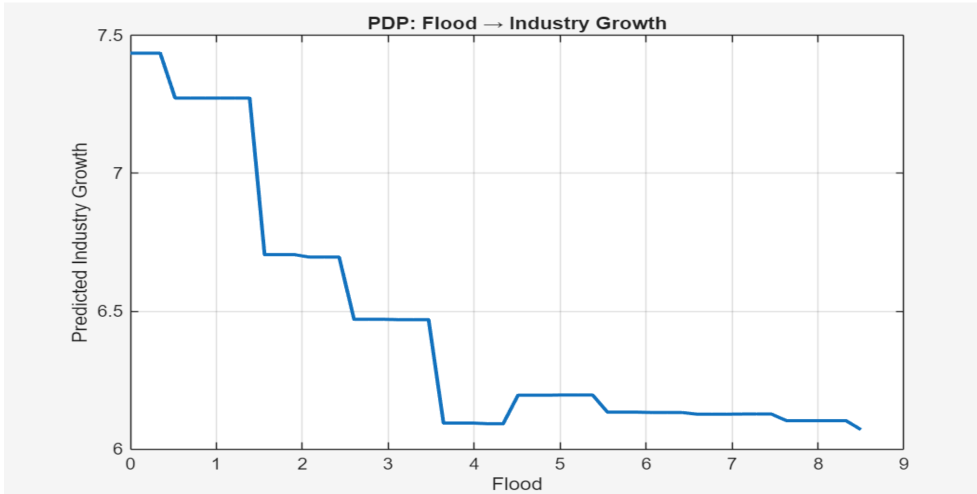
The drought PDP in Figure 4.12 exhibits a step-like pattern, with a shift associated with the presence of drought. While this may seem surprising, it's likely the result of the interaction between drought events and other factors, such as demand or the policy response. Here, as with the GDP model, the binary drought variable likely adds to the step-like nature of the PDP, and it is worth interpreting this result as being dependent on various other factors.

Figure 14. PDP: Temperature → Industrial Growth



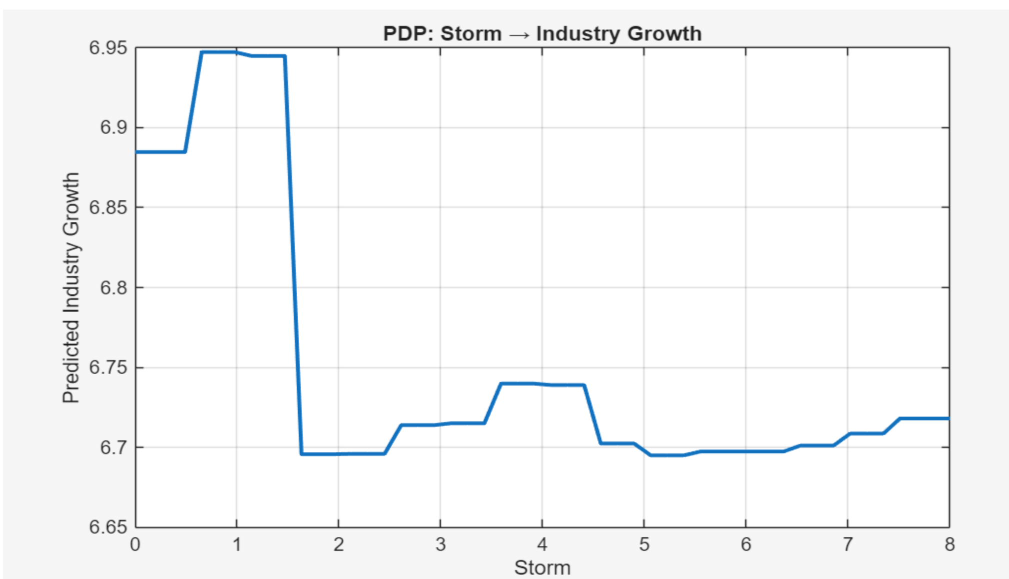
Source: Author’s own calculation (2026)

Figure 15. PDP: Flood → Industrial Growth



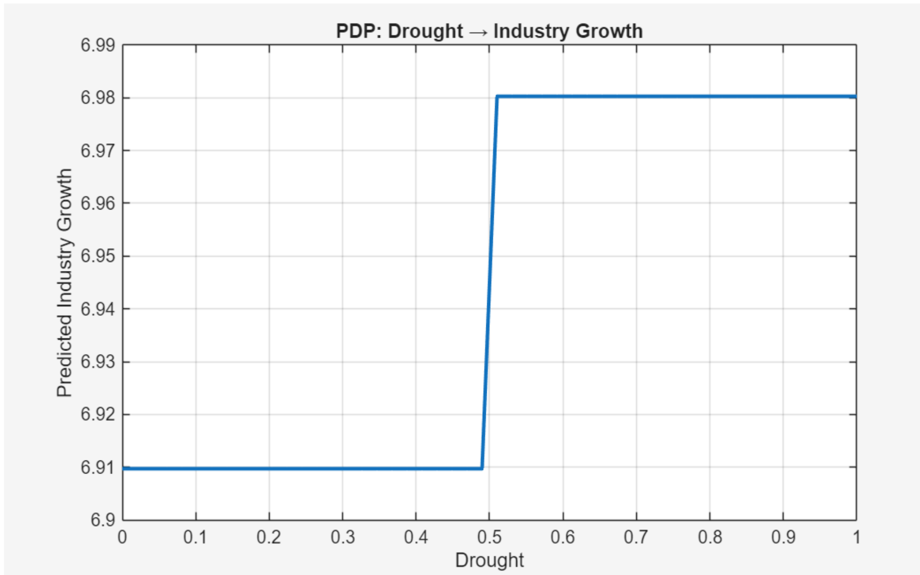
Source: Author’s own calculation (2026)

Figure 16. PDP: Storm → Industrial Growth



Source: Author’s own calculation (2026)

Figure 17. PDP: Drought → Industrial Growth



Source: Author's own calculation (2026)

The PDP for temperature (Figure 4.13) shows a strong nonlinear, threshold relationship with industrial growth. Temperature levels below 25-26°C are associated with relatively high levels of industrial growth, with a steep decline at higher temperatures. It has a subsequent recovery and plateau. The abrupt drop is a result of industrial productivity being highly sensitive to heat stress, and the stabilization is an indication of some adaptation to the increase in temperature. In the flood PDP (Figure 4.14) there is a monotonic decline in industrial growth with increasing flood frequency. This finding is a testament to the lack of resilience of industrial infrastructure to floods, as multiple events result in ongoing production and supply chain disruptions. The regularity of this pattern offers good evidence of the adverse effect of floods on industry.

The PDP for storm activity (Figure 4.15) shows a more complex, but negative, relationship. It shows a drop in industrial growth with increasing storms, and subsequent leveling off. This implies that while low storm frequencies may be able to be accommodated, more frequent storms cause long term damage. Variability is related to differences in the intensity and resilience of the storms. In Figure 4.16 we observe a step-like pattern in the drought PDP, where drought is associated with a change in industrial growth. As with the GDP model, this finding needs to be interpreted with care. The lack of variability in the drought observations and its indirect link to industrial production, indicate that the effect is likely to be caused by interactions with other variables.

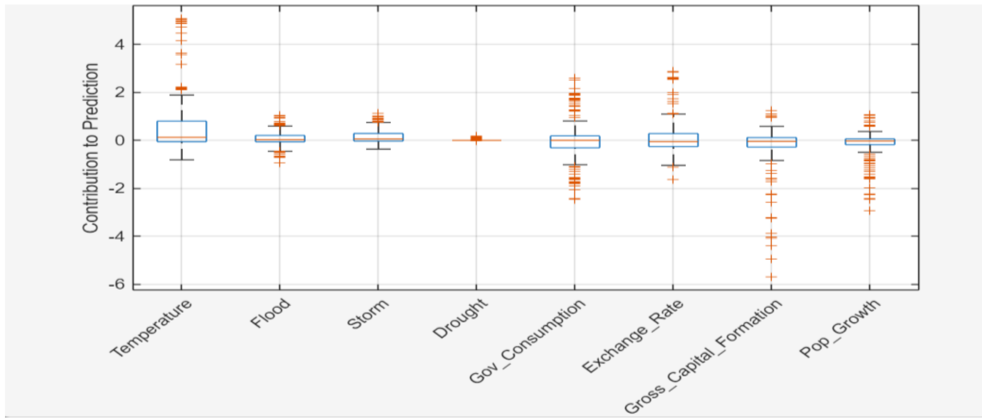
This PDP analysis of the three models gives strong support for nonlinear and threshold effects of climate shocks. Temperature always has a threshold effect, with strong impacts on the economy above the threshold. Floods and storms display cumulative and mostly negative effects on growth variables, with more variable (non-monotonic) effects on inflation. Drought impacts are discrete, but should be taken with a grain of salt because of data issues. These results support the use of flexible models to capture the intricacies of climate–macroeconomic linkages and yield robust empirical evidence in support of this research's aims.

4.3.5 Model Insight, Diagnostics and Stability

This subsection assesses the interpretability, diagnostic and stability of the Random Forest models used in this study. Although machine learning models offer improved prediction performance, it is important to ensure that the model results are robust, interpretable and stable. To this end, we include SHAP-like feature contribution analysis, residual diagnostics, and stability of feature importance rankings in our analysis.

4.3.5.1 Global SHAP-like Feature Contribution Plot

Figure 18. SHAP-like Feature Contribution Distribution



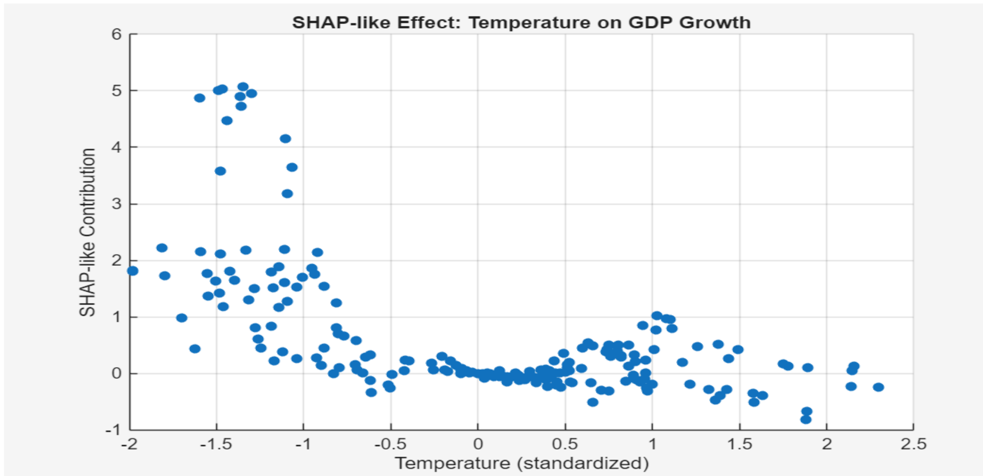
Source: Author’s own calculation (2026)

The global SHAP-like feature contribution distribution shown in Figure 4.17 represents the distribution of each variable's contribution to the prediction of GDP growth. This plot offers a better understanding of both the strength and sign of the feature impacts, in contrast to feature importance measures that only show the strength of the impact. The plot shows that temperature has the broadest spread of contributions, with both highly positive and negative impacts. This verifies that temperature's effect on GDP growth is highly non-linear and dependent on other variables, as shown in the PDP. The combination of positive and negative contributions implies that temperature might boost growth when within a certain range, but have a negative effect in critical situations.

The distributions of flood and storm variables are more peaked but still significant, suggesting moderate impact on the variability of predicted outcomes. By contrast, drought has a stringent distribution, due to its low level of variability and binary characteristic in this data. The economic variables (including government consumption, exchange rate and gross capital formation) also show considerable variability, suggesting the role of macroeconomy in adjusting climate impacts. Overall, the figure shows that climate and economic variables interact to affect model predictions in a nonlinear way.

4.3.5.2 Climate Variables' SHAP-like Contributions

Figure 19. SHAP-like Effect: Temperature on GDP Growth

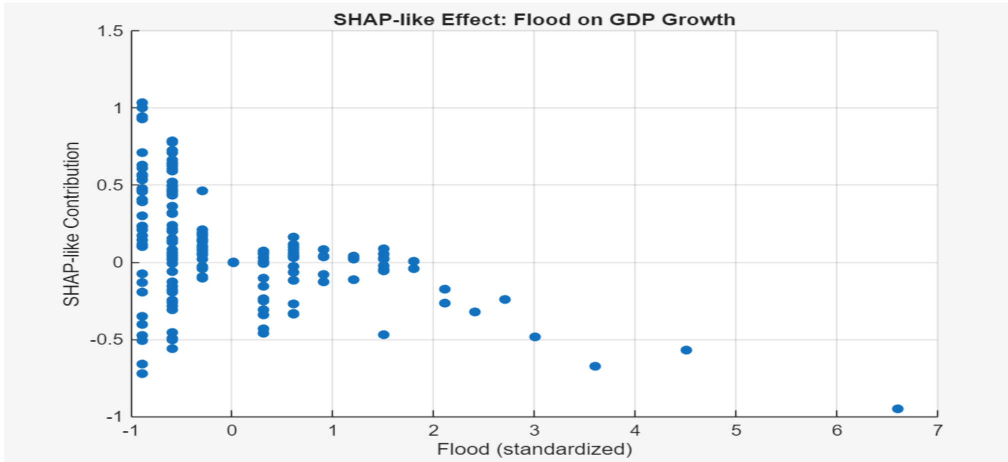


Source: Author’s own calculation (2026)

The SHAP-like scatter plot for temperature (in Figure 4.18) shows the contribution of temperature to GDP growth is non-linear. For low (standardized) temperatures the contribution is very positive, suggesting that low temperatures are linked with better economic growth.

But as temperature rises, contribution decreases significantly and becomes negative, suggesting the existence of a threshold. Above this threshold, warmer temperatures have a negative impact on GDP growth. This finding is consistent with the PDP results, and confirms that the effects of temperature are asymmetric and non-linear.

Figure 20. SHAP-like Effect: Flood on GDP Growth

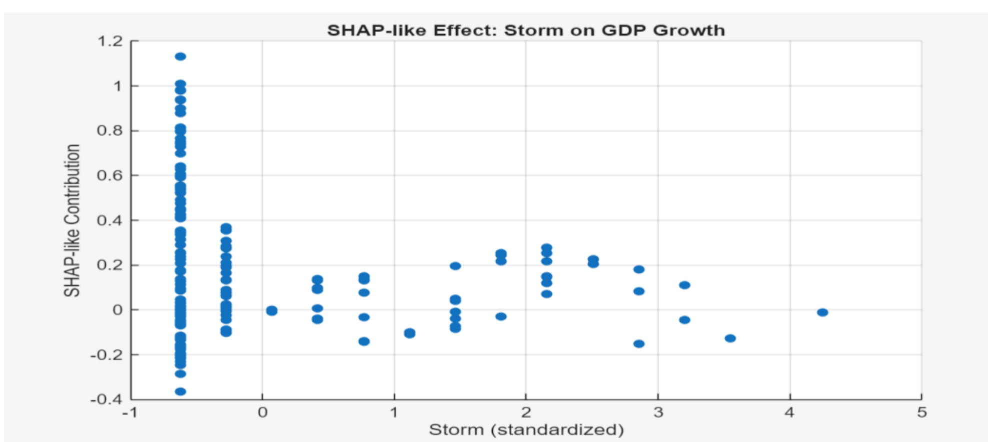


Source: Author’s own calculation (2026)

The SHAP-like plot of flood (Figure 4.19) reveals that for low levels of flood, the impact on GDP is small positive or near zero, whereas high levels increasingly lead to negative impacts. This is consistent with flood having a more adverse impact on GDP growth as it increases.

The spread of points at lower levels of flood suggests some variability due to country-specific resilience. But the general trend shows that as the flood event becomes more severe, it has a more adverse effect on GDP growth.

Figure 21. SHAP-like Effect: Storm on GDP Grow

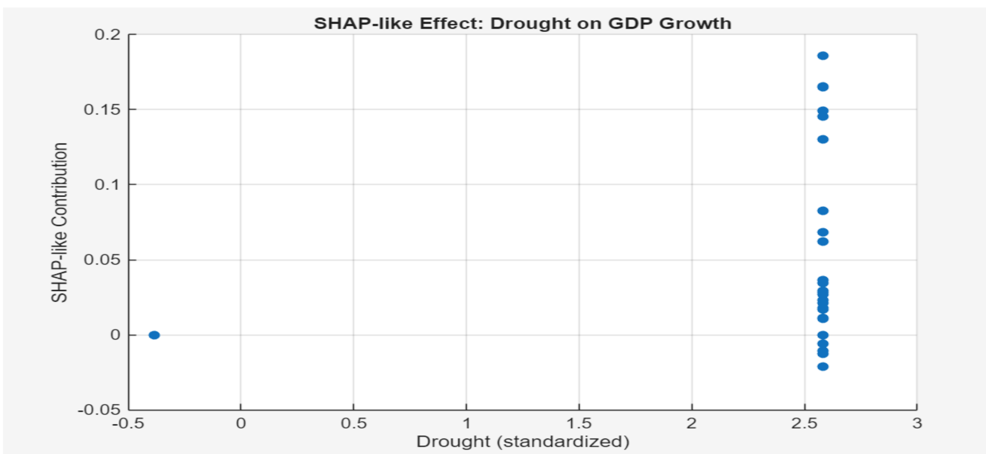


Source: Author’s own calculation (2026)

The SHAP-like value of storms in Figure 4.20 is more diverse. Contributions are highly variable at low levels of storms, suggesting that low-intensity storms can have varying impacts. But at higher levels of storms, the contributions converge towards lower values, which would be indicative of a negative effect.

This finding is consistent with the interpretation of storm impacts to be context-specific, with high intensity storms having more consistent negative effects.

Figure 22. SHAP-like Effect: Drought on GDP Growth



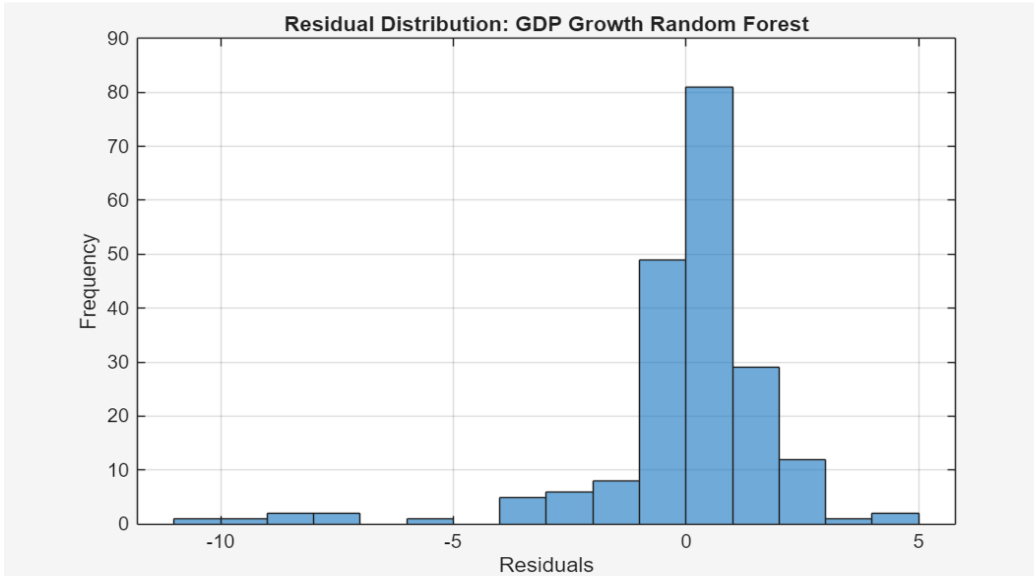
Source: Author’s own calculation (2026)

The SHAP-like plot for drought (in Figure 4.21) shows a clear grouping, due to the binary variable. The values of the contributions are relatively low compared to the effects of other climate variables, which suggests that drought has a less significant impact on GDP.

Some positive effects are noted, but should be viewed with caution. The lack of variability and possible interactions with other variables imply that the effects of droughts depend on the context.

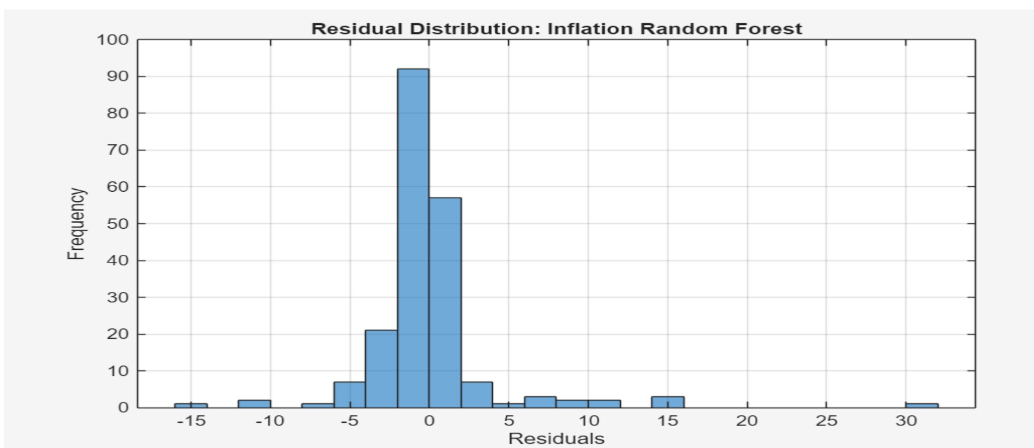
4.3.5.3 Residual Diagnostics

Figure 23. Residual Distribution – GDP Growth Random Forest Model



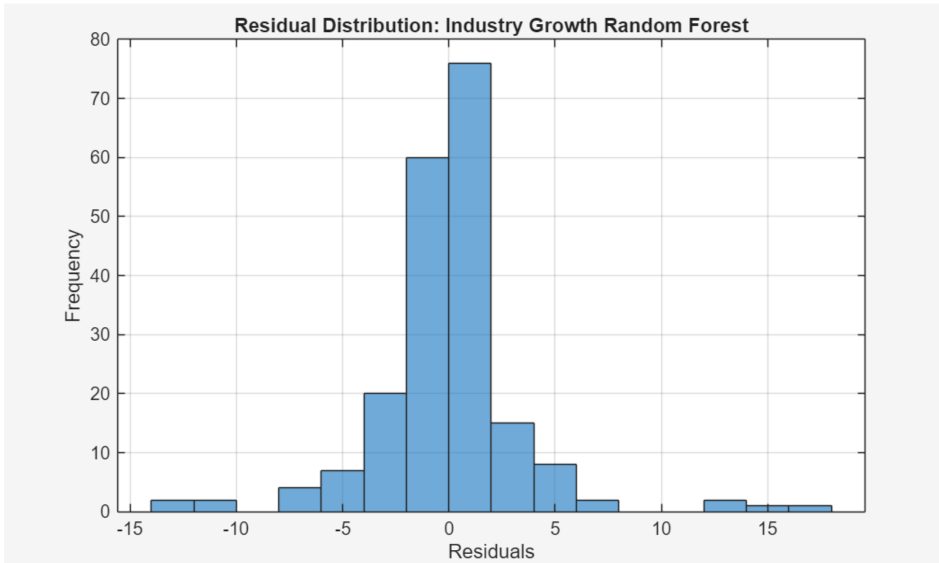
Source: Author's own calculation (2026)

Figure 24. Residual Distribution – Inflation Random Forest Model



Source: Author's own calculation (2026)

Figure 25. Residual Distribution – Industrial Growth Random Forest Model



Source: Author's own calculation (2026)

Figures 4.22-4.24 show residual distributions that can be used to diagnose the performance of the models. In each of the three models, the residuals are centered at zero, suggesting that the models are not biased in their predictions. The distribution of the GDP residuals (Figure 4.22) is fairly symmetric and has most residuals close to zero, implying good accuracy. But there are some large negative residuals, suggesting that it may underestimate some extreme values.

The inflation residual distribution (Figure 4.23) is more dispersed, suggesting more variability and challenges in forecasting inflation. This may be due to o

factors impacting inflation that are not accounted for in the model. The residual distribution of industrial growth (Figure 4.24) is relatively symmetric with a cluster around zero but some positive outliers. This suggests a generally good fit with some errors in predictions for the extremes. In summary, the residual analyses show that the models give reasonable and unbiased predictions with acceptable errors for the challenging data.

4.3.5.4 Feature Importance Stability

Table 8. Feature Importance Stability

stability_corr
0.9896

We assess the stability of the feature importance rankings by calculating the correlation between the rankings of different model runs. For the GDP model, the stability coefficient is 0.9896, showing that the results are very stable.

The high correlation close to one indicates that the variable rankings are almost identical in different runs of the model. This shows that the results from feature importance analysis are not artefacts of randomness, but represent consistent and meaningful patterns in the data.

4.3.5.5 Overall Interpretation

The results of the SHAP-like analysis, diagnostic checks of the residuals and the stability of the feature importance indicate that the Random Forest models are stable and interpretable. These results confirm the existence of nonlinear and asymmetric effects of climate variables, and indicate that temperature is the most important predictor of macroeconomic dynamics.

The stability of feature importance rankings and patterns in the residuals suggest that the models reflect significant and robust relationships in the data. These findings confirm the effectiveness of machine learning approaches in this research, and reinforce the insights about the effects of climate shocks on macroeconomic stability.

4.4 Discussion of Results

This section brings together the empirical results of the benchmark econometric models and the machine learning model, in the context of the proposed theory and the previous studies. The analysis is organized by the three research questions to offer a holistic view of the impact of climate shocks on macroeconomic stability in a number of ASEAN countries.

4.4.1 Impacts of Climate Shocks on Macroeconomic Stability (RQ1)

The first research question focuses on the impact of climate shocks on macroeconomic stability measures, such as GDP growth, inflation and industrial growth. Both OLS and Random Forest results show that climate shocks are important in determining macroeconomic outcomes.

The econometric findings imply that climate shocks, especially temperature and extreme weather, have negative impacts on economic growth and industrial growth. These results are backed up by the random forest results, as temperature is identified as the most important predictor in all models. The PDP and SHAP-like results also show that there are significant declines in GDP growth and industrial output at higher temperature levels.

These results are consistent with the theoretical approaches outlined in Chapter 2, such as the climate damage function, which predicts that climate change has increasing costs with rising temperatures. The negative impact on GDP growth and industrial output at higher temperatures is consistent with the view that climate change has an impact on productivity, the efficiency of capital and economic activity.

With respect to inflation, the findings are less clear. Although climate shocks like floods and droughts generate supply-side shocks, the impact on inflation is not as clear as for the growth variables. This is due to the nature of inflation, which is a function of both supply and demand. Climate shocks could raise production costs, thus triggering price hikes, but could also cause economic shocks, decreasing the demand, hence mixed effects.

In general, our findings support the view that climate shocks have important and complex effects on macroeconomic stability, with more pronounced and robust effects on real output than on prices.

4.4.2 Threshold and Nonlinear Effects of Climate Shocks (RQ2)

The second research question explores whether there are nonlinear and threshold effects from climate shocks on the macroeconomy. This research question is supported by our evidence.

Both the Partial Dependence Plots for GDP growth and industrial growth show nonlinear effects, especially with temperature. At mid temperature values there is a threshold where economic growth starts to decline. This is supported by a SHAP-like analysis, where it can be seen that the contribution of temperature switches from positive to negative.

This discovery aligns with a theory about ‘nonlinear damage functions' – finding that the economic impact of climate change will start to rise at specific levels. The existence of such thresholds is relevant as it suggests the economic damages from climate change may be underestimated when using linear approaches.

Nonlinear effects are also seen with extreme weather events. When floods happen, their impacts have a compounding negative impact on economic growth, and storms can have various impacts depending on their severity. The variations in PDP and SHAP plots for storms indicate that storm impacts are not evenly distributed across all storms and are related to factors, such as storm resilience and policy response.

Drought effects are by contrast less systematic and are step-wise changes because of their binary nature. The results of this study reveal that there is an association between the drought events and the changes in the macroeconomic indicators, but the impacts are not as clearly demonstrated, possibly due to the lack of detail of the drought impacts in the data used in this study.

The presence of nonlinear, threshold effects is an important finding of the current study, as it highlights the need to use flexible modelling techniques to better understand climate–economy relationships.

4.4.3 Most important predictors of Macroeconomic performance (RQ3)

Research question (RQ3) seeks to answer the question of what are the important drivers of macroeconomic performance? Both the feature importance and SHAP-like analysis reveal the importance of the different climate and macroeconomic variables.

In all models, temperature is the most influential predictor and confirms the relevance of temperature on the economic performance. Macroeconomic variables, such as government consumption, exchange rate and gross capital formation, are among the important determinants of economic resilience and vulnerability that follow.

The flood and storms also have an important role in the GDP and industrial growth models. These account for the effects of physical disruptions, which impact infrastructure, production and supply chains. The importance of these variables highlights the importance of extreme weather conditions with respect to short-term economic dynamics.

The importance of drought variables is reduced because of their low variability (in this sample) and because they have less direct impacts on the economy. But it could have greater impacts on particular industries, such as agriculture.

From our results, we conclude that macroeconomic results are due not only to climatic conditions, but also to economic conditions. This underlines the importance of comprehensive policy formulation which should consider both environmental and economic issues.

4.4.4 Link with Theory

The results largely corroborate the theoretical framework in Chapter 2. The nonlinear temperature effects are in line with climate damage function theory, while the effects of extreme weather events are in line with the notion of physical climate risk. The findings also embody the channels of impacts outlined in the theoretical framework. Climate shocks affect the economy through multiple pathways, such as through losses in productivity, losses in infrastructure, supply chain shocks and price shocks. These channels are not independent of each other and sometimes do not always produce the desired effects. What's more, the analysis suggests the role of adaptation and resilience. The relationship between vulnerability and economic structure/policy appears to be strong as countries with greater climate exposure and worse macroeconomic conditions appear to be less able to cope with climate change.

4.4.5 Sustainable Finance

This study's results have several implications for sustainable finance, especially when it comes to climate risk management and investment. First, temperature is a salient risk factor and thus the physical climate risk should be taken into account in financial modelling and investment. The actions taken by banks and policy makers should take the non-linear and threshold effects of climate changes on the economy into account.

Second, the impact of floods and storms is a reminder of the importance of climate-resilient infrastructure. Green financial products like green bonds and climate funds will help finance climate resilient infrastructure and projects that will help lower vulnerability to extreme weather events. Third, the relationship between climate factors and macroeconomic indicators indicate that climate risk is not in silo but is integrated within the economy. This highlights the need for comprehensive ESG strategies for risk management. Fourth, the application of machine learning methods in this study shows how innovative analytical methods can enhance climate risk management. These methods have the potential to enhance forecasting and provide guidance to decision making in the context of sustainable finance.

4.4.6 Overview of Key Insights

Based on the results of this study, it is concluded that the climate shocks have a significant impact on macroeconomic stability in ASEAN countries. Results indicate the importance of nonlinearities and threshold effects, point out the drivers of economic performance and highlight the importance of climate risk for economic outcomes.

Combination of the two techniques, econometric and machine learning, allows to have a more comprehensive perspective over these dynamics, in which interpretability and accuracy are added. These findings add to the emerging body of research on climate economics and provide important insights for policymakers and financial sector actors on how to tackle climate risks.

CHAPTER V
CONCLUSION AND POLICY IMPLICATIONS

5.1 Introduction

This chapter provides the final synthesis of the research, comprising the empirical findings, theory building and policy implications of the research. The objective of this study was to gauge the impact of climate change shocks on macro-economic stability in a selected ASEAN countries by GDP growth, inflation and industrial growth for the period 2000 – 2024. Using a mix of econometric and machine learning approaches, the research sought to offer a detailed insight into the impact of climate variables on macroeconomic variables.

The research arises from the increasing realization that climate change causes environmental impacts, but also significant macroeconomic and financial risks. ASEAN economies are highly vulnerable to both slow onset climate change and extreme weather events due to the geographical and sectoral exposure to climate change. Therefore, it is critical to be aware of the economic impacts of these shocks, and to consider them in policy-making for future economic resilience.

The study has tackled this problem using a two-fold approach. First, the average linear impacts of climate variables on macroeconomic ones were estimated using baseline econometric models. Then, Random Forest models were used to model nonlinear impacts, threshold effects and interactions. This combination of methods enabled the study to have enough interpretability and accuracy to capture the entire spectrum of the climate-macroeconomic relationship.

The results presented in Chapter 4 show that climate shocks play an important and multifaceted role on macroeconomic stability. In particular, temperature was identified as the most significant factor, and threshold and non-linear relationships were observed for growth and industrial activities. In addition, extreme climatic events like floods and storms exhibited significant impacts, both through their impact on infrastructure and manufacturing. Climate shocks, on the other hand, had a more complex effect on inflation, with effects on both supply and demand.

Drawing on these insights, this chapter seeks to provide an overview of the main findings, point out the contributions of this research and discuss their policy and sustainable finance implications. The chapter is organized as follows. Section 5.2 presents an overview of the empirical findings, in connection with the research questions. Section 5.3 discusses the theoretical and methodological insights. Section 5.4 outlines the policy implications, in particular with regard to climate risk management and sustainable finance. The weaknesses of the study are discussed in Section 5.5 and suggestions for future studies are provided in Section 5.6. The chapter closes with some final thoughts on the need to incorporate climate issues in macroeconomic and financial policies.

5.2 Overview of Key Findings

This part provides an overview of the main empirical results of the study, by combining the findings of the econometric and machine learning approaches. Overall, the results indicate that climate shocks can have significant and complex effects on macroeconomic stability in some of the ASEAN economies, with the size and sign of the impacts varying depending on the macroeconomic variable.

According to our results, real economic activity indicators (GDP growth and industrial growth) are significantly affected by climate shocks. Temperature is the most important climate variable because there is good evidence of a relationship between increased temperature and a decline in economic performance. The finding is the same in both models, and supported by the nonlinearities in the machine learning analysis. Finally, extreme weather events like floods and storms show negative effects on the economy, due to their effects on infrastructure, production and supply chains. These findings suggest that climate shocks place direct limits on economic activity by limiting potential output, especially in areas susceptible to climate change.

On the other hand, the effect of climate shocks on inflation is not as clear-cut. Some of the supply-side factors that have the potential of driving up prices are climate shocks, but the effect on inflation can be due to demand, exchange rates and monetary policy. Therefore, there is no consistent reaction of inflation to climate shocks, reflecting the intricacies of price dynamics under the impact of climate shocks.

One of the main insights of the paper is that there are nonlinear and threshold effects between climate factors and macroeconomic variables. The findings from Partial Dependence Plots and SHAP-like plots offer strong evidence that there are nonlinear effects of temperature on economic outcomes. Instead, there is some set temperature that, when exceeded, the harmful effects of temperature are magnified. Accordingly, an economy is better able to cope with moderate climate change than with less-than-optimal environmental conditions. These nonlinear relationships hold for extreme climate events as well, for instance, for floods, which have a cumulative negative impact on economic growth and for storms, which have varying impacts depending on the level and context.

This study also shows the role of both climatic and macroeconomic variables in economic growth. Other macroeconomic factors, such as government consumption, exchange rate and gross capital formation are important determinants to assess the economic resilience of countries to face climate shocks, apart from temperature and extreme weather. These factors influence the economic resilience by determining investment, fiscal space and stability in the exchange market, and thus, the overall effect of climate risks.

In addition, the findings show that the application of machine learning techniques adds to our knowledge gained from econometric models. While the econometric analysis provides information about the sign and average size of the relationships, the machine learning analysis shows that there are nonlinear dynamics, interactions and variable importance patterns. This synergic approach will allow us to better understand the climate-macroeconomic relationship and of the drawbacks of linear models.

Combined with the findings of the other studies, the findings from this study indicate that climate shocks have a significant impact on the macroeconomic stability of the economies in the ASEAN region. The impact is more significant for measures of growth, with a more complex set of interactions impacting inflation dynamics. The nonlinear and threshold evidence emphasized the need to use more flexible modelling techniques as well as gave strong evidence for the study's proposed theoretical framework. These findings help to better understand the economic impacts of climate change, and inform the policy and financial decisions in the context of sustainable development.

5.3 Contributions of the Study

This study offers a number of contributions to the fields of climate economics, macroeconomic stability and sustainable finance. The ones listed are empirical, as well as methodological and all can help to understand the impacts of climate shocks on economies, particularly emerging and vulnerable economies.

First, it provides new empirical evidence on the impact of climate shocks on macroeconomic stability in the ASEAN region, which is especially vulnerable to climate change, but for which little empirical evidence exists. Through its focus on several macroeconomic variables, such as GDP growth, inflation and industrial production growth, the study paints a broader picture of the impacts of climate on various aspects of the economic performance. This has the benefit of giving a better overview of the impact of climate shocks and highlights that climate shocks affect different macroeconomic variables differently.

Second, the study adds to the existing knowledge by explicitly modelling the presence of nonlinear and threshold effects of climate variables, especially temperature. Most earlier studies have relied on linear models to capture the impacts of climate change on macroeconomic variables, while this study demonstrates that impacts of climate shocks on macroeconomic variables are nonlinear. The identification of critical thresholds, where the economic impact is larger, is an important contribution as it means that linear methods may not be able to capture the full economic impacts of climate change. This discovery has policy implications – that is, urgent need to act before critical thresholds are being breached.

Lastly, the study is an advance of methods adopted in the field of climate economics as a result of the merging of the econometric models with machine learning. In the case of panel OLS models, the predictions are transparent and learn the means of the different variables; Random Forest models can model interactions, identify important variables, and predict means. This holistic approach overcomes the limitations of stand-alone methods and provides a more holistic way of working. In particular, the application of Partial Dependence Plots and SHAP-like analysis makes the machine learning models more interpretable, and helps push the emerging field of explainable artificial intelligence in economics further.

Fourth, the paper adds to the knowledge of the role of climate risk transmission by emphasizing the importance of both climate and macroeconomic variables. The findings show that the impact of climate shocks on economic indicators can be direct but most of the indirect effects are downstream via macroeconomic variables such as investment and fiscal policy and the exchange rate. It has now come to light that this holistic perspective emphasizes the importance of climate risks not as environmental risks but as part of the economic dynamics.

Fifth, the research makes an important contribution to the field of sustainable finance by the linkage of climate shocks and macroeconomic stability. Through the evidence that climate variables play a critical role in economic activity, the study offers empirical evidence for the need to consider climate risk in financial decisions. The finding that temperature is the most important risk factor and the presence of nonlinear effects indicate the importance of considering physical climate risks in investment models, risk management strategies and policy. The result has implications for the design of green finance and ESG investment products and strategies, and for the design of investments that are resilient to climate change.

Lastly, this research can be used for policy-oriented research as it provides evidence for support of climate adaptation and mitigation policy. The study's findings on the main drivers of economic vulnerability and the existence of threshold effects provide insights on how to develop policies to improve economic resilience. The results highlight the need for proactive rather than reactive climate risk strategies, focusing on risk prevention rather than dealing with the consequences.

The key policy learning from the study is to embed empirical evidence and innovative methodology and policy learning. Through its integration of climate economics, macroeconomic analysis and sustainable finance, this research offers a holistic perspective on the economic impacts of climate change and strategies to cope with them.

5.4 Policy Implications

This study has important policy, financial and economic development implications for policymakers, financial institutions and those engaged in economic and sustainable development. The study's findings that the impacts of climate shocks are large and nonlinear in terms of macroeconomic stability, suggest that climate risk management should be incorporated into economic policy and financial strategies.

One implication is that policymakers should consider climate change as a macroeconomic risk, rather than an environmental concern. The strong and lasting response of GDP growth and industry output to temperature suggests that long-term climate change could impact productivity, output and economic stability. Governments should, therefore, include climate variables in their macroeconomic forecasting, fiscal and development policies. That means that national economy and climate adaptation and mitigation strategies must be in line to guarantee economic stability.

The finding of nonlinear effects and threshold effects also highlight the need for action. Once reaching a certain threshold, climate's influence on the economy is significantly increased. This indicates that policy time lag could have very high costs. Policies aiming for prevention, such as policies aimed at limiting emissions or climate adaptation policies and investments in the "green" technology should be prioritized to not exceed critical thresholds.

The second implication is related to resilient infrastructure. Losses due to flooding and storms to economic growth and manufacturing activity clearly underscore the critical importance of infrastructure and supply chains to economic performance and the risk of adverse impacts from extreme weather events. The focus of government investments should be on climate-proof infrastructure, including flood control, climate-proof transport infrastructure and climate-proof industrial infrastructure. By making infrastructure more resilient, not only are economic losses minimized but so is vulnerability to climate change.

The study also shows the importance of macroeconomic policy in dampening the effects of climate change. Macroeconomic variables like government consumption, exchange rate and gross capital formation affect the climate impacts. This finding suggests the use of fiscal and monetary policy in building resilience. For instance, government expenditure can help in recovery and adaptation processes and a sound macroeconomic environment can help cushion the shock.

The results are very robust for the climate risk integration in finance, from a sustainable finance perspective. The study's findings that climate variables are important determinants of economic performance means financial institutions need to consider the impacts of physical climate risks in their investment and risk management strategies. This involves climate risk stress-testing, climate risk disclosure schemes and sustainable investment strategies.

The research also highlights the need for the development of green finance instruments, such as green bonds, climate funds and ESG investment strategies. These can serve as a way to raise finance for climate-resilient projects. The integration of finance and sustainability will help to create a more sustainable and low-carbon future, which can be achieved through the cooperation of policymakers and financial institutions.

Finally, this research shows how using machine learning methods in climate risk analysis can be beneficial. The development of data and analytical skills by governments and academics should be promoted to improve climate–economic projections. This can help to identify nonlinearities and interactions that will enhance policy outcomes.

To conclude, the policy lessons of this study highlight the importance of a comprehensive and forward-thinking approach to manage climate risks. To enable macroeconomic stability in the context of the increasing climate challenges, climate considerations should be embedded in macroeconomic policies, infrastructure should be made more resilient and sustainable finance should be mobilized, as well as introducing new analytical tools.

5.5 Limitations of the Study

Although this study offers valuable insights into the links between climate shocks and macroeconomic stability, there are some limitations.

The study is based on country aggregate data and may not reflect regional and sectoral variations in climate impacts. Climate shocks can have region- and sector-specific impacts and more detailed data may reveal more about these effects. Second, some of the climate variables (e.g. drought) have relatively low variation in the data, as a result of their measurement. This limits the potential to adequately model their effects, and could lead to site-specific outcomes. Third, while the Random Forest models are able to capture nonlinearities, they do not infer causality. The results should thus be considered as strong associations, rather than causal.

Lastly, the study is carried out in some countries in the ASEAN region, and may limit the generalizations to other countries. However, the modelling approach can be applied in other places. These caveats notwithstanding, the study is robust empirically; by using multiple models, cross-validation and stability check to ensure the results are valid and significant.

5.6 Directions for Future Research

This study will serve as a stepping stone to future studies that can take advantage of the results and limitations of the current study.

Greater disaggregation and frequency of data, such as regional or sectoral, could be used in future to account for regional impacts of climate shocks. This would help to gain a better understanding of the reaction of various sectors and regions to climate variability. Secondly, other climate indicators, including rainfall intensity, heatwaves or severity of disaster could be used in future studies to better understand climate risks. Potentially better measures of climate shocks could lead to more accurate empirical findings and a better understanding of the channels.

Third, future research should also consider financial and market-based indicators such as credit, stock market or indicators of green finance to further link sustainable finance and climate shocks. This would allow for future research to directly address the questions of what effect climate risks have on financial markets and investment decisions. Fourth, future research would be able to try other machine learning methods, like gradient boosting or deep learning models to evaluate the performance of these models and gain further insight into the nonlinear dynamics.

Finally, causal inference methods such as IV or quasi-experimental would enable a more robust causal relationship between climate risk and macroeconomic variables, besides the correlation-based approach followed here. Put simply, these are just some of the ways in which these opportunities can be extended in climate–macroeconomics, and how it can be made more useful for policy and financial purposes.

5.7 Conclusion

This research aimed to assess the effects of climate shocks on macroeconomic stability in a group of ASEAN countries over 2000-2024. The study employed both panel econometric and Random Forest machine learning models to provide an all-round assessment of linear and non-linear impacts of climate shocks on GDP growth, industrial growth and inflation.

The results indicate that climate shocks play an important role in the macroeconomic stability, with robust and strong impacts on GDP growth and industrial growth. The most important variable in all the models is temperature, which reflects the overall and long-lasting impact of climate change. Weather shocks (floods and storms) have also been found to impact the economy and primarily through impacts on infrastructure and production. The influence of climate change on inflation, however, is not so simple, as it is dependent on the interactions between the various effects of climate change on the supply side and the general economic situation.

This research is important because of the finding of the presence of nonlinear and threshold effects in the relationship between climate and macroeconomics. The results show that the impact of climate on the economy is non-linear – meaning that climate's impact on the economy grows beyond a certain threshold. This analysis highlights the need to go beyond linear models and offers valuable insights into the possible biases in traditional risk analyses when it comes to climate change. This helps to further enhance the rigor and insight gained from the econometric and machine learning models. The econometric models provide average treatment effects that can be interpreted, whereas the machine learning models provide intricate interactions, variable importance and other effects. This allows to get a more complete view on the pathways of impacts of climate shocks on economic stability.

More generally, the research underlines the emerging need for considering climate in macroeconomic policy and finance. The results of this study confirm the hypothesis, namely that climatic conditions represent an economic risk factor that can have an effect on growth, stability and development. This poses a dilemma which must be addressed at various levels: policy, finances and research. Finally, this work adds to the growing body of research in climate economics, by offering empirical evidence of the nuanced and nonlinear impacts of climate shocks on the economy's stability. This research emphasizes on the need for anticipatory and multiple climate risk management approaches and provides further ground for sustainable and climate resilient economic systems.

REFERENCES

Aghion, P., Antonin, C., & Bunel, S. (2021). The power of creative destruction: Economic upheaval and the wealth of nations. Harvard University Press. https://www.hup.harvard.edu/books/9780674979906

Aiyar, S., Calomiris, C. W., & Wieladek, T. (2016). How does credit supply respond to monetary policy and bank minimum capital requirements? European Economic Review, 82, 142–165. https://doi.org/10.1016/j.euroecorev.2015.07.021

Alekseev, G., Amer, S., Gopal, M., Kuchler, T., Schneider, J., Stroebel, J., & Wernerfelt, N. (2020). The effects of COVID-19 on U.S. small businesses. Journal of Finance, 75(6), 2971–3001. https://doi.org/10.1111/jofi.13043

Allen, F., Gu, X., & Jagtiani, J. (2021). A survey of fintech research and policy discussion. Review of Corporate Finance, 1(3–4), 259–339. https://doi.org/10.1561/104.00000004

Andersson, M., Bolton, P., & Samama, F. (2016). Hedging climate risk. Financial Analysts Journal, 72(3), 13–32. https://doi.org/10.2469/faj.v72.n3.1

Angrist, J. D., & Pischke, J. S. (2009). Mostly harmless econometrics: An empiricist's companion. Princeton University Press. https://press.princeton.edu/books/hardcover/9780691120355/mostly-harmless-econometrics

Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. Annual Review of Economics, 11, 685–725. https://doi.org/10.1146/annurev-economics-080217-053433

Asian Development Bank. (2021). Climate risk country profile: Philippines. ADB.

Asian Development Bank. (2022). Climate risk country profile: Indonesia. ADB.

Asian Development Bank. (2023). Climate risk country profile: Vietnam. ADB.

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). COVID-induced economic uncertainty. NBER Working Paper No. 26983. https://doi.org/10.3386/w26983

Bank for International Settlements. (2021). Climate-related financial risks: A survey on current initiatives. BIS.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. Nature Climate Change, 7(4), 283–288. https://doi.org/10.1038/nclimate3255

BIS. (2022). Green finance and climate risk management. Bank for International Settlements

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? Journal of Financial Economics, 142(2), 517–549. https://doi.org/10.1016/j.jfineco.2021.01.005

Bolton, P., Després, M., Pereira da Silva, L., Samama, F., & Svartzman, R. (2020). The green swan: Central banking and financial stability in the age of climate change. Bank for International Settlements

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. Nature, 527, 235–239. https://doi.org/10.1038/nature15725

Cevik, S., & Jalles, J. T. (2022). Climate change and inflation. IMF Working Paper. Link

Chen, C., Liaw, A., & Breiman, L. (2004). Using random forest to learn imbalanced data. University of California, Berkeley.

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD Conference, 785–794. https://doi.org/10.1145/2939672.2939785

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? Journal of Economic Literature, 52(3), 740–798. https://doi.org/10.1257/jel.52.3.740

Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). Climate value at risk of global financial assets. Nature Climate Change, 6(7), 676–679. https://doi.org/10.1038/nclimate2972

Dabla-Norris, E., Ji, Y., Townsend, R., & Unsal, D. F. (2015). Identifying constraints to financial inclusion and their impact on GDP and inequality. IMF Working Paper.

Davis, S. J. (2016). An index of global economic policy uncertainty. NBER Working Paper No. 22740.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. American Economic Journal: Macroeconomics, 4(3), 66–95.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate–economy literature. Journal of Economic Literature, 52(3), 740–798.

Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the U.S. American Economic Journal: Applied Economics, 3(4), 152–185.

Dietz, S., & Stern, N. (2015). Endogenous growth, convexity of damage and climate risk: How Nordhaus' framework supports deep cuts in carbon emissions. The Economic Journal, 125(583), 574–620.

Dosi, G., Pereira, M. C., Roventini, A., & Virgillito, M. E. (2020). Causes and consequences of hysteresis: Aggregate demand, productivity, and employment. Industrial and Corporate Change, 29(6), 1377–1406.

Fankhauser, S., & Tol, R. S. J. (2005). On climate change and economic growth. Resource and Energy Economics, 27(1), 1–17.

Feyen, E., Utz, R., Zuccardi Huertas, I., Bogdan, O., & Moon, J. (2020). Macro-financial aspects of climate change. World Bank Policy Research Working Paper.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. Annals of Statistics, 29(5), 1189–1232.

Friedman, J. H. (2002). Stochastic gradient boosting. Computational Statistics & Data Analysis, 38(4), 367–378.

Friedman, J. H., Hastie, T., & Tibshirani, R. (2009). The elements of statistical learning (2nd ed.). Springer.

Furceri, D., Loungani, P., Ostry, J. D., & Pizzuto, P. (2021). Will COVID-19 have long-lasting effects on inequality? Evidence from past pandemics. Review of Income and Wealth, 67(1), 3–24.

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. Annual Review of Financial Economics, 13, 15–36. https://doi.org/10.1146/annurev-financial-102620-103311

Gourinchas, P. O. (2020). Flattening the pandemic and recession curves. MIT Sloan Management Review.

Grinsted, A., Moore, J. C., & Jevrejeva, S. (2010). Reconstructing sea level from paleo and projected temperatures. Climate Dynamics, 34(4), 461–472.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. Quarterly Journal of Economics, 110(2), 353–377.

Hansen, L. P., & Sargent, T. J. (2008). Robustness. Princeton University Press.

Hansen, J., Sato, M., & Ruedy, R. (2012). Perception of climate change. Proceedings of the National Academy of Sciences, 109(37), E2415–E2423.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning (2nd ed.). Springer.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 770–778.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. Proceedings of the National Academy of Sciences, 107(35), 15367–15372.

Hsiang, S. M., Burke, M., & Miguel, E. (2013). Quantifying the influence of climate on human conflict. Science, 341(6151), 1235367.

Intergovernmental Panel on Climate Change. (2021). Climate change 2021: The physical science basis. Cambridge University Press.

Intergovernmental Panel on Climate Change. (2022). Climate change 2022: Impacts, adaptation and vulnerability. Cambridge University Press.

Intergovernmental Panel on Climate Change. (2023). Climate change 2023: Synthesis report. Cambridge University Press.

International Monetary Fund. (2020). Global financial stability report: Markets in the time of COVID-19. IMF.

International Monetary Fund. (2021). World economic outlook: Managing divergent recoveries. IMF.

International Monetary Fund. (2022). Climate change and financial stability. IMF.

International Monetary Fund. (2023). World economic outlook: Navigating global divergences. IMF.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2016). The great mortgaging: Housing finance, crises, and business cycles. Economic Policy, 31(85), 107–152.

Jordà, Ò., Singh, S. R., & Taylor, A. M. (2020). The long-run effects of monetary policy. Journal of Economic Literature, 58(2), 405–447.

Kahn, M. E., Mohaddes, K., Ng, R. N., Pesaran, M. H., Raissi, M., & Yang, J. C. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. Energy Economics, 104, 105624. https://doi.org/10.1016/j.eneco.2021.105624

Kalkuhl, M., & Wenz, L. (2020). The impact of climate conditions on economic production: Evidence from a global panel of regions. Journal of Environmental Economics and Management, 103, 102360.

Keynes, J. M. (1936). The general theory of employment, interest and money. Macmillan.

Kling, G., Volz, U., Murinde, V., & Ayas, S. (2021). The impact of climate vulnerability on firms' cost of capital and access to finance. World Development, 137, 105131.

Koubi, V. (2019). Climate change and conflict. Annual Review of Political Science, 22, 343–360.

Levin, A. T., & Sinha, A. (2020). Inflation expectations and climate risk. IMF Working Paper.

Li, X., & Li, S. (2021). Climate risk and corporate investment: Evidence from global markets. Journal of Financial Stability, 54, 100870.

Litterman, R. (2013). Pricing climate risk appropriately. Financial Analysts Journal, 69(5), 17–20.

Lloyd's. (2018). Climate change and insurance sector risks. Lloyds of London.

Lombardi, M. J., Mohanty, M. S., & Shim, I. (2017). The real effects of household debt in the short and long run. BIS Working Papers.

Loungani, P., Rush, M., & Taveira, A. D. (2020). Global inflation dynamics in the post-crisis period. IMF Working Paper.

Maddison, A. (2007). Contours of the world economy, 1–2030 AD: Essays in macro-economic history. Oxford University Press.

Mankiw, N. G. (2021). Macroeconomics (10th ed.). Worth Publishers.

McKinsey Global Institute. (2020). Climate risk and response: Physical hazards and socioeconomic impacts. McKinsey & Company.

Molnar, C. (2022). Interpretable machine learning: A guide for making black box models explainable (2nd ed.). https://christophm.github.io/interpretable-ml-book/

Monasterolo, I. (2020). Climate change and the financial system. Annual Review of Resource Economics, 12, 299–320.

Monasterolo, I., & Raberto, M. (2018). The EIRIN flow-of-funds behavioural model of green fiscal policies and green sovereign bonds. Ecological Economics, 144, 228–243.

Mora, C., Dousset, B., Caldwell, I. R., Powell, F. E., Geronimo, R. C., Bielecki, C. R., Counsell, C. W., Dietrich, B. S., Johnston, E. T., Louis, L. V., Lucas, M. P., McKenzie, M. M., Shea, A. G., Tseng, H., Giambelluca, T. W., Leon, L. R., Hawkins, E., & Trauernicht, C. (2017). Global risk of deadly hea

t. Nature Climate Change, 7(7), 501–506.

Nordhaus, W. D. (1991). To slow or not to slow: The economics of the greenhouse effect. The Economic Journal, 101(407), 920–937.

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. Proceedings of the National Academy of Sciences, 114(7), 1518–1523.

Network for Greening the Financial System. (2019). A call for action: Climate change as a source of financial risk. NGFS.

Network for Greening the Financial System. (2021). NGFS climate scenarios for central banks and supervisors. NGFS.

Network for Greening the Financial System. (2023). Progress report on climate-related financial risks. NGFS.

OECD. (2020). Climate risks and financial markets. Organisation for Economic Co-operation and Development.

OECD. (2022). Financing climate futures: Rethinking infrastructure. OECD Publishing.

OECD. (2023). Global outlook on climate adaptation. OECD Publishing.

Pastor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. Journal of Financial Economics, 142(2), 550–571.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica, 74(4), 967–1012.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289–326.

Pindyck, R. S. (2013). Climate change policy: What do the models tell us? Journal of Economic Literature, 51(3), 860–872.

Pörtner, H. O., Roberts, D. C., Tignor, M., Poloczanska, E. S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., & Rama, B. (Eds.). (2022). Climate change 2022: Impacts, adaptation and vulnerability. Cambridge University Press.

Rajan, R. G., & Zingales, L. (1998). Financial dependence and growth. American Economic Review, 88(3), 559–586.

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. Handbook of Macroeconomics, 2, 71–162.

Ritchie, H., & Roser, M. (2020). CO_2 and greenhouse gas emissions. Our World in Data.

Romer, D. (2019). Advanced macroeconomics (5th ed.). McGraw-Hill Education.

Romer, P. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5), S71–S102.

Rudebusch, G. D. (2021). Climate change is a source of financial risk. Economic Letter, Federal Reserve Bank of San Francisco.

Sachs, J. D., Woo, W. T., Yoshino, N., & Taghizadeh-Hesary, F. (2019). Why is green finance important? Asian Development Bank Institute Working Paper.

Sadorsky, P. (2021). Renewable energy consumption and income in emerging economies. Energy Economics, 99, 105258.

Schnabel, I. (2021). Climate change and monetary policy. European Central Bank Speech.

Schneider, S. H., & Kuntz-Duriseti, K. (2002). Uncertainty and climate change policy. Climatic Change, 52(1–2), 1–24.

Shashua-Bar, L., & Hoffman, M. E. (2000). Vegetation as a climatic component in urban street design. Energy and Buildings, 31(3), 221–235.

Shiller, R. J. (2015). Irrational exuberance (3rd ed.). Princeton University Press.

Shukla, P. R., Skea, J., Slade, R., Al Khourdajie, A., van Diemen, R., McCollum, D., Pathak, M., Some, S., Vyas, P., Fradera, R., Belkacemi, M., Hasija, A., Lisboa, G., Luz, S., & Malley, J. (Eds.). (2022). Climate change 2022: Mitigation of climate change. Cambridge University Press.

Sims, C. A. (1980). Macroeconomics and reality. Econometrica, 48(1), 1–48.

Stock, J. H., & Watson, M. W. (2019). Introduction to econometrics (4th ed.). Pearson.

Taylor, J. B. (1993). Discretion versus policy rules in practice. Carnegie-Rochester Conference Series on Public Policy, 39, 195–214.

Tol, R. S. J. (2018). The economic impacts of climate change. Review of Environmental Economics and Policy, 12(1), 4–25.

Tooze, A. (2021). Shutdown: How COVID shook the world's economy. Viking.

Tufekci, Z. (2014). Big data: Pitfalls, methods and concepts. First Monday, 19(7).

Ursúa, J. F., & Wilson, D. J. (2020). Financial crises and economic growth. Journal of Economic Perspectives, 34(4), 231–252.

United Nations. (2021). The sustainable development goals report. UN.

United Nations Environment Programme. (2022). Emissions gap report. UNEP.

United Nations Environment Programme. (2023). Adaptation gap report. UNEP.

Van der Ploeg, F., & Rezai, A. (2020). The risk of policy tipping and stranded carbon assets. Journal of Environmental Economics and Management, 100, 102258.

Van der Ploeg, F., & Withagen, C. (2015). Global warming and the green paradox. Journal of Environmental Economics and Management, 70, 1–14.

Varian, H. R. (2014). Big data: New tricks for econometrics. Journal of Economic Perspectives, 28(2), 3–28.

Vogt-Schilb, A., Hallegatte, S., & Rozenberg, J. (2015). Marginal abatement cost curves and climate policy. Energy Policy, 81, 193–206.

Volz, U., Beirne, J., Ambrosio Preudhomme, N., Fenton, A., Mazzacurati, E., & Renzhi, N. (2020). Climate change and sovereign risk. Asian Development Bank Institute.

Wagner, G., & Weitzman, M. L. (2015). Climate shock: The economic consequences of a hotter planet. Princeton University Press.

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. Review of Economics and Statistics, 91(1), 1–19.

World Bank. (2020). World development report 2020: Trading for development in the age of global value chains. World Bank.

World Bank. (2021). World development report 2021: Data for better lives. World Bank.

World Bank. (2022). World development indicators. World Bank.

World Bank. (2023). Global economic prospects. World Bank.

World Bank. (2024). Climate change knowledge portal. World Bank.

Xie, Y., & Mo, J. (2022). Climate risk and economic growth: Evidence from global panel data. Energy Economics, 110, 106012.

Xu, R., Yu, P., Abramson, M. J., Johnston, F. H., Samet, J. M., Bell, M. L., Haines, A., Ebi, K. L., Li, S., & Guo, Y. (2020). Wildfires, global climate change, and human health. New England Journal of Medicine, 383(22), 2173–2181.