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A Mixed-Method Analysis of Nationally Determined Contributions and their Connection to Broader Sustainability Objectives

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Introduction

Climate change is arguably the most relevant challenge that we will face in our times, with unprecedented impacts in scope and scale, affecting every aspect of Earth's system and requiring immediate, drastic actions to mitigate the consequences of increased adverse anthropogenic activity.

Since the 1800s, human activities have become the main driver of climate change, unequivocally contributing to global temperature increases through the emission of greenhouse gases. According to the IPCC, in the period between 2011 and 2020, global surface temperatures have increased by 1.1°C above pre-industrial levels[1].

The continuous increase in GHG emissions over the past 200 years has caused several changes in the Earth's climate system, increasing the magnitude and frequency of extreme weather and climate-related events such as heatwaves, droughts, and storm, which have disproportionately affected vulnerable communities.

Further increases in future emissions would additionally exacerbate the extreme effects of climate and weather hazards, increasing the complexity of climate-related risks and making them more difficult to manage.

While some consequences of climate change, such as sea level rises, are unavoidable, their intensity can be limited through deep, rapid, and sustained reductions in global greenhouse emissions. Decreasing the amount of GHG emitted in the atmosphere would not only limit the intensity of already irreversible changes, but would also reduce the likelihood of reaching tipping points, which would trigger abrupt and long-lasting changes in the climate system.

Since the establishment of the United Nations Framework Convention on Climate Change during the 1992 Rio "Earth Summit", the number of climate policies aiming to mitigate the possible adverse impacts of climate-related risks has substantially increased, both thanks to a deeper understanding of climate change and its relationship with socio-economic development, as well as to increasing international policy efforts.

The Paris Agreement stands as one of the most significant international climate treaties aiming to address the global challenge of climate change. Adopted in 2015, this landmark accord brings together the great majority of countries with the shared goal of limiting

[1] Lee Hoesung et al., *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, IPCC, March 2023.

global temperature rise to well below 2°C above pre-industrial levels, ideally pursuing efforts to achieve a maximum increase of 1.5°C.

The Agreement emphasizes the need for deep reductions in global greenhouse gas emissions and establishes a framework for countries to set Nationally Determined Contributions with progressively ambitious climate mitigation and adaptation targets. The implementation of these policies is essential to avoid facing increasingly severe climate change impacts and is crucial for achieving a climate-resilient future.

Mitigation actions often present synergies with other aspects of sustainable development, as climate change does not only represent an environmental issue, but also a profound social and economic challenge, affecting communities, livelihoods, and economies worldwide. Its impacts extend beyond the ecological sphere, disrupting food security, water resources, public health, and economic stability. The 2030 Agenda for Sustainable Development, with its 17 Sustainable Development Goals, highlights the interconnectedness between climate change and broader development objectives, as many SDGs can be directly influenced by climate action.

Thus, addressing the risks posed by climate change becomes essential not only to mitigate the environmental consequences that would occur if mean global temperatures were to increase, but also to limit the possible socio-economic consequences that would occur, supporting the transition towards more sustainable development pathways.

In this context, evaluating the Paris Agreement becomes fundamental to understand its effectiveness in addressing the global challenge of climate change. Periodic assessments are crucial for monitoring progress, ensuring transparency, and fostering accountability among countries. By evaluating the implementation of NDCs, it becomes possible to assess not only the ambition of individual nations but also the likelihood of achieving global temperature targets. This is essential to determine whether countries are on track to meet their mitigation and adaptation goals or if further efforts are needed to close the ambition gap. Furthermore, assessing country ambition and the feasibility of reaching emission reduction targets provides critical insights into how well-positioned nations are to effectively manage the socio-economic impacts of climate change and align with broader sustainable development objectives.

With this in mind, the present thesis sought to determine how country ambition is related to the probability of achieving pledged climate targets and how it can be connected to the

broader goals of the Sustainable Development Goals by analysing the content of the Nationally Determined Contributions of 17 G20 members. These economies are collectively responsible for over two-thirds of global greenhouse gas emissions, making their actions crucial to the success of both the Paris Agreement and the 2030 Agenda for Sustainable Development.

The first chapter provides a provides a comprehensive summary of the Paris Agreement, the 2030 Agenda for Sustainable Development, and the G20, explaining their interconnectedness and importance in shaping global climate and sustainability efforts. The second chapter assesses the ambition embedded within the NDCs of the G20, evaluating the emission reduction targets of each member and comparing them by calculating percentage emissions changes that they would generate. Chapters three and four focus on determining the probability that G20 members have of achieving their NDC emissions targets in 2030 through the adoption of a stochastic, regression-based extension of the IPAT framework that simulates future carbon emissions. Lastly, chapter five explores the connections between the climate actions defined in each G20 member's NDC and broader objectives outlined in the Sustainable Development Goals, both by analysing already available data and incorporating the use of artificial intelligence to identify connections in NDCs that had not yet been examined.

Chapter 1

Contextual Framework: Paris Agreement, 2030 Agenda, G20

This chapter will provide a comprehensive overview of the international commitments and frameworks that form the foundation of our analysis. In particular, it will revolve around three key elements: the Paris Agreement, the 2030 Agenda for Sustainable Development, and the G20.

It will first summarise the Paris Agreement, describing its goals, scope, and implementation mechanisms, with a particular focus on Nationally Determined Contributions, which are the main reference documents used within our work. Then, it will provide an overview of the 2030 Agenda for Sustainable Development, a comprehensive global framework that aims to address a wide range of challenges to achieve a transition toward sustainable development, which at its core has 17 Sustainable Development Goals (SDGs). Lastly, it will focus on providing a description of the G20, an international forum that brings together the world's largest economies to coordinate global economic and governance policy.

These three frameworks shape the global agenda on climate change and sustainability and are closely interconnected, with each one reinforcing and supporting the goals of the others. The Paris Agreement's focus on limiting the rise in global average temperatures and enhancing climate resilience can be closely tied to the broader sustainability objectives outlined in the 2030 Agenda. On the other hand, many of the Agenda's Sustainable Development Goals (SDGs) can only be achieved through significant climate action. Additionally, the G20 has a pivotal role in this context, as its members collectively contribute the more than 2/3 of global greenhouse gas emissions, which makes their progress crucial to both the success of the Paris Agreement and the 2030 Agenda.

Therefore, integrating these three dimensions in our analysis allows us to obtain a comprehensive assessment on the evolution of climate targets, and their convergence with broader sustainability goals.

1.1. The Paris Agreement

The Paris Agreement is a legally binding international climate accord that was adopted in 2015 by 195 parties at the UN Climate Change Conference held in Paris.

The Agreement seeks to enhance the implementation of the 1992 United Nations Framework Convention on Climate Change (UNFCCC) and strengthen the global response towards climate change. It aims to do so by creating a common framework to limit increases in global mean temperatures to well below 2°C above pre-industrial levels by the end of the century, while striving to limit them to 1.5°C to avoid significant adverse impacts that could result from further growths in global average temperature. Beyond its temperature goals, the Agreement also emphasises the importance of climate change adaptation and resilience, urging countries to strengthen their capacities to withstand the adverse effects that result from climate change and safeguard their communities and ecosystems. Additionally, it also recognises the need for financial flows that are consistent with climate-resilient and low-emission pathway, which are critical for supporting developing countries in their climate actions and ensuring that they can fully participate in the global transition towards a low-carbon society.

The Agreement adopts a bottom-up approach, where parties are given a wide margin of discretion when it comes to determining their contributions to tackle the challenges posed by climate change. Unlike its predecessor, the 1997 Kyoto Protocol, which relied on a "targets and timetables approach" and imposed legally binding emissions reduction commitments, the Paris Agreement relies on a "pledge and review" approach which is based on commitments that are determined on a national level.

Another substantial difference between the two international treaties is represented by their scope. The Kyoto Protocol differentiated between developed (Annex I) and developing (non-Annex I) countries, with the former having a legal obligation to reduce their greenhouse gas (GHG) emissions. The Paris Agreement, on the other hand, does not make such distinction, and all parties have the obligation to participate in the emission reduction efforts needed to reach its goals.

Nonetheless, the Agreement does acknowledge that there are differences among its members when it comes to capacities and duties towards climate change, and thus emphasises the need to implement its contents according to the UNFCCC principle of "common but differentiated responsibilities and respective capabilities", thus also reinforcing the need for developed countries to provide financial assistance to less endowed and more vulnerable countries.

1.1.1. Nationally Determined Contributions

Within the framework of the Paris Agreement, all countries must communicate the actions that they will undertake to reduce their greenhouse gas emissions and build resilience to adapt to the impacts of climate change within Nationally Determined Contributions (NDCs).

The treaty, recognising that its goals can only be achieved in the long-term, is built on the ratcheting up of both individual and aggregate ambition over time. Consequently, starting from 2020, NDCs must be submitted every five years to the UNFCCC and must represent a progression compared to previous ones, reflecting the highest possible degree of ambition that can be achieved by parties.

These documents are at the core of the treaty and are critical to the achievement of its long-term goals, as they contain information on targets, policies, and measures for reducing national emissions and climate change impacts.

However, while the Agreement does mandate that each participating country must periodically update the information regarding its mitigation actions and their implementation (Article 4.9.), and that each successive NDC submissions has to represent an increased level of ambition (Article 4.3.), it does not prescribe any additional obligations regarding the content or the form of the NDCs. This has resulted in the submission of a heterogenous set of Nationally Determined Contributions and has led to a lack of transparency and to issues when it comes to the comparison of mitigation efforts and targets.

Together, the climate actions put in place by the participating countries will determine whether the long-term of the Paris Agreement will be achieved and the consequence of climate change will be mitigated. Thus, Nationally Determined Contributions play a key role in illustrating the progress made in the effort to transition towards the sustainable development of our society.

1.2. The 2030 Agenda for Sustainable Development

The United Nations 2030 Agenda for Sustainable Development, adopted in 2015 by all UN Member States, is a global framework designed to guide the world towards a more sustainable and equitable future by 2030.

At its core, the 2030 Agenda has 17 Sustainable Development Goals (SDGs) and, which address a wide array of global challenges, including eradicating extreme poverty and hunger, improving health and education, achieving gender equality, providing access to clean water and sanitation, promoting sustainable economic growth, and taking action to combat climate change and its related impacts (Figure 1).

The SDGs, together with their 169 associated targets, are designed to be comprehensive and integrated, as the Agenda recognises that the areas of action are highly interconnected and a holistic approach is required to balance the three main areas of sustainability: economic, social, and environmental.

The 2030 Agenda is universal, as it applies to all countries, regardless of whether these are considered developed or developing, and emphasises the principle of "leaving no one behind", ensuring that sustainable development reaches even the most vulnerable and marginalised parts of society. Such a framework requires global cooperation, where national and international efforts are accompanied by actions and projects put in place by businesses, civil society, and individuals.

Figure 1.1. *UN Sustainable Development Goals*

Source: *United Nations Sustainable Development – Communications Materials*

A significant contribution to the achievement of the Sustainable Development Goals could be given by the Nationally Determined Contributions that have to be submitted in accordance to the Paris Agreement. By aligning climate action, which focuses on greenhouse gas emission reduction and climate change adaptation, with broader social,

economic, and environmental policies countries, NDCs can drive progress across multiple SDGs, enhancing resilience, reducing inequalities, and ensuring a more sustainable future for all.

1.3. Group of Twenty

The G20 (or Group of Twenty) is an intergovernmental forum for economic cooperation that plays a critical role in "defining and strengthening global architecture and governance on all major international and economic issues".[2]

It unites 19 of the world's largest national economies (Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Korea, Mexico, Saudi Arabia, South Africa, Russia, Turkey, United Kingdom, and United States of America), as well as the European Union and the African Union, and ensure constant dialogue and collaboration between developed and developing nations.

The G20 was founded in 1999, in the wake of a series of financial crises of the 1990s such as the Mexican peso crisis in 1994, the Asian financial crisis in 1997, and the Russian financial crisis in 1998. These events underscored the need for a more inclusive platform, where both developed and emerging economies could collaborate to stabilise the global financial system. Initially, the G20 served as a forum for finance ministers and central bank governors to discuss and coordinate economic policies, focusing primarily on macroeconomic issues such as fiscal policy, monetary policy, and exchange rate mechanisms.

The scope and significance of the G20 changed significantly during the global financial crisis of 2008. As the crisis intensified following the collapse of the Lehman Brothers bank, it became clear that a broader, more coordinated international response was necessary. Thus, in November of the same year, the first-ever G20 Leaders' Summit was convened in Washington D.C., transforming the forum from a ministerial-level meeting into a crucial summit for global leadership on economic issues.

Since then, the G20 Leaders' Summit has become an annual event, and the forum has evolved and broadened its agenda to address a wide range of global challenges that go beyond economic and financial issues, such as sustainable development, climate change,

[2] G20, *About the G20*, 2024: https://www.g20.org/en/about-the-g20

global health, energy transition, food security and fighting corruption. These topics are discussed through two parallel workstreams: the Finance Track, which focuses on economic and financial issues; and the Sherpa Track, which concentrates on broader policy areas.

From an operative perspective, the G20 adopts a rotating presidency system, where each year a different member country takes on the role of setting the agenda and hosting the Leaders' Summit. The country holding the presidency coordinates the group's activities with the support of the previous and subsequent presidencies, forming what is known as the G20 Troika, a system that ensures continuity and coherence in the group's work. The importance of the G20 is highlighted by the fact that, when considered collectively, its member countries represent around 85% of global Gross Domestic Product (GDP), 75% of global trade and 66% of the world population.[3]

In addition to this, the G20 member states also account for approximately 76% of global greenhouse gas emissions[4], and play a pivotal role in the transition towards sustainable development. As the largest contributors of global emissions, the policies and actions taken by these nations directly influence the trajectory of global climate change efforts.

The G20's commitment to reducing emissions, promoting renewable energy, and supporting sustainable development is essential for achieving the Paris Agreement's goal of limiting global warming to below 2°C, as well as to the SDGs of the UN 2030 Agenda. By leveraging their economic and political influence, G20 countries can drive transformative changes that are necessary for a sustainable and equitable global future.

[3] G20, *Brasil's G20 presidency: Understand the G20 and Brasil's responsibilities at the presidency*, 2024:
https://www.g20.org/en/e-book-brasil-na-presidencia-do-g20

[4] United Nations Environment Programme, *Emissions Gap Report 2023: Broken Record – Temperatures hit new highs, yet world fails to cut emissions (again)*, Nairobi, November 2023.

Chapter 2

Analysis of the Ambition of G20 NDC Target Emissions

The Paris Agreement, through its bottom-up approach, allows parties to autonomously determine their contributions to the reduction of global GHG emissions, as it offers limited indications on the scope and content of Nationally Determined Contributions. In fact, while parties are required to provide information on how their NDCs contribute to Article 2.1 (a) of the Agreement and how they consider them to be fair and ambitious, there are still no criteria for the identification of each country's fair share. This lack of guidance has led to the adoption of differing methods for the development of NDCs, which vary in scope, content, and length, resulting in transparency and comparability in assessing each party's level of ambition.

Nonetheless, determining the ambition embedded within each country's NDC and comparing ambitions across countries is crucial for the achievement of the goals of the Agreement. It allows to evaluate whether collective efforts are sufficient to mitigate the negative consequence of climate change and whether emission reductions are distributed in an equitable and fair way, promoting the stability of the Agreement and its "pledge and review" approach.

The absence of a common burden-sharing scheme has led to the development of several third-party assessments of the ambition level contained within each country's NDC. Peterson et al. investigate the determinants of NDC ambition enhancement through a mixed-method approach, finding that countries were more likely to enhance their emission reduction targets if they engaged in stakeholder consultations.[5]

Aldy et al. use integrated assessment models to analyse country pledges, showing a discrepancy among county efforts, suggesting insufficient levels global ambition.[6]

Pan et al. develop a framework based on six equity principles to allocate reduction targets within global emission scenarios consistent with meeting the goals of the Paris Agreement

[5] Peterson Lauri et al., *What determines climate ambition? Analysing NDC enhancement with a mixed-method design*, in *npj Climate Action*, 21 (2), Springer Nature, Online Publication, August 2023.

[6] Aldy Joseph et al., *Economic tools to promote transparency and comparability in the Paris Agreement*, in *Nature Climate Change*, 6, 1000-1004, Springer Nature, Online Publication, August 2016.

and compare them with NDC targets, showing that most countries need to increase their ambition by 2030 to meet the Agreements goals. [7]

In this chapter, we will proceed to describe the framework that we adopted to analyse the level of ambition contained within the NDCs of G20 members. We will first describe the adopted methodology and relative assumptions in the next paragraph and subsequently proceed to illustrate the results of our analysis both on a regional and intensity level, as well as on an individual country level.

2.1. Methodology: Normalising NDCs to Determine Country Ambition

To determine country ambition within the context of Nationally Determined Contributions targets, we decided to use the methodology developed by King et. al in "*Normalisation of Paris Agreement NDCs to enhance transparency and ambition*", which sets out to determine and compare the ambition of countries' NDCs by analysing individual pledges, classifying them in four categories, normalising them to enhance comparability, calculating changes in emissions between the NDC target year and the last available year, and analysing the results on a regional and per-capita intensity basis.

2.1.1. Subject of Analysis

While King et al. perform their analysis on the conditional NDC targets of 147 parties, the scope of our analysis different. We focus our efforts on evaluating and comparing the ambition levels of the latest NDC targets submitted by G20 member countries. These collectively account for approximately 2/3 of global emissions, comprising some of the major world emitters, and thus can be considered a good sample to analyse the overall progress towards the achievement of the Paris Agreements' goals.

In our approach, France, Germany, and Italy were not analysed separately, since all 27 Member States of the European Union have submitted one collective NDC, and thus have been assessed collectively. Additionally, since data on GHG emissions was only available up until 2022, our analysis did not consider the African Union, which became an official member of the G20 in 2023.

[7] Pan Xunzhang et al., *Exploring fair and ambitious mitigation contributions under the Paris Agreement goals*, in *Environmental Science & Policy*, 74, 49-56, Elsevier, Online Publication, August 2017.

Lastly, our analysis is focused only on unconditional NDC targets, as we want to investigate the change in emission levels that would result from the reductions to which countries have completely committed themselves.

2.1.2. Groupings of NDC Pledges

Since the Paris Agreement gives countries freedom in determining the content of their NDC, there are inevitably differences in the ways that these formulate their NDC targets. To account for theses discrepancies, King et. al firstly divide countries into four groups, according to the type of emission reduction target formulated within their NDC:

- ***Absolute Emission Reduction***: which includes all those countries who submitted a pledge containing an absolute percentage emission reduction for a target year relative to a historic base year;
- ***Business As Usual (BAU) Reduction***: which includes all countries whose NDCs contain a percentage reduction in emissions for a target year relative to a business-as-usual scenario, as well as those that have submitted a fixed emission trajectory target;
- ***Emission Intensity Reduction***: which includes countries that have pledged to reduce the intensity of their GHG emissions per unit of GDP relative to a historic base year;
- ***Projects Absent of GHG-emissions Targets***: which includes countries whose NDCs do not include any explicit details regarding their GHG emission reduction targets.

Subsequently, to assess the ambition level of each pledge type, an analysis is performed by region and emission intensity per-capita, which allows for a systematic comparison of countries with similar geopolitical characteristics.

We adopted a similar approach to determine the ambition level of G20 countries, grouping them according to their pledge type, but we adopted a different classification of pledge types. Since within the context of our analysis no countries were found to be absent of any specific emission reduction targets, we decided to modify the last grouping and create a separate classification for those countries that have submitted an absolute level of GHG emissions that cannot be exceeded in the target year, which were previously included in the BAU group, thus allowing for a more coherent separation of pledge types.

2.1.3. Normalising NDC Targets

To assess the ambition level of each analysed country, we initially proceeded to calculate the amount of GHG emissions that would be generated in the target year if the reductions that were pledged within each NDC with respect to the base year were achieved.

For those countries that have set an intensity-related emission reduction target, we had to determine future GDP levels to calculate the emissions that would be generated in the target year. If a projection for the target year GDP was provided within the NDC by the country, we adopted said forecast for our assessment, otherwise, we decided to adopt the long-term GDP projections provided by the OECD.

To provide a comprehensive and comparable picture of the possible GHG emissions that would be generated in a scenario where countries are able to meet their unconditional NDC emission reduction targets, and in accordance to the framework adopted by King et al., our analysis included emissions related to LULUCF for all countries. This implied that, for those countries that did include LULUCF in their NDC pledge, we had to proceed to create a forecast by applying an exponential smoothing model to LULUCF emission trends between 1990 and 2021 (last available year), and adding the forecasted emissions to those that would be generated in the target year according to the NDC pledge.

We decided to adopt the additive Holt-Winters exponential smoothing model[8], where LULUCF time series are decomposed in two main components: level, which represents the baseline value of the time series at a point in time; and trend, which represents the direction and rate of change in the level of the series of over time. These components are updated over time using smoothing equations, which assign a decreasing weight to observations as time moves forward, and are added to create a forecast of future emissions. The code we used to implement the Holt-Winters model to historical LULUCF data can be found in Appendix I.

Subsequently, to make emission reductions comparable across countries, we calculated the percentage change in emissions that would be generated between the year for which emission data was last available (in our case 2022), and the target year of each NDC.

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[8] Alam Teg, Al Arjani Ali, *A Comparative Study of CO2 Emission Forecasting in the Gulf Countries Using Autoregressive Integrated Moving Average, Artificial Neural Network, and Holt-Winters Exponential Smoothing Models*, in *Advances in Meteorology*, John Wiley & Sons, December 2021.

Lastly, after we determined the percentage change in emissions for each examined G20 member, we grouped them according to their emission pledge type, and performed an assessment on a regional level, where we divided countries according to the world region classification of the World Bank, and on a per-capita intensity level, where we grouped countries in five percentiles according to the intensity of their emissions per-capita, which allows us to provide a broad overview of the ambition levels for each category.

2.1.4. Data

To determine the ambition level of each analysed country, we had to obtain historical data between 1990 and 2022 on GHG emission levels, both including and excluding LULUCF; as well as the historical and future data between 2005 and 2030 on the GDP of some G20 members.

Historical data of GHG emissions that include LULUCF, expressed in Mt CO_2e, was obtained through the Emissions Database for Global Atmospheric Research (EDGAR) Community GHG Database. Accordingly, historical information on GHG emissions that does not include LULUCF, expressed in Gg CO_2e and converted in Mt CO_2e, was extracted from the PRIMAP database, and was used to determine target emissions for countries that did not include LULUCF in their NDC target. Additionally, for such countries, information on historical LULUCF from 1990 to 2021 to adopt for exponential smoothing forecasts was obtained through the Historical Country Greenhouse Gas Emissions Data of Climate Watch, expressed in Mt CO_2e.

Data on historical and future GDP adopted to determine the emission intensity of some G20 countries was obtained through the OECD Long-term baseline projections for GDP, expressed in Purchasing Power Parity (PPP) using 2015 constant international dollars.

Lastly, in order to determine the future intensity of emissions per capita, we utilised data on forecasted population growth provided by the 2024 UN World Population Prospects.

2.2. Ambition Analysis: Regional and Per-Capita Intensity Results

In this paragraph we will illustrate the results of our regional and per-capita intensity analysis of G20 members, which allows us to provide a broad overview of the change in emissions that would be generated if NDC targets were to be achieved, as well as to determine which pledge types can generally be considered to lead to the highest ambition.

After we calculate the percentage change in GHG emissions between the target and the base year for each G20, we proceeded to group them according to their pledge type and to the World Bank division of world regions, which partitions the world in seven regions: East Asia and Pacific; Europe and Central Asia; Latin America and Caribbean; Middle East and North Africa; North America; South Asia; and Sub-Saharan Africa.

The results of our regional analysis are summarised in Table 2.1., where for each region and emission pledge type, we indicate: the number of countries that belong within said grouping; their share of global emissions; and the percentage change in their emissions in 2030 with respect to 2022.

Table 2.1. *Normalised NDC Targets of the G20 by Pledge and Region*

Region	Pledge Type												Total Regional % Change
	i. Absolute Emission Reduction			*ii. BAU Reduction*			*iii. Intensity Reduction*			*iv. Absolute Level of Emissions*			
	N° of Countries	Share of Global Emissions	% Change by 2030	N° of Countries	Share of Global Emissions	% Change by 2030	N° of Countries	Share of Global Emissions	% Change by 2030	N° of Countries	Share of Global Emissions	% Change by 2030	
East Asia & Pacific	3	5%	-39%	1	2%	57%	1	29%	-4%	-	-	-	-5%
Europe & Central Asia	3	12%	-30%	1	1%	1%	-	-	-	-	-	-	-27%
Latin America & Carribean	-	-	-	1	2%	-21%	-	-	-	2	3%	-9%	-13%
Middle East & North Africa	1	2%	-40%	-	-	-	-	-	-	-	-	-	-40%
North America	2	13%	-41%	-	-	-	-	-	-	-	-	-	-41%
South Asia	-	-	-	-	-	-	1	7%	114%	-	-	-	114%
Sub-Saharan Africa	-	-	-	-	-	-	-	-	-	1	1%	-21%	-21%
G20 Total	9	31%	-36%	3	5%	20%	2	36%	20%	3	4%	-12%	-5%

Note: *Deeper shades of green indicate bigger emission reductions, while deeper shades of red indicate larger increases in emissions*

We find that category i. pledges lead to the greatest ambition level in terms of pledged GHG emission reductions, with countries falling within this category representing 31% of global emissions and pledging an overall reduction of 36%. Additionally, we find that category iv. pledges also lead to positive emission reductions, with an overall reduction of 12%, and thus can be associated with high ambition levels. Contrarily, we find that category ii. and category iii. pledges generally lead to increases or, at best, to low decreases in emission levels, with countries belonging to these categories increasing their combined emissions by 20% in 2030 compared to 2022.

On a regional level, the most frequent pledge type are absolute emission reductions, with most regions having a majority of countries with such pledge types. These are followed by absolute level of emission type pledges and BAU reduction pledges.

Our results show that almost all regions have submitted pledges that would lead to positive changes in the future, with most aiming to obtain emission reductions that surpass 30% of those generated in 2022. The only exception being the South Asia region, where emissions would more than double in the future according to the submitted NDC targets. After our regional analysis, in order to verify how emission intensity affects the type of reduction pledge and the ambition level adopted by countries, we proceeded to calculate the present emission intensity per-capita for each of the analysed countries and grouped them in five percentiles. Then, using forecasted data on population and each countries target emission level, we determined the future intensity per-capita and the percentage change that would be generated with respect to present values.

Table 2.2. *Normalised NDCs of the G20 by Pledge Type and Intensity Per-Capita*

	Pledge Type												
	i. Absolute Emission Reduction			*ii. BAU Reduction*			*iii. Intensity Reduction*			*iv. Absolute Level of Emissions*			
Percentile	N° of Countries	Share of Global Emissions	% Change by 2030	N° of Countries	Share of Global Emissions	% Change by 2030	N° of Countries	Share of Global Emissions	% Change by 2030	N° of Countries	Share of Global Emissions	% Change by 2030	**Ttoal Intensity % Change**
Highest 20%	3	4%	-45%	-	-	-	-	-	-	-	-	-	-45%
60% - 80%	3	17%	-36%	-	-	-	-	-	-	-	-	-	-36%
40% - 60%	1	2%	-35%	-	-	-	1	29%	-2%	1	1%	-31%	-6%
20% - 40%	1	7%	-38%	1	1%	-3%	-	-	-	1	1%	-11%	-30%
Lowest 20%	1	1%	-44%	2	4%	17%	1	7%	99%	1	2%	-9%	51%
G20 TOTAL	9	31%	-37%	3	5%	12%	2	36%	16%	3	4%	-14%	-11%

Note: *Deeper shades of green indicate bigger emission intensity reductions, while deeper shades of red indicate larger increases in emission intensity*

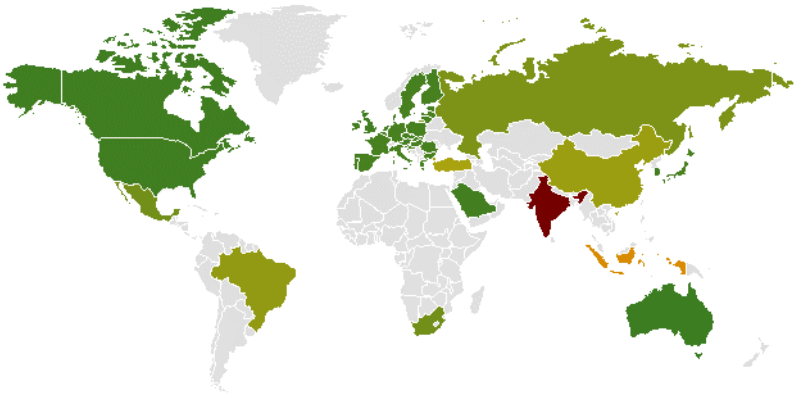
Table 2.2. shows that absolute emission reduction pledges have been adopted by countries belonging to all emission intensity percentiles, being the only pledge type adopted by the two highest ranked groups and outperforming other pledge types in every other group in terms of the reduction of emission intensity per-capita that they would generate. Our results also show that business-as-usual reductions have been mostly adopted by countries with the lowest emission intensity, and generally lead to low reductions or increases emission intensity per-capita. A similar situation is also present with intensity reduction pledges, which lead to the steepest increase in emission intensity in the lowest percentile group. Lastly, "absolute level of emission" pledges are adopted by countries falling within the lowest three percentiles, and generally lead to positive variations in the per capita intensity of country emissions.

Overall, our analysis has led us to conclude that the NDC targets set by G20 countries would collectively lead them to reduce their absolute levels of GHG emissions by 5% and the intensity of their emissions per-capita by 11% by 2030 compared to 2022, with absolute emission reduction pledges generating the highest and intensity reduction pledges generally leading to the lowest ambition levels.

2.3. Ambition Analysis: Country Results

This paragraph will provide a description of the results of our ambition analysis for each examined G20 member using the previous regional groupings. We will focus on describing the type of pledge that the country has adopted in its NDC, how we proceeded determine the future level of emissions that are implied its targets, and the ambition level that can be attributed to the country, represented by the percentage change in emissions that would be generated if unconditional NDC targets were to be met. A summary of our results can be observed in Figure 2.1. below.

Figure 2.1. *Normalised NDC Targets by G20 Member*



	Region																
	East Asia & Pacific					*Europe & Central Asia*				*Latin America & Carribean*			*Middle East & North Africa*	*North America*		*South Asia*	*Sub-Saharan Africa*
	AUS	CHN	IDN	JPN	KOR	EU27	GBR	RUS	TUR	ARG	BRA	MEX	SAU	CAN	USA	IND	ZAF
Pledge Type	i	iii	ii	i	i	i	i	i	ii	iv	iv	ii	i	i	i	iii	iv
2022 Emissions (Mt CO2)	571	15,685	1,241	1,183	726	3,588	427	2,580	688	383	1,310	820	811	757	6,017	3,943	535
Share of Global Emissions	1.1%	29.2%	2.3%	2.2%	1.3%	6.7%	0.8%	4.8%	1.3%	0.7%	2.4%	1.5%	1.5%	1.4%	11.2%	7.3%	1.0%
2030 Target (Mt CO2)	326	15,014	1,954	745	435	2,212	252	2,137	695	349	1,200	644	483	447	3,551	8,444	420
% Change	-43.0%	-4.3%	57.5%	-37.0%	-40.0%	-38.4%	-41.0%	-17.2%	1.1%	-8.9%	-8.4%	-21.4%	-40.3%	-40.9%	-41.0%	114.1%	-21.4%

Note: *Deeper shades of green indicate bigger emission reductions, while deeper shades of red indicate larger increases in emissions*

2.3.1. East Asia and Pacific

A significant amount of the analysed G20 member countries is located within the East Asia and Pacific region, and they have varying degrees of emission quantities and differing NDC pledge types and goals. In this region we can find countries such as Australia, China, Indonesia, Japan, and South Korea.

In its latest NDC, Australia set an unconditional emission reduction targets which aims to lower GHG emissions by 43% in 2030 compared to 2005 levels. To determine the variation in emissions that would be produced by this absolute emission reduction target, we applied the percentage reduction to Australia's emissions in 2005, and concluded that there would be an emission reduction of 43.0% compared to 2022 levels, indicating that the country's NDC has a high ambition level.

Within its updated NDC, China has set an emission intensity reduction type pledge, in which it commits to reduce the carbon intensity of its GDP by 65% compared to 2005 levels. To determine whether such target would translate in an absolute reduction of greenhouse gas emissions, we proceeded to calculate the emission intensity of China's GDP in 2005 and proceeded to apply the percentage reduction that was stated in the country's NDC submission. Afterwards, with the use of OECD long-term GDP forecasts, we calculated that China's absolute GHG emissions in 2030 would decline by only 4.3% compared to 2022 levels, which translates in a low ambition level for the country.

Indonesia's updated Nationally Determined Contribution includes an emission reduction target of 31.89% compared to a BAU projection that would lead to emissions of 2.869 Gt CO_2e in 2030. After applying the target reduction to the BAU emission levels, we concluded that Indonesia would effectively increase its greenhouse gas emissions by 57.5% compared to 2022 levels, and thus that there is no ambition of achieving an emission reduction.

In its updated submission, Japan has set an absolute emission reduction goal of 46% compared to 2013 levels. However, the country adopts a gross-net approach in setting its target, meaning that it does not include LULUCF emissions in its base year, but does account for future LULUCF credits in target year. Thus, after applying this approach to our emission calculation, we determined that Japan would lower its emissions by 37.0% compared to 2022 levels, which highlights high ambition levels.

Lastly, South Korea has committed itself to reducing its greenhouse gas emission by 40% below 2018 levels in 2030. This type i. pledge would effectively translate to a reduction of the same percentage amount compared to 2022 levels, and thus can be associated to a high level of ambition.

2.3.2. Europe and Central Asia

Out of the G20 members, the European Union, the United Kingdom, Russia, and Turkey are included in the Europe and Central Asian region. With the exception of Turkey, which has submitted a type ii. pledge, all of these countries have committed themselves to absolute emission reductions in their NDC documents.

The European Union has submitted an updated NDC where the 27 Member States collectively commit themselves to reducing the total GHG emissions of the EU by at least 55% below 1990 levels by 2030. This target would lead to an absolute emission reduction of 38.4% compared to 2022 levels, indicating a high level of ambition.

The United Kingdom, being no longer a member of the European Union, has submitted an individual Nationally Determined Contribution in which it undertakes the goal of reducing its emissions by at least 68% relative to 1990 levels. This would translate to an emission reduction of 41.0% compared to 2022 levels, which can be associated to a high ambition level.

Russia has submitted an NDC target in which it pledges to limit its GHG emissions to a quantity that does not exceed 70% of 1990 levels. While this target seems ambitious, the Russian Federation had extremely high levels of emissions in 1990, and the target effectively generates a reduction of 17.2% in emissions compared to 2022, indicating a modest level of ambition by the country.

Turkey aims at reducing its GHG emissions by 41% compared to a business-as-usual scenario where it would reach emission levels of 1,175 Mt CO_2e in 2030. After applying this reduction to the BAU scenario emissions, we found that the target level of emissions of 695 Mt CO_2e would generate an increase in emissions of 1.1% compared to those produced in 2022. This indicates that the country has no ambition to reduce its greenhouse gas emission levels.

2.3.3. Latin America and Caribbean

The Latin America and Caribbean region includes Argentina, Brazil, and Mexico, with the first two countries submitting absolute level of emission type pledges, and the last one submitting an BAU reduction pledge.

In its latest NDC submissions, Argentina has committed itself to not exceeding 349 Mt CO_2e emissions by 2030, which means that the country would implement an 8.9% reduction in emissions compared to current levels, showing a low level of ambition.

Brazil has set out to limit its GHG emissions in 2030 to a maximum of 1.2 Gt CO_2e, which translated to an 8.4% reduction in emissions compared to 2022 levels, and indicates a low ambition level within the NDC.

The updated NDC of Mexico contains an emission reduction target of 35% compared to a business-as-usual projection which estimates that the country would generate 991 Mt CO_2e by 2030. Since the country adopts a net-gross approach, after we applied the reduction target to the BAU emissions, we proceeded to calculate the difference between the 2030 target emissions and 2022 GHG emissions that did not include LULUCF. We estimate that Mexico would reduce its emissions by 21.4% compared to 2022 levels, which is an indicator of moderate ambition by the country.

2.3.4. Middle East and North Africa

The only G20 country located within the Middle East and North Africa region is Saudi Arabia which, in its updated Nationally Determined Contribution, has set an absolute emission reduction goal of 278 Mt CO_2e in 2030 compared to 2019 levels. After determining the level of GHG emissions in the target year, we concluded that it would generate an emission reduction of 40.3% compared to 2022, and thus that Saudi Arabia can be considered to have a high ambition level.

2.3.5. North America

The North America regions consist of two countries, Canada, and the United States, both of which have submitted absolute emission reduction targets.

Canada has submitted and updated NDC to the UNFCCC secretariat, in which it commits to reduce its emissions by at least 40-45% below 2005 levels. Taking in consideration the lowest reduction to which the country has unconditionally pledged to achieve, we have

determined that it would generate an emission reduction of 40.9% compared to 2022 levels, which highlights a high ambition level contained within the NDC target.

In their latest NDC submission, the United States have set an emission reduction target of 50% compared to 2005 levels. This would imply a reduction in greenhouse gas emissions of 41.0% compared to 2022 levels, which shows a high degree of ambitions.

2.3.6. South Asia

The only G20 member that is located within the South Asia region is India, which has submitted and updated NDC document where it sets out to reduce the emission intensity of its GDP by 45% compared to 2005 levels, without the inclusion of emissions stemming from LULUCF.

To determine the level of emission that is implied for 2030 by Indias NDC target, we initially calculated the intensity of the country's GDP in the base year, using OECD data on GDP, expressed in 2015 PPP international US dollars, and historical GHG emissions that do not include the contribution of LULUCF. Afterwards, we applied Indias percentage reduction target to calculate the target emission intensity for the year 2030.

Since we could only determine the future level of GHG emissions by knowing the future levels of Indias GDP, we decided to use the projections provided by the country in its NDC, which we converted from 2011-12 prices to 2015 PPP international US dollars in order to proceed with our assessment. Lastly, once we had established the future GDP projection for the country, we used it together with the target intensity level to determine the amount of greenhouse gases that India would generate in 2030 if its target was met.

However, since we are adopting a framework where we include emissions stemming from LULUCF to determine the level of ambition of the analysed countries, we had to calculate this component through the application of the Holt-Winters exponential smoothing model, and add them to the target level of emissions implied by Indias NDC.

After we finished our analysis, we concluded that Indias NDC target would lead the country to increase its emissions by 114.1% compared to 2022 level. Thus, since the country would effectively double its emissions by implementing the goals contained within its NDC submissions, it can be affirmed that India does not have any ambition to reduce its emissions in the future.

2.3.7. Sub-Saharan Africa

Out of the 17 G20 members that we considered for our ambition analysis, only South Africa can be located within the Sub-Saharan Africa region.

Within its latest NDC submissions, South Africa aims at achieving an annual GHG emission level of 350-420 Mt CO_2e in 2030. We decided to consider the higher bound of this absolute level of emissions pledge for our analysis, since we want to determine the reduction that would be generated if South Africa were to achieve the lowest unconditional target to which it has committed itself to. Our results show that this NDC target would lead South Africa to reduce its GHG emissions by 21.4% in 2030 compared to 2022 levels, demonstrating an intermediate level of emission reduction ambition.

2.4. Conclusive Remarks

The normalisation of NDC targets that we performed through the adopted framework has allowed us to determine the reduction levels that would be achieved by each G20 member through the adoption of their unconditional goals, while also making these targets comparable and allowing us to determine the level of ambition of each analysed country. Overall, our assessment has led us to conclude that the majority of the examined countries should be able to achieve a reduction in their future emissions compared to present levels if they implemented and achieved their targets. However, the ambition level among the G20 members varies greatly. Countries such as Australia, Canada, Japan, Saudi Arabia, South Korea, the United Kingdom, and the United States, together with the European Union, demonstrate a high level of ambition in their NDC targets with respect to their emission reduction goals. While they would still lead to an improvement in the quantity of GHG released in the atmosphere, the NDCs of Mexico, Russia, and South Africa can be associated with a more contained level of ambition when it comes to their emission reduction targets. Additionally, the NDC submissions of Argentina, Brazil and China imply a low level of ambition, as they all lead to reductions in GHG emissions of less than 10% compared to their current levels.

Lastly, the updated NDC pledges of India, Indonesia, and Turkey represent an exception to the emission reduction trends that have been observed in the other G20 members, since the targets contained within these submissions would lead to increases in each country's GHG emissions in the future, although with different degrees. While Turkey would

increase its emission by only 1% compared to present levels, Indonesia would generate a growth in its emissions by more than half of current levels, and India would more than double the quantity of greenhouse gases that it is currently emitting in the atmosphere if it were to fully implement its NDC submission. Thus, we conclude that no ambition to mitigate their current contributions to global GHG emissions can be associated to these countries.

Chapter 3

CO-STIRPAT for Measuring the Probability of Achieving NDC Targets: Methodology

Determining the probability that countries have of achieving their Nationally Determined Contributions target levels of emissions by 2030 is crucial for evaluating the effectiveness of the Paris Agreement, as it provides an insight into whether a country is on track to meet its climate objectives, or if its targets are insufficiently supported by action. By aligning their ambition levels with realistic emission reduction paths, countries can enhance their international credibility while also contributing to meet the Agreement's goal of keeping temperature increases below 2°C by the end of the century.

Verifying if NDC commitments correspond to realistic and feasible pathways allows to assess whether current policies, economic trajectories and technological advancements can be considered sufficient to achieve the needed emission reductions, holding countries accountable, fostering transparency, and enabling global cooperations. It also allows policy makers to understand the gaps in current policies and to make more informed decisions on how to updated and enhance their strategies.

There is a wide body of literature forecasting future emission levels and analysing the likelihood that countries participating in the Paris Agreement have of achieving their submitted NDC contributions.

Liu and Raferty[9] use Bayesian time series models to generate statistically-based probabilistic forecasts of the main drivers of future global CO_2 emissions, the emissions themselves, and the resulting global average temperature change. They find that there would be a 26% probability of staying below a 2°C increase in temperatures if all countries were able to meet their NDC contributions and reduce their emissions at the same rate after 2030.

Dong et al.[10] predict the probability of achieving CO_2 emissions targets pledged by the Intended Nationally Determined Contributions (INDC) of the ten largest emitters based

[9] Liu R. Peiran, Raftery E. Adrian, *Country-based rate of emissions reductions should increase by 80% beyond nationally determined contributions to meet the 2 °C target*, in Communications Earth & Environment, 2 (29), Springer Nature, February 2021.

[10] Dong Cong et al., *What is the probability of achieving the carbon dioxide emission targets of the Paris Agreement? Evidence from the top ten emitters*, in *Science of The Total Environment*, 622-623, 1294-1303, Elsevier, May 2018.

on emission trends registered in the 1991-2015 time period. Through the use of trend extrapolation and back propagation neural network models, they determine that China, India, and Russia should be able to achieve their INDC pledges, while the other top emitters will likely be unable to reach the desired levels of emissions. They also concluded that this would result in at least a 26.5% increase in the volume of CO_2 emissions produced by the top ten emitting countries in 2030, compared to 2005 levels.

Elzen et al.[11] utilises official governmental estimates and independent national and international studies of the G20 countries to compare GHG emission levels projected under current climate policies with those that would be achieved under the targets of Nationally Determined Contributions. They find that six countries (China, India, Indonesia, Japan, Russia, and Turkey) are projected to meet their NDC targets, while eight G20 members (Argentina, Australia, Canada, the European Union, South Korea, South Africa, and the United States) are expected to miss their climate goals. For the remaining member countries, the research results to be inconclusive, either due to a lack of information or to a high uncertainty in their projections.

Lastly, the UNEP 2023 Emission Gap Report[12], which tracks the gap between the emission pathway needed to limit temperature increases to 1.5° and the one that would materialise under current country commitments, finds that only China, India, Mexico, Russia, Saudi Arabia, and Turkey are likely to meet their NDC submissions, and estimates that G20 members will fall short of their latest targets by 1.2 $GtCO_2e$ by 2030.

To determine the probability that each of the considered G20 members had to achieve their NDC target GHG emission level, we decided to adopt and replicate the Component-Oriented STIRPAT (CO-STIRPAT) model, developed by Jin Ick within his work "*Probability of Achieving NDC and Implications for climate Policy: CO-STIRPAT Approach*".

Within this chapter, we will proceed to illustrate the theoretical framework of this model and subsequently provide a step-by-step description of the replication code that we developed within the Python programming language.

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[11] Elzen den Michel et al., *Are the G20 economies making enough progress to meet their NDC targets?*, in Energy Policy, 126, 238-250, Elsevier, March 2019.

[12] UNEP, *Emissions Gap Report 2023: Broken Record – Temperatures hit new highs, yet world fails to cut emissions (again)*, Nairobi, November 2023.

3.1. Theoretical Basis

The theoretical foundations of the CO-STIRPAT models are deeply rooted in the IPAT equation, which describes human-related impacts on the environment through a multiplicative relationship:

$$I = P * A * T \tag{3.1}$$

Where environmental impact (*I*) results from the interaction between population (*P*), affluence (*A*) and technology (*T*).

The principal assumption of the CO-STIRPAT is that a specific application of the IPAT model, the Kaya Identity, provides a reliable portrayal of the factors that contribute to the production of CO_2 emissions stemming from human activities. The identity, developed by Japanese energy economist Yoichi Kaya, can be represented by a simple mathematical formula:

$$CE = P * \frac{GDP}{P} * \frac{E}{GDP} * \frac{CE}{E} = P * GDPPC * EI * CI \tag{3.2}$$

Where carbon emission (*CE*) of a given region or country are described by the product of four elements: population (P); GDP per-capita (GDPPC); energy intensity (EI), and carbon intensity (CI). This specific application of the IPAT system disaggregates the technological factor into energy intensity (the amount of energy required to produce one unit of economic output) and carbon intensity (the amount of CO_2 emissions generated by the production of one unit of energy), which provides a more detailed understanding of the influence that energy and economic systems have on carbon emissions.

The application of the Kaya Identity allows the CO-STIRPAT model to analyse the interactions within the context of the ImPACT (Integrated Model of Population, Affluence, Consumption, and Technology) framework, which further refines the IPAT model by incorporating consumption patterns and their impact on environmental outcomes.

To fully capture the complexity and variability of these interactions, the CO-STIRPAT adopts a statistical approach similar to that used in the STIRPAT (Stochastic Impacts by

Regression on Population, Affluence and Technology) model. This allows for an empirical analysis of the stochastic relationship between the variables, which are subject to variability and nonlinearity.

By incorporating the structural clarity of the Kaya Identity, the detailed considerations of the ImPACT framework, and the statistical rigor of the STIRPAT model, the CO-STIRPAT provides a comprehensive approach for the analysis of the drivers of human-related CO_2 emissions.

3.2. Framework

Considering that CO_2 is the main component of emissions for all countries and assuming that the GHG emission reduction targets contained within Nationally Determined Contributions will be applied in the same percentage amount to each greenhouse gas, the CO-STIRPAT framework determines the probability of achieving a given level of GHG emissions approximating it to the probability of achieving a given level of CO_2 emissions. The model determines the probability of achieving a given level of emissions by integrating predictive modelling with uncertainty quantification techniques.

3.2.1. Predicting Future Emissions with the Kaya Identity

The first part of the model involves fitting historical data of Kaya Identity components with logistic functions to determine future carbon emissions values. Logistic functions are well-suited to modelling growth processes that start slowly, accelerate, and then decelerate as they approach a saturation point.

The framework can be summarised through the following set of equations:

$$C_t = \prod_{i \in I} X_{i,t} \tag{3.3}$$

$$X_{i,t} = \frac{\beta_{i,0}}{\{1 + [-\beta_{i,1}(t - \beta_{i,2})]\} + \varepsilon_{i,t}} \tag{3.4}$$

$$\varepsilon_{i,t} \sim N(\mu_i, \sigma_i^2) \tag{3.5}$$

Where $X_{i,t}$ represents an element of the Kaya Identity, $I = \{P, GDCPC, EI, CI\}$, at a specific point in time, t, and C_t corresponds to the carbon emissions obtained by multiplying each element of the Kaya Identity. Within the logistic function, a real-valued number is charted to a value between the lower asymptote, 0, and the higher asymptote, $\beta_{i,1}$, and $\beta_{i,2}$, representing the slope at the inflection point, is used to measure the growth behaviour of the variable. The predicted factors will increase through time in cases where $\beta_{i,1} < 0$, and decrease in cases where $\beta_{i,1} > 0$, forming an S-shaped curve with inflection point at $t = \beta_{i,2}$.

Once the logistic model is fitted to the historical data of each Kaya Identity component, residuals for each one are analysed to determine the goodness of fit of the logistic function. This is done by calculating the mean, variance, skewness, and kurtosis for the data of each parameter. Additionally, the CO-STIRPAT also calculates the Jarque-Brera normality statistic in order to determine whether or not the considered parameter has a normal distribution. The statistic, which combines the skewness and kurtosis of a given dataset to determine whether they match those of a normal distribution, can be mathematically described by the following equation:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{3.6}$$

Where S is the skewness, K the kurtosis, and n is the size of the data sample.

If the analysis of regression residuals show that the logistic model fits the parameters well, the CO-STIRPAT uses these functions to estimate the future values of the parameters and proceeds to calculate the future values of carbon emissions.

3.2.2. Determining the Distribution of Future Carbon Emissions

Non-linear regression models, such as the one adopted within the CO-STIRPAT framework, are inherently affected by uncertainty, which has to be measured.

The **Jacobian matrix** represents the partial derivatives of the logistic model predictions with respect to the model parameters (L, k, and x0). This matrix captures how small changes in the model parameters impact the predicted Kaya components.

The framework attempts to quantify this uncertainty by firstly calculating the Jacobian matrix for each Kaya Identity components. This matrix

The framework attempts to quantify this uncertainty by firstly calculating the Jacobian matrix, which describes how small changes in input variables affect an output variable by calculating the partial derivative of the predicted output with respect to each of the parameters of the logistic model.

For a given set model of parameters $\theta = [\beta_{i,1}, \beta_{i,2}, \beta_{i,3}]$, and a model that predicts an outcome $X_{i,t}$ based on said parameters, the Jacobian matrix can be defined as:

$$J = \begin{pmatrix} \frac{\partial X_1}{\partial \theta_1} & \frac{\partial X_1}{\partial \theta_2} & \cdots & \frac{\partial X_1}{\partial \theta_n} \\ \frac{\partial X_2}{\partial \theta_1} & \frac{\partial X_2}{\partial \theta_2} & \cdots & \frac{\partial X_2}{\partial \theta_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial X_m}{\partial \theta_1} & \frac{\partial X_2}{\partial \theta_2} & \cdots & \frac{\partial X_m}{\partial \theta_n} \end{pmatrix} \tag{3.7}$$

Where X_i is the predicted output for the *i*-th data point, θ_j is the *j*-th parameter of the model, and each element $\frac{\partial X_i}{\partial \theta_j}$ represents the sensitivity of the predicted value to the changes in a specific parameter.

The Jacobian matrix is then used within the CO-STIRPAT to determine the variance-covariance matrix:

$$V = \sigma^2 (J^T J)^{-1} \tag{3.8}$$

Where J^T is the transpose of the Jacobian matrix and σ^2 is the variance of the residuals (the difference between the observed and predicted values).

The Jacobian matrix and the variance-covariance matrix are then used to account for uncertainty within the context of the Delta Method. This statistical technique approximates the variance of a function of random variables, which in this case is represented by the predicted Kaya Identity components:

$$Var\ (X_i) \approx J * V * J^T \tag{3.9}$$

The method allows to account for the uncertainty in the predictions of each Kaya Identity component. While the Delta Method is useful for estimating the variance of a non-linear function of random variable, it relies on the assumption that estimates are approximately normal, and thus might not be a reliable in cases of high non-linearity and small sample size. In such situation, the CO-STIRPAT framework adopts the Monte Carlo simulation, which can provide a better understanding of uncertainty by considering the potential nonlinearity and potential asymmetry in the distribution of predicted values. The variance of each Kaya Identity component can then be used to determine their standard deviation, which in turn can be used to determine the standard deviation of the predicted CO_2 emissions:

$$\sigma_{C_t} = C_t * \sqrt{\frac{\sigma_{P_t}}{P_t} + \frac{\sigma_{GDPPC_t}}{GDPPC_t} + \frac{\sigma_{EI_t}}{EI_t} + \frac{\sigma_{CI_t}}{CI_t}} \tag{3.10}$$

Where the standard deviation of the predicted Kaya Identity, σ_{C_t}, is equal to the product between the predicted values, C_t, and the square root of the sum of the relative uncertainties of each component in time *t*.

Once the standard deviation of predicted CO_2 emissions has been estimated, the CO-STIRPAT model uses it to calculate confidence intervals for emission predictions, which allows it to provide a range of values within which true future emissions are likely to fall given the inherent uncertainty of the model's predictions.

The last step of the CO-STIRPAT framework involves a comparison between the CO_2 emissions that have been estimated with the logistic function with their confidence intervals, and the target carbon emission pathway contained within Nationally Determined Contributions. The comparison allows to determine the probability of that a given party of the Paris Agreement has of achieving the target level of emissions it has set within its NDC.

3.3. Implementation of the CO-STIRPAT

This paragraph will provide an overview of our replication of the Component-Oriented STIRPAT model that has been developed with the Python programming language, which can be found in detail in Appendix II.

We have divided our approach in two separate parts, developing two separate codes to analyse the goodness of fit of the logistic model to Kaya Identity parameters and to determine the probability that each analysed G20 member has to achieve their NDC emission target levels by 2030.

3.3.1 Logistic Model

As shown in Table 3.1., in the first part of our framework, after converting our data into a format that can be easily manipulated and analysed within Python and determining the four Kaya Identity components, we proceed to define the logistic function, which models data by using its maximum value, *L*, growth rate, k, and midpoint, x0, as parameters. Afterwards, we define a logistic model that uses non-linear regression to estimate the best parameters for the logistic function and applied it to each component and calculate their covariances.

Once the historical data for each Kaya Identity component is fitted with the logistic model, residual statistics are calculated to assess whether the model can be considered a good fit to the data or not.

Table 3.1. *Logistic Function and Logistic Model Code*

```
def logistic(x, L, k, x0):
    return L / (1 + np.exp(-k * (x - x0)))

def fit_logistic_model(xdata, ydata):
    p0 = [max(ydata) * 1.1, 1 / (max(xdata) - min(xdata)), np.median(xdata)]
    try:
        params, cov = curve_fit(logistic, xdata, ydata, p0=p0, maxfev=25000)
        return params
    except RuntimeError as e:
        print(f"Error fitting model: {e}")
        return None
```

3.3.2. Probability Determination

The second part of our approach uses the fitted Kaya Identity components to calculate future CO_2 emissions and determine the probability that said emissions will be equal or lower than those of the target emission level pathway.

To do so, it defines a function that generates prediction for each Kaya Identity component from 2022, the last observed year, and 2030, the target year for Nationally Determined Contributions.

Then, it calculates the Jacobian matrix and a function that uses the Jacobian matrix and the variance-covariance to determine the variance and standard deviation of each component (Table 3.2.).

After calculating the variances of the Kaya Identity components, the framework determines the variance of the predicted carbon emissions and subsequently calculates the confidence intervals at a 95% level.

Lastly, the model compares the predicted carbon emissions with those found in the target emission pathway, calculated by combining the logistic function with a modulated decay function, and determines the probability that the target level will be met in each year through a normal distribution approximation.

Table 3.2. *Jacobian Matrix and Parameter Standard Deviation Code*

```
def calculate_jacobian(x, params):
    L, k, x0 = params
    x_sym, L_sym, k_sym, x0_sym = symbols('x L k x0')
    logistic_expr = L_sym / (1 + exp(-k_sym * (x_sym - x0_sym)))
    partials = [diff(logistic_expr, var) for var in (L_sym, k_sym, x0_sym)]
    jacobian_func = lambdify((x_sym, L_sym, k_sym, x0_sym), partials, 'numpy')
    return np.array([jacobian_func(x_val, L, k, x0) for x_val in x])

def predict_with_confidence(params, cov, x):
    predictions = predict_logistic(params, x)
    J = calculate_jacobian(x, params)
    variance = np.dot(J, np.dot(cov, J.T))
    std_error = np.sqrt(np.diag(variance))
    return predictions, std_error
```

3.4. Data

To determine the probability that each of the analysed G20 members will achieve their NDC targets, we obtained information on Kaya Identity components for each year in the period between 1990 and 2022, the last year for which data on each variable was available.

The UN 2024 World Population Prospect provided data on population, expressed as the total number of persons of both sexes, and was converted in millions of individuals to allow for the determination of the descriptive statistics to allow for consistency in results. For GDP, we used data from the World Bank's World Development Indicators, expressed in Purchasing Power Parity (PPP) using 2021 constant international dollars. This expression of GDP is suitable as it accounts for differences in the cost of living across countries, providing a more accurate comparison of economic output. We also converted GDP into units of $1,000 to assure consistency between the values of our data. Primary Energy Consumption data, expressed in Exa Joules, was sourced from the Energy Institute, and converted into Giga Joules to align with our analytical framework. Finally, carbon emissions data, originally expressed in million tonnes of CO_2, was obtained from the Global Carbon Budget 2023, and converted into tonnes to ensure uniformity across all data components.

After obtaining data for each of the parameters, we proceeded to create a single CSV file containing all of the acquired data for the observed period to facilitate their usage within our analysis framework.

Chapter 4

CO-STIRPAT for Measuring the Probability of Achieving NDC Targets: G20 Country Results

We applied our CO-STIRPAT model to 17 G20 members to determine the probability that each one had to achieve the target level of emissions that was implied within their NDC pledges.

In this chapter, we will provide the results of our analysis for each of the examined members, a summary of which is provided in Table 4.1. below.

Table 4.1. *Probability of G20 Members Achieving their NDC targets by 2030*

Country	2022 Emissions (Mt CO2)	2030 Target Emissions (Mt CO2)	Target Change (Mt CO2)	Target Change %	2030 Predicted Emissions (Mt CO2)	Predicted Change (Mt CO2)	Predicted Change %	Probability of Achieving Target
Argentina	198	181	-17.6	-8.9%	182	-16.2	-8.2%	49.3%
Australia	404	231	-173.9	-43.0%	276	-128.1	-31.7%	29.4%
Brazil	498	456	-42.0	-8.4%	582	84.6	17.0%	2.1%
Canada	560	331	-229.1	-40.9%	445	-114.6	-20.5%	25.3%
China	11,297	10,815	-482.8	-4.3%	9,689	-1,608.7	-14.2%	82.3%
European Union	2,929	1,806	-1,123.3	-38.4%	2,258	-670.6	-22.9%	0.0%
India	2,840	6,081	3,241.6	114.1%	3,907	1,067.4	37.6%	99.9%
Indonesia	734	1,156	421.8	57.5%	546	-188.0	-25.6%	85.4%
Japan	1,075	677	-397.7	-37.0%	759	-316.1	-29.4%	30.5%
Mexico	522	410	-111.8	-21.4%	278	-243.9	-46.7%	76.2%
Russia	1,669	1,383	-286.3	-17.2%	1,406	-263.5	-15.8%	49.5%
Saudi Arabia	689	411	-278.1	-40.3%	747	58.3	8.5%	0.1%
South Africa	418	328	-89.6	-21.4%	268	-149.8	-35.8%	58.9%
South Korea	637	382	-254.8	-40.0%	568	-68.6	-10.8%	0.6%
Turkey	438	443	4.8	1.1%	283	-154.7	-35.3%	92.2%
United Kingdom	343	202	-140.6	-41.0%	178	-165.3	-48.2%	77.5%
United States	5,114	3,018	-2,096.1	-41.0%	3,167	-1,946.9	-38.1%	30.0%

Note: *Deeper shades of green indicate higher probability of achieving target, while deeper shades of red indicate lower probability*

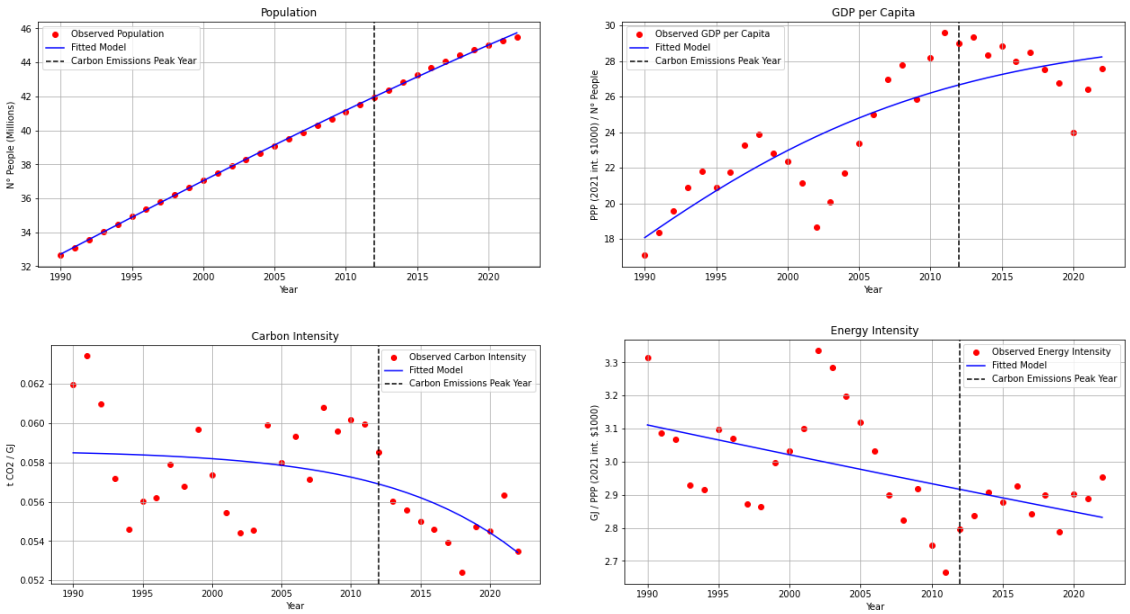
We will first illustrate the results of the application of the logistic model the Kaya Identity components, providing graphic visualisations, as well as descriptive statistics for the residuals for each component, which determine the goodness of fit of the logistic model, and the correlation matrix between the components, which can highlight possible relationships. Then, we will proceed to describe the results of our Kaya Identity carbon emission forecasts and the probability that countries have of achieving their NDC targets.

4.1. Argentina

As we have previously determined, Argentina has set a maximum level of emissions of 349 Mt CO2e, that it aims to not exceed in 2030, and which translates to a modest ambition of achieving an 8.9% reduction in emissions compared to 2022.

The first step of our CO-STIRPAT framework involved applying the logistic model to population, GDP per-capita, energy intensity, and carbon intensity data obtained for the period between 1990 and 2022. The results of the fitting process can be seen in Figure 4.1., in which the red dotted lines represent the historical values and the blue continuous line represents the fitted values for each considered component. The figure shows a great variability through the years in the observed values of almost all components, except for population, which has steadily grown since 1990. The growth in population, as well as the long-term growth in GDP per-capita, can be associated to an increase in the overall level of Argentina's carbon emissions, while the reduction in energy intensity and carbon intensity positively contributes the lowering them.

Figure 4.1. *Argentina's Fitted Kaya Identity Components*



The ability of the logistic model to accurately represent the overall trend of the observed data for each component can is illustrated in Table 4.2., which contains the descriptive statistics of the residuals for each considered element.

Table 4.2. *Argentina's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0000	0.0846	-0.2976	0.0556	0.4912	0.7822
GDPPC	0.0013	1.9927	-0.8261	0.1676	3.7917	0.1502
CI	0.0000	0.0023	0.1980	-0.8743	1.2667	0.5308
EI	0.0000	0.1368	0.4689	0.0551	1.2132	0.5452

The calculated residual summary statistics indicate that the logistic function has fitted each component well. In particular, the Jarque-Bera statistic, which uses a variable's skewness and kurtosis to verify whether it follows a normal distribution, presents high p-values for each fitted element, which indicates that residuals do not significantly deviate from a normal distribution, and implies that the logistic model is a good fit.

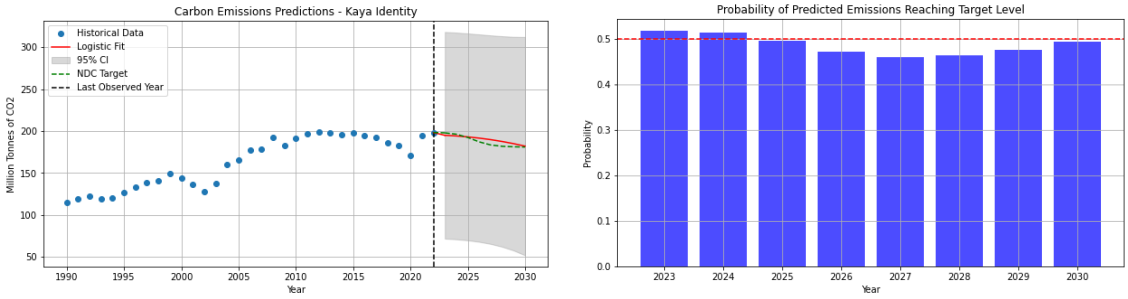
Table 4.3. illustrates the correlation coefficients between each analysed variable, showing a strong negative relationship between carbon intensity and population, as well as between energy intensity and GDP per capita. This suggests that an increase in population is associated with a shift toward more efficient or lower-carbon energy production, possibly due to technological improvements or more ambitious policy measures. Additionally, the negative correlation between energy intensity and GDP per capita indicates that Argentina's economic growth may be driven by less energy-intensive sectors or improvements in energy efficiency, rather than by energy-heavy industries

Table. 4.3. *Argentina's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1			
GDPPC	0.1150	1		
CI	-0.5537	0.2115	1	
EI	-0.1422	-0.8509	-0.2212	1

Lastly, we used the logistic model and forecasted the values of each component from 2022 to 2030, and used these forecasts to determine future carbon emissions that would be generated by Argentina given its historical trends. Figure 4.2. shows the forecasted CO_2 emissions as well as the probability that Argentina has of reaching its target levels of emissions for each predicted year.

Figure 4.2. *Argentina's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



The CO-STIRPAT model highlights that, while the country should be able to decrease its carbon emissions by 8.2% from 198 Mt CO2, it will most likely be unable to reach the 181 Mt CO2 target set out in its NDC. The probability of reaching the target emission level in 2030 stands at 49.3%, as the country's forecasted emissions increasingly deviate from the target pathway implied by its NDC.

4.2. Australia

In its latest NDC submission, Australia has set a GHG emission reduction target of 43% below 2005, which translates to a reduction by the same amount compared to 2022 levels. The graphical representation of the application of the CO-STIRPAT model to Australia's historical data shown in Figure 4.3. allows us to determine that the observed values of the Kaya factors have followed a consistent path, with the exception being carbon intensity, which has varied for most part of the time series and seen a decrease only in later years. The figure also suggests that the logistic model has produced an adequate representation of the data for each component, since the fitted lines are able to capture the direction in which the variables have been moving.

However, the descriptive statistics calculated on the residuals of each component do not confirm this idea. Table 4.4., which provides the results for these statistics, shows that the logistic model cannot be considered a good fit for the country's GDP per-capita, as is evidenced by the low p-value of the Jarque-Bera test.

Figure 4.3. *Australia's Fitted Kaya Identity Components*

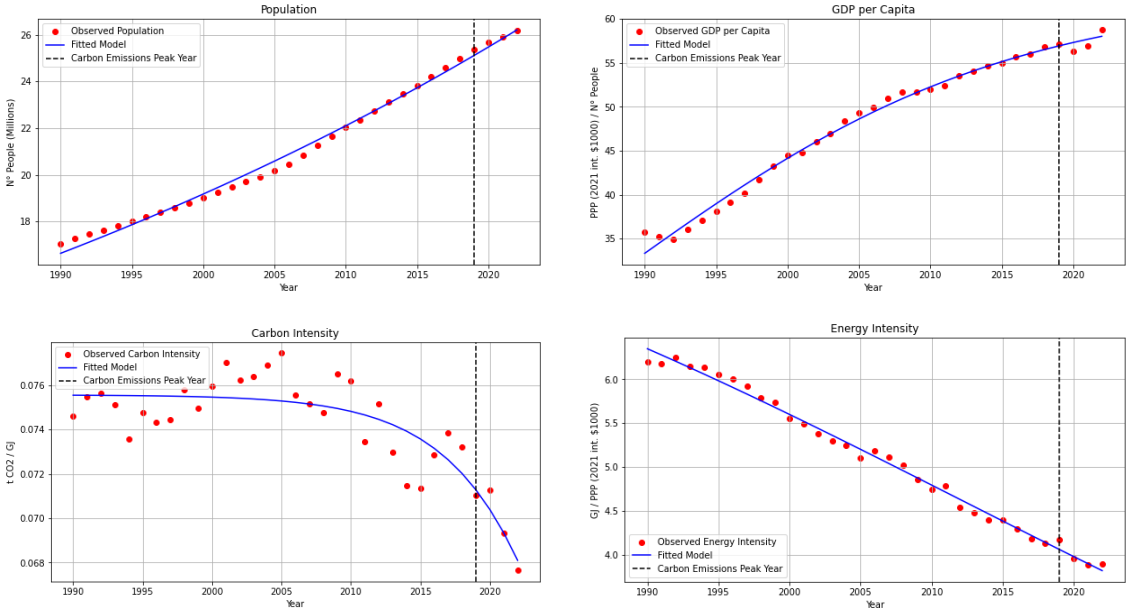


Table 4.4. *Australia's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0015	0.2324	-0.1734	-0.8536	1.1671	0.5579
GDPPC	0.0017	0.7083	1.0498	2.4192	14.1088	0.0009
CI	0.0000	0.0012	-0.2101	-0.6138	0.7608	0.6836
EI	0.0001	0.0677	-0.1117	-1.0047	1.4567	0.4827

To verify the impact that the poor representation of GFP per-capita could have on the other variables, we analysed the interconnections between the Kaya components through a correlation matrix. The matrix, presented in Table 4.5., gives us a deeper look into the relationships between GDP per-capita and the other variables, allowing us to conclude that there is generally a weak to moderate relationships with the other factors, indicating that changes in this variable have relatively weak impacts on the other ones.

Table. 4.5. *Australia's Correlation Matrix*

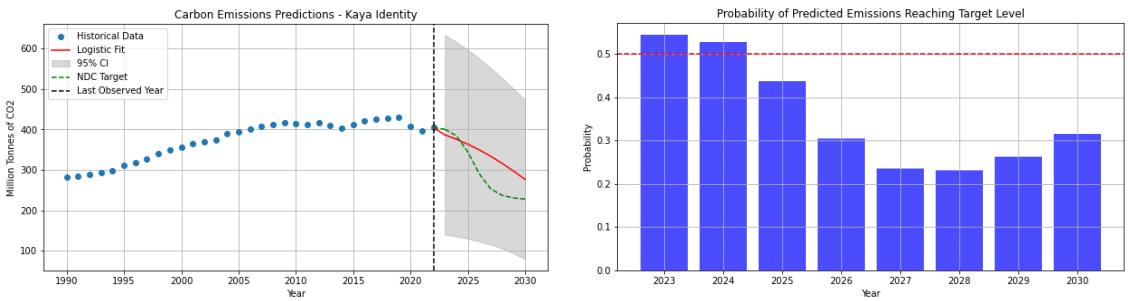
Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.1725	1.0000		
CI	-0.4276	0.1419	1.0000	
EI	-0.0115	-0.4248	-0.3680	1.0000

Taking this into account, we decided to verify how GDP per-capita could influence the final results of the Kaya Identity by performing an OLS regression analysis. The analysis, which allowed us to regress the historical values of the identity's carbon emissions on its determinants, led us to conclude that, while GDP per-capita has a considerable impact on carbon emissions, it becomes significantly lower when compared to that of energy intensity and carbon intensity, which are well represented by our logistic model, as is evidenced by their residual statistics.

Thus, while our model does produce values for GDP per-capita with lesser accuracy, the low impact of this variable on both the other Kaya components, as well as on the overall determination of carbon emissions, allow us to assume that this will not greatly influence our forecasts and probability calculation.

Taking this in consideration, we proceeded to determine the probability that Australia had of achieving its NDC target in 2030 by calculating the expected future values of the country's CO_2 emissions. The results of our model, which can be seen in Figure 4.4., suggest that the country will decrease its carbon emissions by about 128 Mt by 2030.

Figure 4.4. *Australia's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



However, the probability that the country will achieve its target emissions by 2030 is low, standing at only 29.4%. This is due to the fact that the forecasted change in emissions would only result in a 38% reduction compared to 2022 levels, a value that stands above the pledged NDC target.

4.3. Brazil

Brazil's NDC, updated in October of 2023, has identified a maximum amount of GHG emissions of 1.2 Gt CO_2e, that the country commits to not exceed by 2030. This pledge

translates in an emission reduction of 8.4% compared to the amounts of GHG that the country is currently emitting.

Considering CO_2 emissions to be a valid proxy through which to determine the probability that the country has of achieving its GHG emission goal, we decided to apply the same percentage reduction to carbon emissions and determined the target level of CO_2 that the country is aiming to achieve.

After that, we proceeded to implement our logistic model and fit the data on the country's population, GDP per-capita, energy intensity, and carbon intensity. The results of the fitting process, shown in Figure 4.5., highlight that population, GDP per-capita, and energy intensity have generally grown in magnitude from 1990, while carbon intensity has seen high variability in its values, without a steady trend in its movement.

Figure 4.5. *Brazil's Fitted Kaya Identity Components*

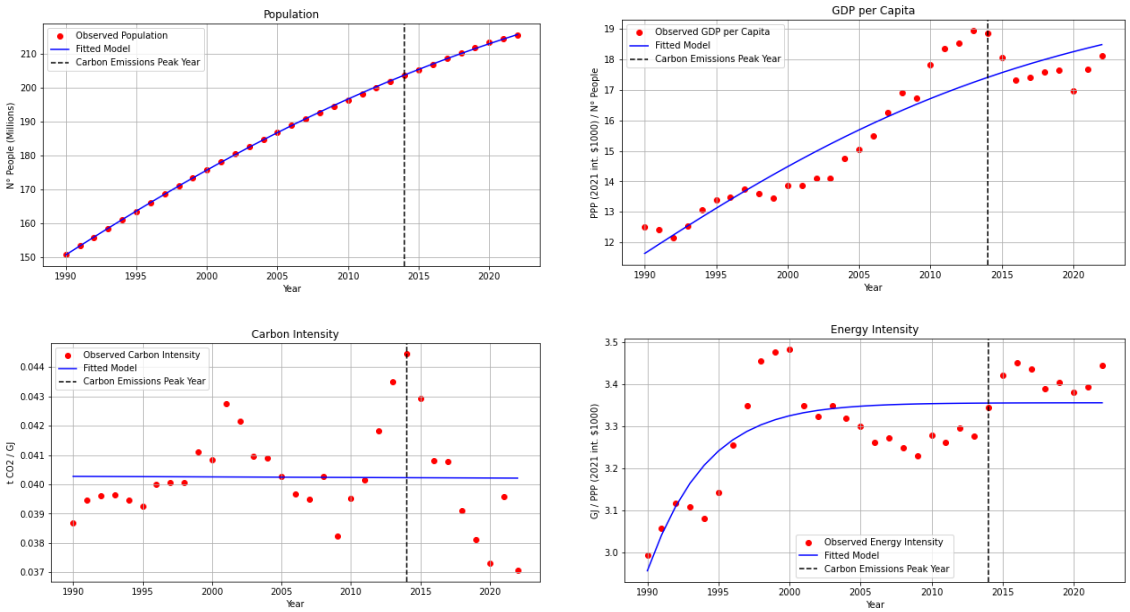


Table 4.6. *Brazil's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	-0.0001	0.1747	0.2820	-0.8755	1.4914	0.4744
GDPPC	0.0013	0.7958	0.6042	-0.5125	2.3688	0.3059
CI	0.0000	0.0016	0.5382	0.3520	1.7634	0.4141
EI	0.0000	0.0807	0.3078	-0.7169	1.2279	0.5412

The Jarque-Bera p-values of the residual statistics, presented in Table 4.6., confirm that the logistic function provides an appropriate representation of the analysed factors, and that the residuals for each one have a normal distribution.

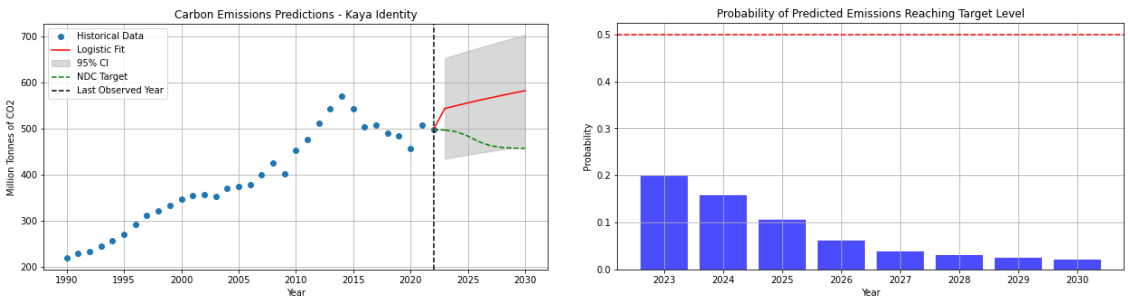
The correlation matrix (Table 4.7) shows a strong negative relationship between Brazil's GDP per capita and its population. Given that both factors have experienced consistent growth trends, this could indicate that economic output is not being distributed equally among the population.

Table. 4.7. *Brazil's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.8121	1.0000		
CI	-0.1098	0.2914	1.0000	
EI	0.4422	-0.4566	0.0307	1.0000

After determining that the logistic function is a good fit, we applied the CO-STIRPAT model to forecast future values for each component, and used the forecasted values to determine the prospected pathway that will be followed by Brazil's CO_2 emissions. Then we compared the results with the emission pathway implied by the country's NDC, and calculated the probability that these will be reached. The result of our analysis can be seen in Figure 4.6., which shows that Brazil is predicted to increase its emissions by 17%, from 497 Mt CO_2 in 2022 to 582 Mt CO_2 in 2030. Thus, the country's probability of achieving the levels of carbon emissions implied by its NDC target is extremely low, standing at only 2.1% in 2030.

Figure 4.6. *Brazil's Forecasted CO_2 emissions and Probability of Meeting NDC Target*

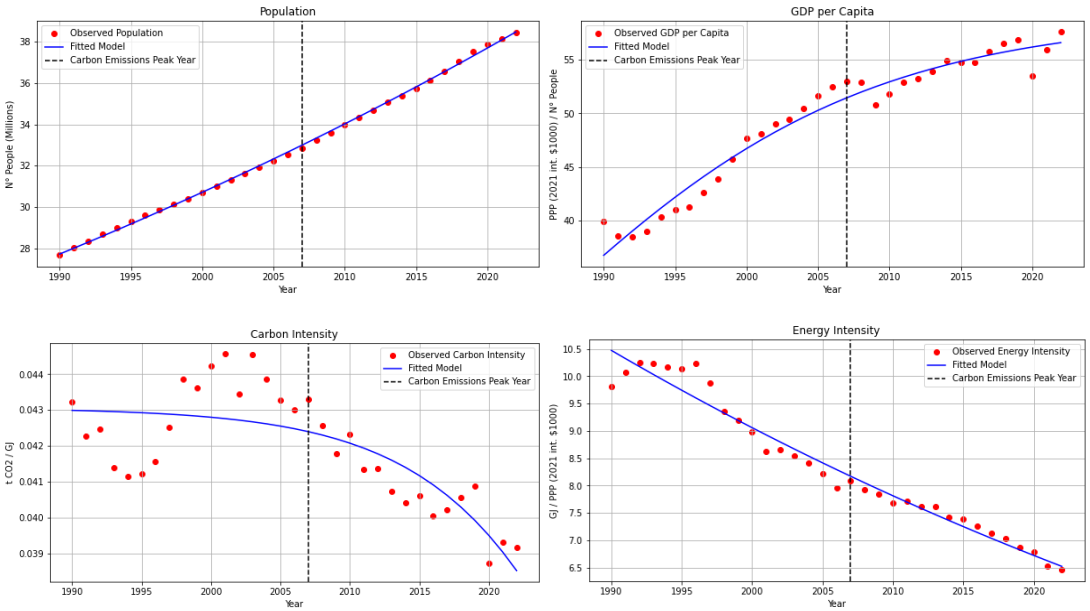


4.4. Canada

The Canadian government has set an emission reduction target of 40% compared to 2005 levels by 2030, which we determined would lower the quantity of greenhouse gases by 40.9% compared to those emitted by the country in 2022. While this shows a high ambition level by the country, it also highlights that there has been little change in emitted GHG in the past 17 years.

This could be a result of the opposite directions in which the components that determine the levels of carbon emissions in our model have been moving. As can be seen in Figure 4.7., population and GDP per-capita start from the lower levels in 1990 and progressively increase through time, reaching their upper asymptote in the last observed year. Contrarily, even though they follow different trajectories over time, both carbon intensity and energy intensity present a generally decreasing trend.

Figure 4.7. *Canada's Fitted Kaya Identity Components*



The fitted lines in the figure can be considered as a suitable representation of the direction in which the observed data has evolved over time, as is confirmed by the J.B. statistic in Table 4.8., which exhibits p-values that are above 0.05 for all components of the Kaya Identity, and thus allow us to affirm that the logistic model applied with the CO-STIRPAT is a good fit for the observed data.

Table 4.8. *Canada's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0002	0.0903	0.5979	-0.4996	2.3095	0.3151
GDPPC	0.0016	1.2014	0.0750	0.1381	0.0572	0.9718
CI	0.0000	0.0010	0.0224	-0.8380	0.9684	0.6162
EI	0.0001	0.2366	0.0894	1.5428	3.3168	0.1904

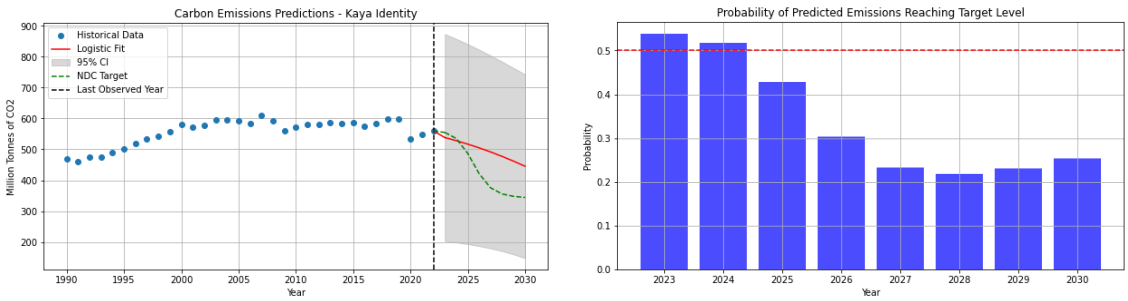
The correlation matrix presented in Table 4.9. highlights that Canada's data is generally moderately correlated, with a strong negative relationship emerging between energy intensity and GDP per capita. This reflects a structural shift in the Canadian economy and improvements in energy efficiency, which are responsible for the decline in energy intensity[13].

Table. 4.9. *Canada's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.5203	1.0000		
CI	-0.3367	0.5380	1.0000	
EI	0.5586	-0.7041	-0.5982	1.0000

Once we verified that the logistic function is a good fit for the data and assessed the relationships between each variable and the other ones, we forecasted Canada's carbon emissions up to the year 2030.

Figure 4.8. *Canada's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



[13] National Energy Board, *Canada's Energy Transition: Historical and Future Changes to Energy Systems. An Energy Market Assessment*, Canada Energy Regulator, August 2019. (Updated on July 2022)

The results of our analysis, graphically represented above in Figure 4.8., show that, while the country is on track to decreasing its emissions by about 20% from 2022 levels, it is not on track to meet the demanding goal it has set within its NDC, with only a 25.3% probability of achieving the pledged level of emissions in the target year.

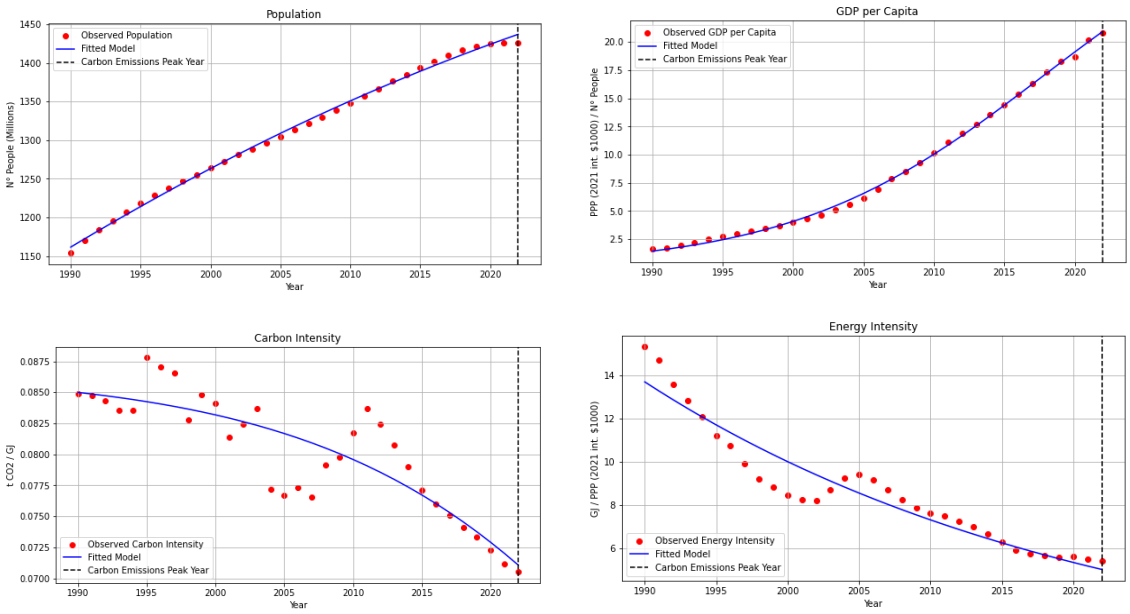
4.5. China

In our previous analysis of China's ambition level, we have determined that its intensity-related emission reduction target would result in a decrease in GHG emissions of only 4.3% compared to present levels, mainly due to the high prospected growth rate in the country's GDP.

To determine the probability that China has of reaching its NDC target, we first had to verify whether the CO-STIRPAT could be considered a good predictive model for the country's data.

The results of the first step of our framework are displayed in Figure 4.9., which shows that the country has seen a steady rise in both its population and its GDP per-capita, while there has been a decreasing trend in carbon and energy intensity, which could signal an improvement in the technology adopted to produce energy.

Figure 4.9. *China's Fitted Kaya Identity Components*



The ability of our logistic function to accurately represent the provided data is demonstrated by the p-values of the J.B statistic presented in Table 4.10., which all have values that greatly exceed 0.05.

Table 4.10. *China's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	-0.0001	4.2376	-0.5048	-0.1772	1.4447	0.4856
GDPPC	0.0174	0.2186	-0.8701	-0.4410	4.4309	0.1091
CI	0.0000	0.0024	-0.2667	0.0081	0.3914	0.8223
EI	0.0137	0.8114	-0.4559	-0.2486	1.2281	0.5411

Table 4.11 shows the correlations between the residuals of the four factors. It highlights weak to moderate relationships between China's Kaya factors, with the strongest being the moderate positive link between carbon intensity and GDP per capita, which reflects the fact that the country's economic growth is still heavily dependent on fossil fuels, particularly coal, which still accounted for more than 60% of the country's energy mix in 202214, despite ongoing efforts to transition to cleaner energy sources.

Table. 4.11. *China's Correlation Matrix*

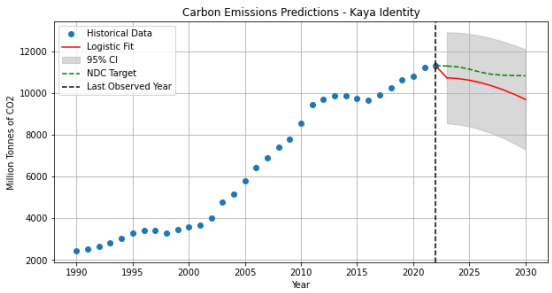
Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	0.3341	1.0000		
CI	0.3497	0.5723	1.0000	
EI	-0.4626	0.0636	-0.2754	1.0000

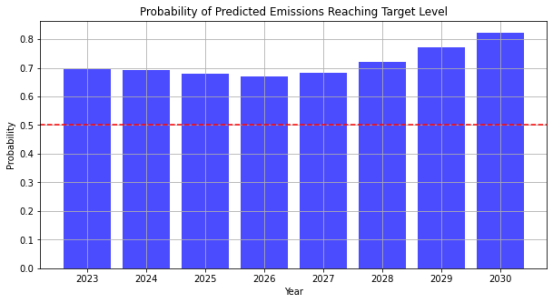
To verify whether China will be able to meet its 2030 emission objective, we estimated the values for the Kaya Identity by using the CO-STIRPAT model to obtain projections for each of its components.

As can be seen in Figure 4.10., China is projected to decrease its CO_2 emissions from 11,297 Mt to 9,688 Mt, which is equal to a 14% reduction compared to 2022 levels.

Figure 4.10. *China's Forecasted CO_2 emissions and Probability of Meeting NDC Target*

[14] International Energy Agency, *World Energy Statistics and Balances*, IEA, July 2024: https://www.iea.org/data-and-statistics/data-product/world-energy-statistics-and-balances





Even when the uncertainty represented by the 95% confidence intervals is taken into consideration, this reduction translates in an 82.3% probability of reaching the emissions levels of its NDC target pathway. Thus, China is very likely to be able to achieve the emission reduction it has committed itself to in its most recent NDC by 2030.

4.6. European Union

The European Union has set an ambitious emission reduction target for 2030 which would see it the 27 Member States lower their collective emissions by 38.4%.

While the EU has historically seen a constant decrease in its carbon emissions, it is important to determine whether it will be able to implement the large-scale reductions needed to achieve its goal by applying our CO-STIRPAT framework.

The results of the logistic fitting process, graphically shown in Figure 4.11., indicate that the four Kaya Identity components have historically had different growth trends. While population and GDP per-capita have steadily increased over the years, the intensity of both energy production and carbon emissions have seen a constant decrease, which could be an indicator of the efforts put forward by the EU to decrease its environmental impacts.

We verified that the adopted logistic model was a good fit for the analysed data by calculating the residual statistics for each one of the considered elements. The results of our analysis, presented in Table 4.12., show that the model provides a reliable representation of the movement of each Kaya component, and thus that it can be used to determine the forecasted values for each one.

Figure 4.11. *EU's Fitted Kaya Identity Components*

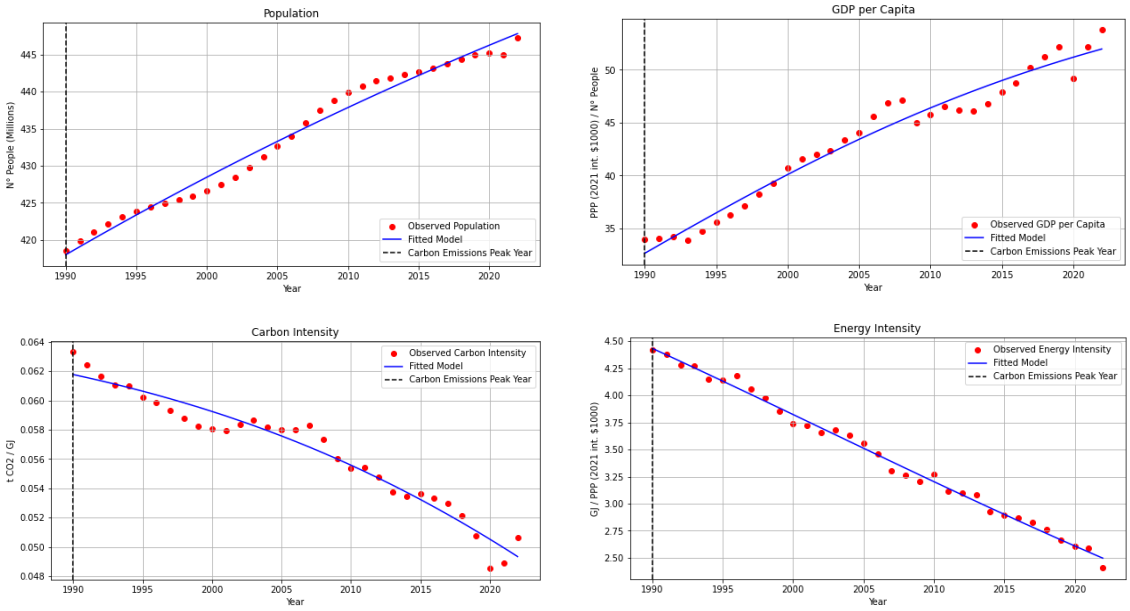


Table 4.12. *EU's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0000	1.2417	-0.0847	-0.9912	1.3905	0.4989
GDPPC	-0.0001	1.1357	0.1059	-0.8863	1.1419	0.5650
CI	0.0000	0.0008	-0.2257	-0.2763	0.3851	0.8248
EI	0.0000	0.0495	-0.0412	-0.6116	0.5236	0.7697

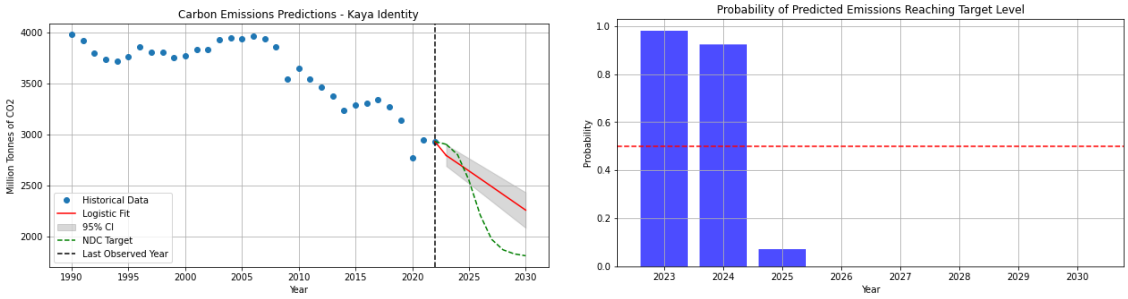
Table 4.13. highlights weak to moderate correlations between the analysed variables, which tells us that they generally move independently from each other.

Table. 4.13. *EU's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.3002	1.0000		
CI	0.4070	0.5294	1.0000	
EI	-0.0113	-0.3602	-0.1577	1.0000

The results of our forecasting and probability analysis, showcased in Figure 4.12., provide a visual representation where the EU seems unlikely to meet its goals.

Figure 4.12. *EU's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



Although it is expected to generate a reduction in its emissions of about 28%, the EU has an extremely low probability of reaching its 2030 target, mainly due to the fact that the target emission pathway implied by its NDC falls outside of the 95% confidence band, and thus outside of the range within which we are certain that future emissions will fall.

4.7. India

India, in a similar way to China, has set an NDC target in which it aims to reduce the intensity of its GDP compared to 2005. However, considering the high growth that is expected for the country's Gross Domestic Product, this formulation would allow the India to increase its emissions by 114.1% compared to current quantities.

To determine the probability that the country has of achieving its unambitious goal, we firs proceeded to fit each Kaya component with the logistic model and verified whether it could be considered a good fit for the data.

Figure 4.13. shows both the observed and the fitted values for all four factors in the period 1990-2022. From the figure we can see that, together with population and GDP per-capita, there has been a steady increase in the carbon intensity of India's energy production, which could signal that there has been little technological development to improve the amount of carbon emissions generated to produce one unit of energy.

Table 4.14. indicates that the fitted lines in the figure can be considered a realistic representation of the trends of three out of the four examined variables. The data for population, having a low J.B. p-value, indicates that there is uncertainty in our predictions and that residuals are not normally distributed.

Figure 4.13. *India's Fitted Kaya Identity Components*

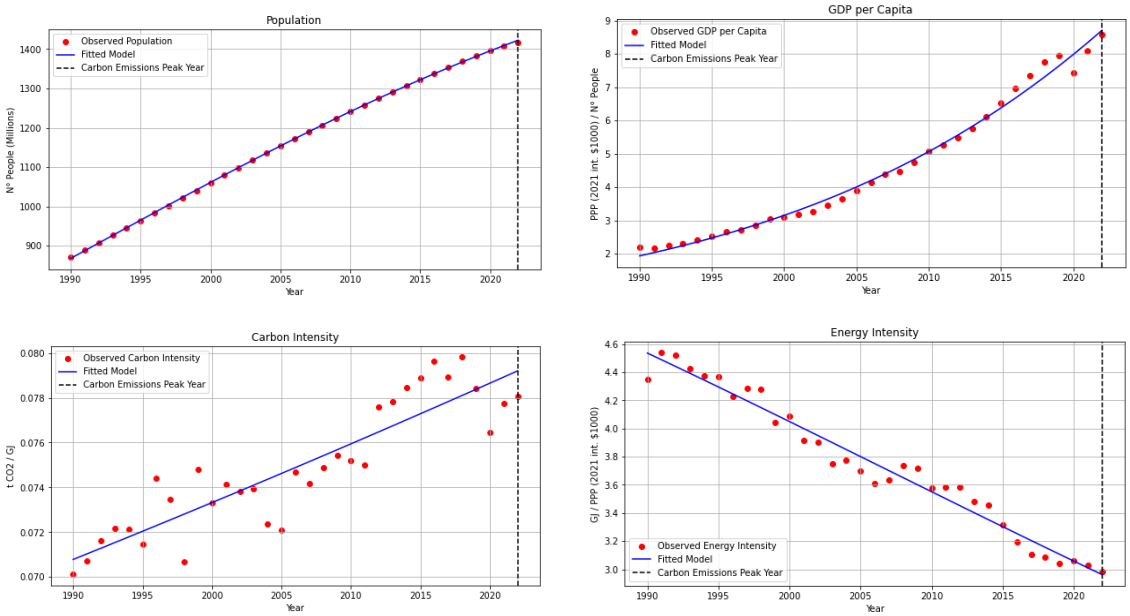


Table 4.14. *India's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0023	1.5001	-1.2679	3.3516	24.2876	0.0000
GDPPC	0.0028	0.1964	0.0365	0.9663	1.2913	0.5243
CI	0.0000	0.0013	-0.1533	-0.7509	0.9047	0.6361
EI	0.0000	0.0867	-0.3092	-0.8480	1.5143	0.4690

However, Table 4.15. tells us that there is a low to medium correlation between this and the other variables, which tells us that changes in population do not have any particular influence on the movement of the other variables.

Table. 4.15. *India's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	0.4171	1.0000		
CI	0.1406	0.5497	1.0000	
EI	-0.3631	-0.1926	0.0176	1.0000

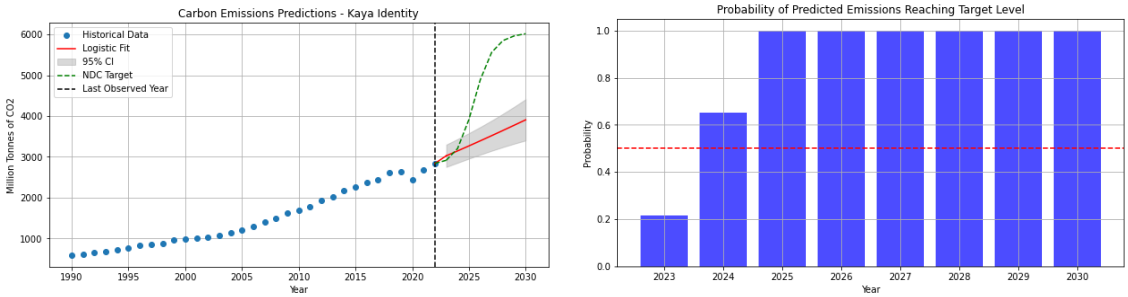
To control the influence that population has on the final calculation of carbon emissions through the Kaya Identity, we performed an OLS regression analysis. The analysis

showed that the impact of the population factor on the calculation of carbon emissions is minimal when compared to other variables.

Thus, taking in consideration the overall very good fit that the logistic model has for the other variables, and the fact the population seems to have very little influence on the latter and on the determination of carbon emissions, we proceeded to predict the future levels of carbon emissions that India is expected to reach, and calculated the probability it has to achieve its NDC objective.

As can be seen in Figure 4.14., our model has allowed us to predict that India should increase its emissions by 38% compared to 2022, given its historical trends. This would allow the country to almost certainly meet the NDC target with little to no effort required.

Figure 4.14. *India's Forecasted CO_2 emissions and Probability of Meeting NDC Target*

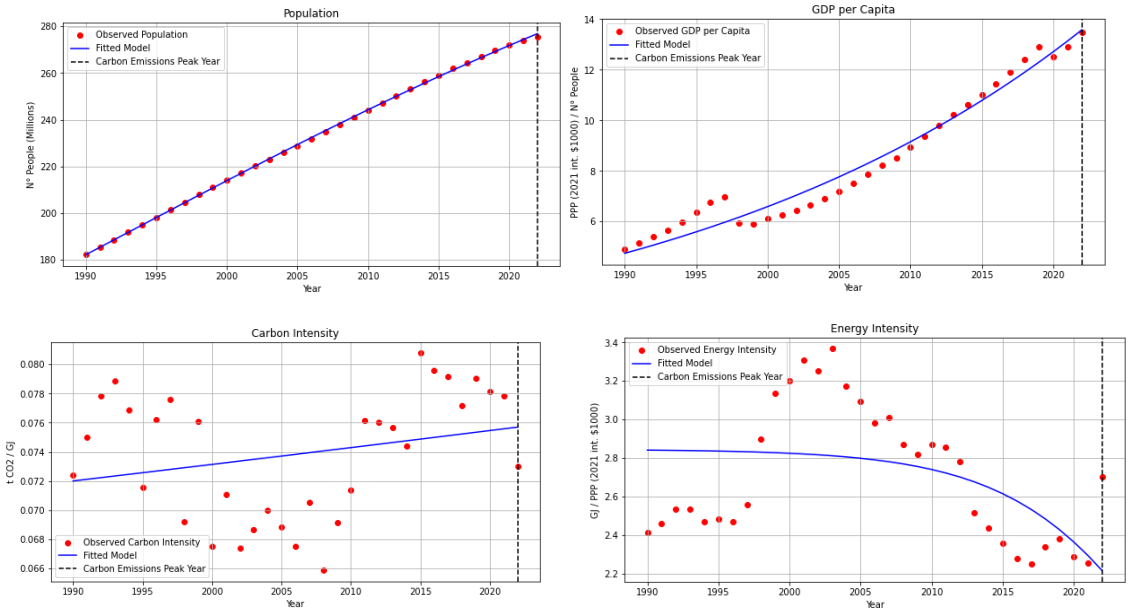


4.8. Indonesia

We previously calculated that Indonesia's NDC goal of reducing its emissions against those forecasted in a business-as-usual scenario would generate an increase in the quantity of GHG that the country emits equal to 57.5% of its 2022 levels.

Before calculating the probability, the country has of achieving this target, we proceeded to fit our logistic model to the historical data for population, GDP per-capita, carbon intensity, and energy intensity. We found that, except for energy intensity, all other factors have increased through time. The observed values for carbon intensity show us that there have been discontinuous movements in the data, where increases in one year were often followed by decreases in the next, and only lately there has been a swift increase in intensity.

Figure 4.15. *Indonesia's Fitted Kaya Identity Components*



The descriptive statistics represented in Table 4.16. show that the logistic model can be considered a good fit for Indonesia's data, as is confirmed by the high p-values of the Jarque-Bera statistic.

Table 4.16. *Indonesia's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0002	0.4326	-0.8028	1.1438	5.3436	0.0691
GDPPC	0.0096	0.4752	0.4070	-0.8447	1.8920	0.3883
CI	0.0000	0.0042	-0.2268	-1.2232	2.3401	0.3104
EI	0.0003	0.3010	0.2660	-1.2163	2.4231	0.2977

Additionally, the correlation matrix represented in Table 4.17. indicates that there are substantial relationships between the considered variables. The strong positive relationship between carbon intensity and GDP per-capita is a direct result of the country's reliance on carbon intensive energy sources, with carbon and oil accounting for more than 60% of its energy mix[15], which implies that economic growth outpaces efforts to transition to cleaner energy sources. The very strong negative relationship between energy intensity and GDP per capita may indicate that Indonesia's economic growth is

[15] International Energy Agency, *World Energy Statistics and Balances*, IEA, July 2024: https://www.iea.org/data-and-statistics/data-product/world-energy-statistics-and-balances

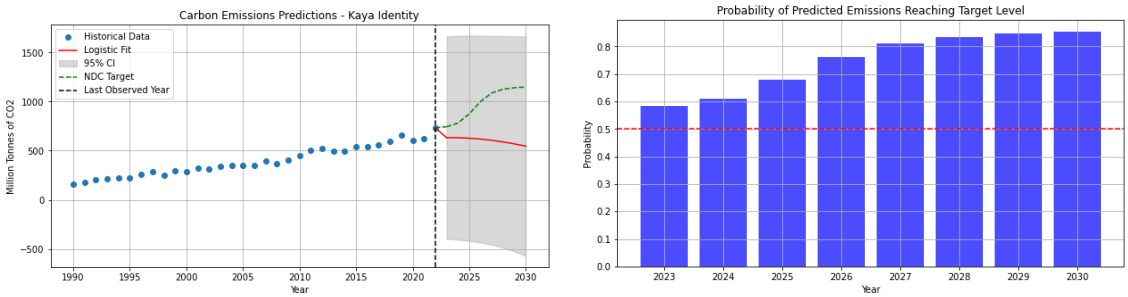
generally accompanied by strong investments in energy efficient technologies. Similarly, the strong negative relationship between energy intensity and carbon intensity suggests that energy efficiency improvements could be reducing the amount of energy needed to produce the same amount of economic output, thus also reducing emissions.

Table. 4.17. *Indonesia's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	0.4501	1.0000		
CI	0.5388	0.7280	1.0000	
EI	-0.5000	-0.8360	-0.7105	1.0000

After we ensured that the CO-STIRPAT framework fit the observed data well, we proceeded to use the logistic function to predict the values for each considered Kaya variable, and then used those to project Indonesia's future carbon emissions.

Figure 4.16. *Indonesia's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



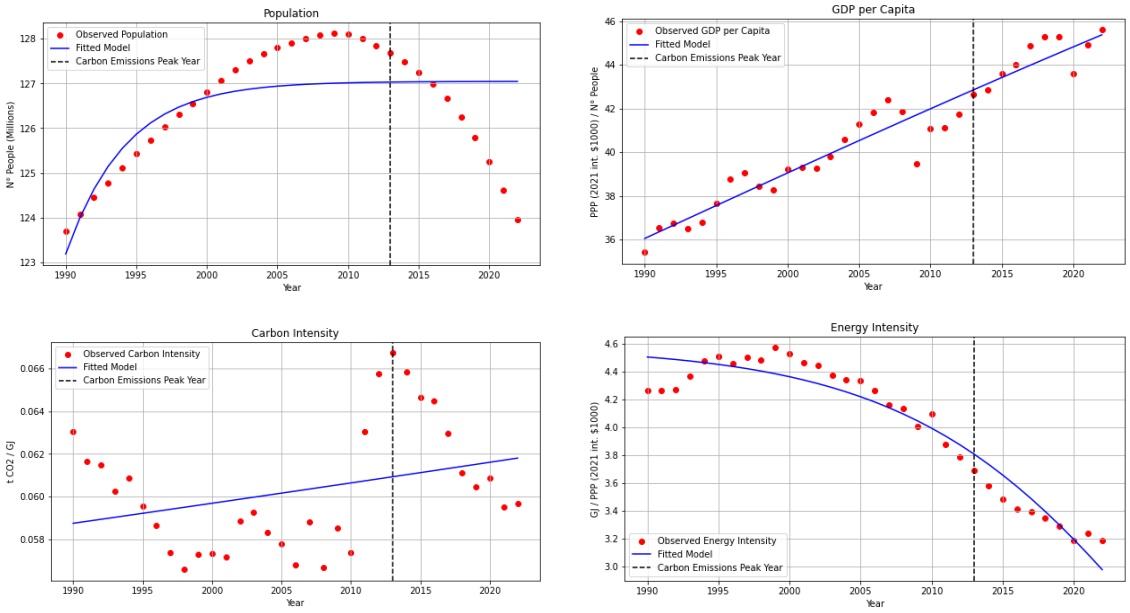
The resulting values, illustrated in Figure 4.16., show that the country is projected to decrease its CO_2 emissions from 733 Mt in 2022, to approximately 545 Mt in 2030. The combination of our results with the fact that the country has set a goal that would actually allow it to increase its emissions in the future translates to an 85.4% probability of reaching the target level of emissions in 2030, even when the high uncertainty represented by the confidence intervals is taken into consideration.

4.9. Japan

The Japanese government has submitted an updated NDC to the UNFCCC Secretariat in which it sets out a target that would lead the country to reduce its emissions by 37.0% compared to 2022.

To verify if Japan will be able to achieve this ambitious objective, we initially fit our logistic model to the country's data for Kaya Identity components. The fitted lines, which can be seen in Figure 4.17., show a growing trend for GDP per-capita and for carbon intensity, while also evidencing a decrease in energy intensity through time and a stabilisation in population around 2005 after a steep increase starting in 1990.

Figure 4.17. *Japan's Fitted Kaya Identity Components*



The figure also shows that the observed values for some of the variables significantly differ from the fitted ones. In particular, the observed values for Japan's population show a steep decline after 2009, which is not captured by the logistic model.

This is confirmed by the descriptive statistics of the variable's residuals, shown in Table 4.18., where the high standard deviation and low J.B. p-value indicate that there is uncertainty in the fitted values and that the residuals are not normally distributed, which leads us to affirm that the logistic model is not a good fit for this variable. However, the other variables present high p-values for the same statistic, indicating that the normality assumption is met and that the model fits the data well.

Table 4.18. *Japan's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0000	0.9999	-1.3747	1.8043	14.8706	0.0006
GDPPC	0.0000	0.7599	-0.6385	0.6099	2.7538	0.2524
CI	0.0000	0.0028	0.5740	-0.9246	2.9877	0.2245
EI	0.0003	0.1269	-0.3273	-0.9214	1.7563	0.4155

The correlation matrix represented by Table 4.19. highlights a strong negative relationship between energy intensity and carbon intensity, which suggests that as Japan improves energy efficiency, it also tends to lower its carbon intensity. This could reflect the country's ongoing efforts to adopt more energy-efficient technologies and transition toward cleaner energy sources.

Table. 4.19. *Japan's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.1140	1.0000		
CI	0.1009	-0.1958	1.0000	
EI	-0.2011	0.1237	-0.8239	1.0000

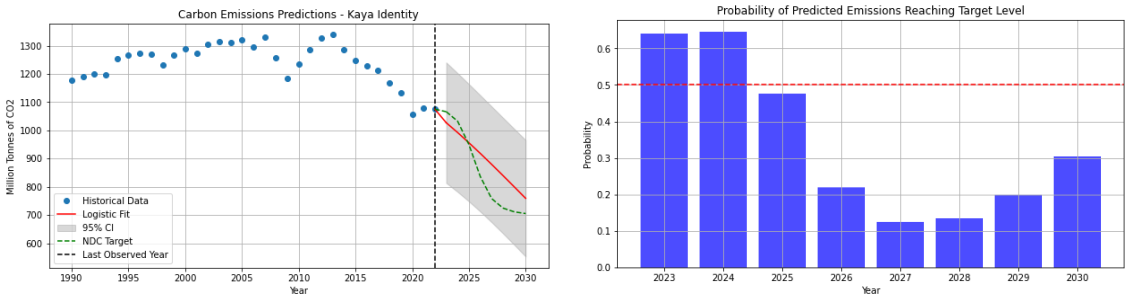
Furthermore, the matrix shows a weak relationship between population and the other analysed variables. This is likely due to Japan's stable population trend since 2005 and the subsequent decline after 2009, which reduces the impact of population changes on economic growth, energy use, and emissions.

To verify the influence that each variable has on the final result of carbon emissions, we performed an OLS regression analysis. The analysis showed that carbon intensity has the greatest influence on the final values of the Kaya Identity, while population has an almost imperceptible impact when compared to the other variables.

Thus, while the p-value for the Jarque-Bera test on population suggests a deviation from normality, the weak correlation between population and other Kaya components and its relatively low influence on the identity suggests that the poor representation of this variable by our logistic model will have little impact on our predictions.

Therefore, we proceeded to determine the future carbon emissions for Japan and calculate the probability that it will achieve its NDC target, acknowledging the deviation in population but assuming that its impact on the results is limited.

Figure 4.18. *Japan's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



The result of our analysis, represented in Figure 4.18, shows that, while the country is expected to decrease its CO_2 emissions by 29% from 2022 levels, it has only a 30.5% probability of reaching its submitted goal of lowering its emissions by 37% by 2030.

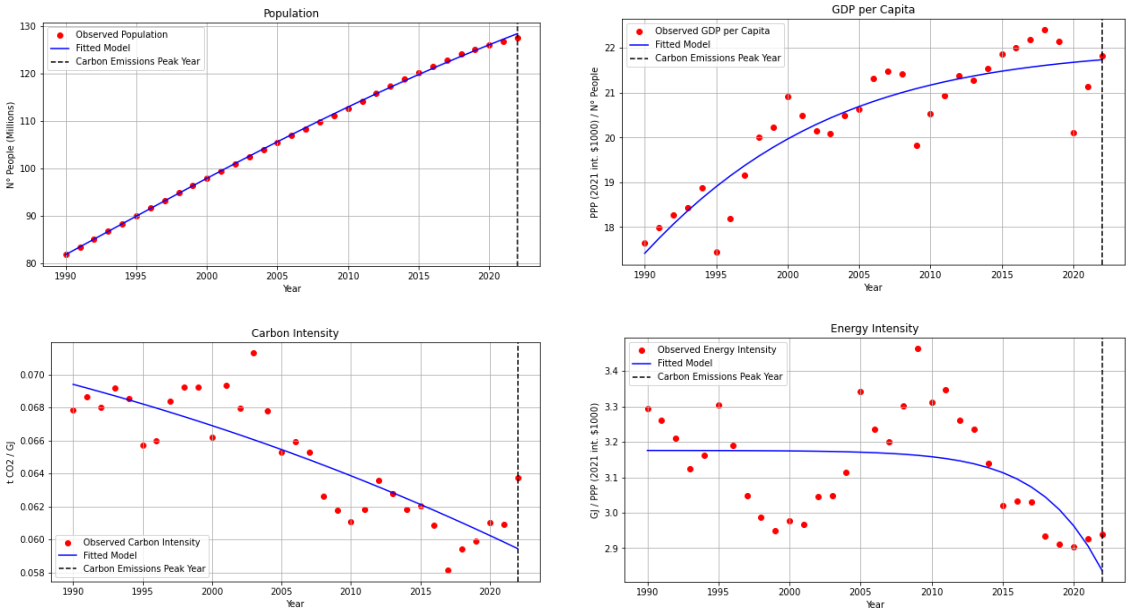
4.10. Mexico

The formulation of Mexico's NDC, in which the country pledges to reduce its emissions compared to what they would amount to in a BAU scenario, would approximately result in a 21.4% decrease in emissions compared to present quantities.

Figure 4.19 captures the pathway that has been historically followed by the country's Kaya Identity factors. It shows that, the country has experienced a steady growth in population, which has been accompanied by an uneven growth in GDP per-capita, an imbalanced decrease in carbon intensity, and a varying trend in the intensity of its energy production.

The figure also contains the result of the fitting process of our logistic model, which has captured the growing trend of population and GDP per-capita, as well as the decreasing trend of carbon intensity and the recent improvement in the country's energy intensity.

Figure 4.19. *Mexico's Fitted Kaya Identity Components*



The goodness of the fit for each variable is described by the statistics in Table 4.20., from which it can be observed that the model provides an adequate representation for population, carbon intensity, and energy intensity.

Table 4.20. *Mexico's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0001	0.2924	-0.4838	0.8521	2.2861	0.3189
GDPPC	0.0001	0.6196	-1.0704	0.5901	6.7809	0.0337
CI	0.0000	0.0019	0.6857	0.4317	2.8426	0.2414
EI	0.0000	0.1295	0.1414	-0.6618	0.7122	0.7004

However, the table also highlights the fact that the logistic function appears to not represent GDP per-capita accurately, as is demonstrated by the high standard deviation and the low p-value of the J.B. statistic, which indicate that the residuals for this variable are widely spread around its mean and that they do not follow a normal distribution.

Although the model does not provide precise values for GDP per-capita, the weak relationship that this variable has with the other Kaya Identity components, as shown in Table 4.21., indicates that it does not have a strong influence on their values.

Table. 4.21. *Mexico's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	0.3014	1.0000		
CI	-0.3187	0.1116	1.0000	
EI	-0.4447	-0.4189	-0.4635	1.0000

To verify the overall impact that the poor fit of our model for GDP per-capita could have on our final results, we proceeded to perform an OLS regression analysis to verify the influence that this variable has historically had on the carbon emissions resulting from the Kaya Identity. The coefficients resulting from the regression tell us that GDP per-capita does have a substantial influence on the determination of carbon emissions, but that this influence is minimal when compared to that of energy intensity and carbon intensity.

Thus, although the lower precision of our model in fitting this variable must be taken into consideration, the weak relationship with the other analysed variables and the comparatively low impact within the Kaya Identity suggests that it will have a low influence on the determination of total carbon emissions.

Therefore, we proceeded to use the CO-STIRPAT framework to assess the likelihood that Mexico has of reaching the level of CO_2 emissions that is implied by its NDC submission.

Figure 4.20. *Mexico's Forecasted CO_2 emissions and Probability of Meeting NDC Target*

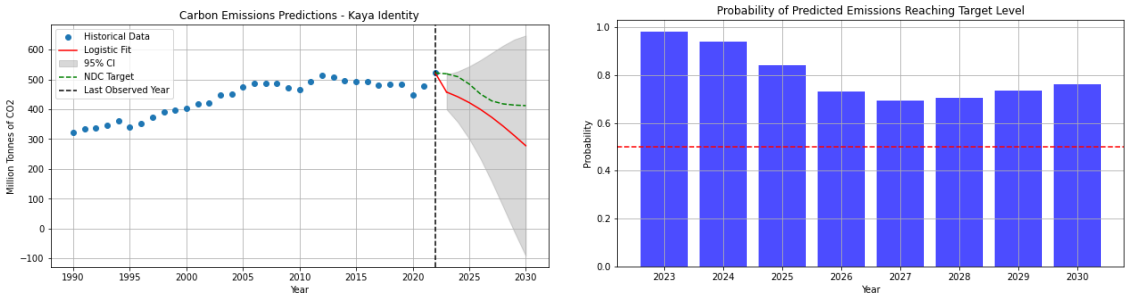


Figure 4.20 shows that Mexico is expected to substantially decrease its emission in the coming years according to the CO-STIRPAT model.

Although our predictions are affected by an increasing degree of uncertainty, as represented by the growing 95% confidence intervals, the country still has a 76.2%

probability of achieving its emission target. Thus, it appears that there is a strong likelihood that Mexico will achieve its pledged levels of emissions by 2030.

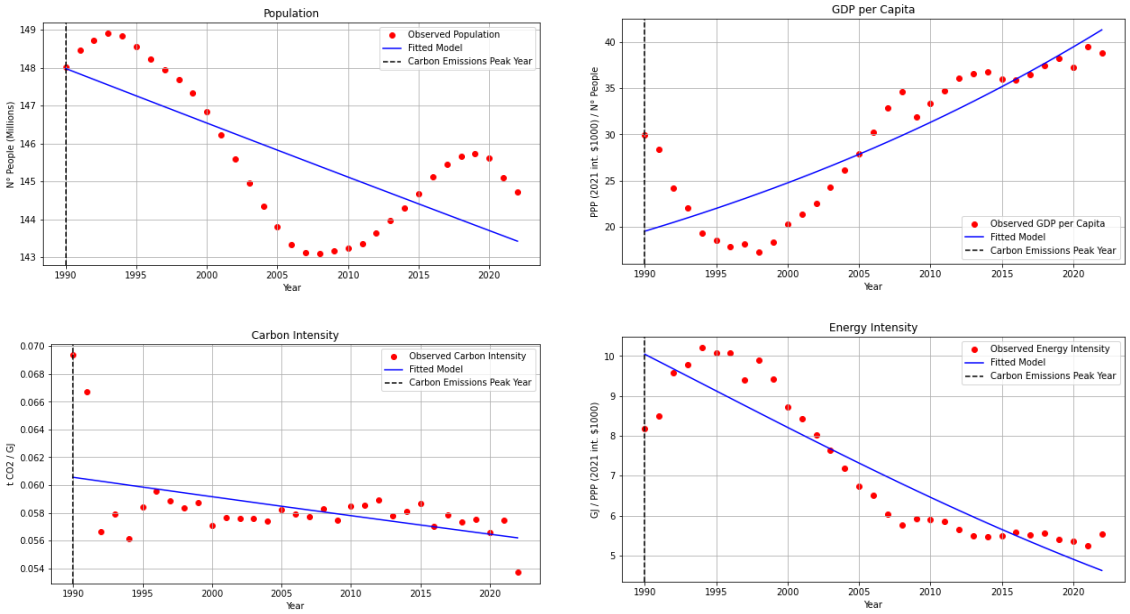
4.11. Russia

The Russian Federation has submitted an updated NDC in which it commits itself to not exceeding 70% of its 1990 GHG emissions by 2030. This submission translates to a 17.2% reduction in emissions compared to those produced in 2022.

Assuming that carbon emissions are a good representation of the overall emissions of the country, and that its NDC implies an equal implementation of its reduction across all greenhouse gases, we set out to verify if Russia will be able to achieve a 17.2% reduction in its CO_2 emissions by 2030 through the application of our CO-STIRPAT model.

The observed values for the Kaya factors and results of the logistic model fit for each one are graphically illustrated in Figure 4.21. below.

Figure 4.21. *Russia's Fitted Kaya Identity Components*



The figure shows that, while Russia has seen an increase in its GDP per-capita and presents steady low values for carbon intensity, its population and energy intensity have experienced steep decreases through the years. While these trends seem to be well represented by our logistic model for most variables, the low p-value of the J.B. statistic

for carbon intensity indicates that the model does not fit the data adequately, as can be seen below (Table 4.22.).

Table 4.22. *Russia's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0001	1.4234	-0.3970	-1.2729	3.0948	0.2128
GDPPC	0.0089	3.8498	0.5915	0.3219	2.0667	0.3558
CI	0.0000	0.0024	1.8569	5.0794	54.4400	0.0000
EI	0.0031	0.7507	-0.3303	-0.3087	0.7312	0.6938

However, while the initial results suggest a significant deviation from normality, we concluded that it was mainly driven by the extremely high values that the variable presented for the years 1990 and 1991. These two data points act as outliners, creating a distortion in the distribution of residuals which leads to an increase in skewness and kurtosis, which in turn results in a very low p-value. Once we removed these two years from the dataset, the Jarque-Bera test resulted in a p-value of 0.9478, indicating that residuals closely follow a normal distribution.

The correlation matrix calculated of variables, presented in Table 4.23., allows us to determine that there are generally strong relationships between Russia's Kaya components.

Table. 4.23. *Russia's Correlation Matrix*

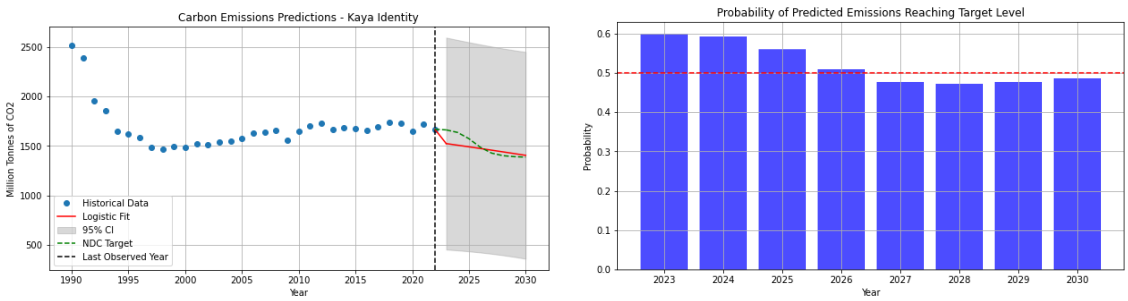
Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.3518	1.0000		
CI	-0.0626	0.6607	1.0000	
EI	0.6448	-0.9036	-0.6315	1.0000

The very strong negative correlation between energy intensity and GDP per capita reflects the increasing energy efficiency associated with economic growth, suggesting that Russia is optimising its energy use and investing in the modernisation of its infrastructure and industrial processes. The strong negative correlation between energy intensity and carbon intensity implies that decreases in energy intensity are generally accompanied by increases in carbon intensity. Together with the strong positive relationship between GDP

per capita and carbon intensity, this indicates that Russia's economic growth is associated with increases in its carbon emissions, suggesting the country's economy is mainly driven by carbon-intensive industries. Lastly, the positive relationship between population and energy intensity is primarily a result of Russia's historical population trends. The decline in population that the country has experienced in recent decades has inevitably led to lower demand for energy, and thus to lower energy intensity. However, the stable low levels of energy intensity that have been registered, even with increases in population, suggest that there have also been technological improvements in energy use.

Through the use of the CO-STIRPAT framework, we have combined the four Kaya Identity factors and produced a forecast for the carbon emissions that Russia is expected to produce from 2022 up to 2030. The results of our projection, which can be observed in Figure 4.22, indicate that the country should be able to achieve a 16% reduction in its CO_2 emissions in the future.

Figure 4.22. *Russia's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



However, this only translates to a 49.5% probability of achieving the submitted NDC target level of emissions, mainly due to the high uncertainty in our predictions, represented by the wide range of our 95% confidence intervals.

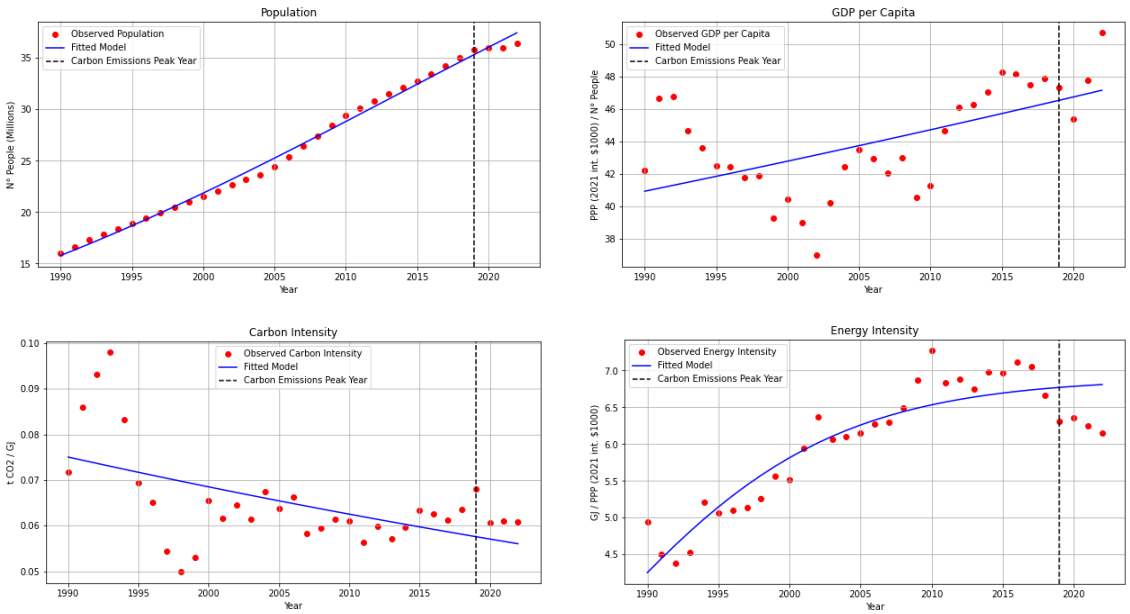
4.12. Saudi Arabia

Saudi Arabia has pledged to reduce its GHG emissions by 278 Mt CO_2e compared to those produced in 2019, which implies a 40.3% reduction compared to 2022 levels.

Assuming that the country intends to reduce its carbon emissions by the same percentage amount, and that the Kaya Identity provides a valid representation of these emissions, we proceeded to fit the CO-STIRPAT's logistic model to the country's historical data.

The results of this process, shown in Figure 4.23., highlights the fact that most of the fitted variables have had a growing pathway through time, with only carbon intensity presenting a decreasing pattern. However, while the data for the country's population has followed a steady path, the same cannot be said for its GDP per-capita and energy intensity, with both variables experiencing periods of growth followed by periods of contraction.

Figure 4.23. *Saudi Arabia's Fitted Kaya Identity Components*



Nonetheless, the logistic model can be considered a valid representation of the direction in which the data has been moving, as is confirmed by the descriptive statistics in Table 4.24, where all variables show high p-values for the J.B. statistic, indicating that the normality assumption for the distribution of residuals holds.

Table 4.24. *Saudi Arabia's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0026	0.4891	-0.7011	-0.7798	3.5398	0.1703
GDPPC	0.0015	2.6725	-0.0745	-0.1276	0.0529	0.9739
CI	0.0000	0.0091	0.4175	1.1398	2.7447	0.2535
EI	0.0009	0.3354	0.2051	-0.3899	0.4404	0.8024

To verify how these four factors influence each other, we calculated their correlation matrix (Table 4.25.).

Table. 4.25. *Saudi Arabia's Correlation Matrix*

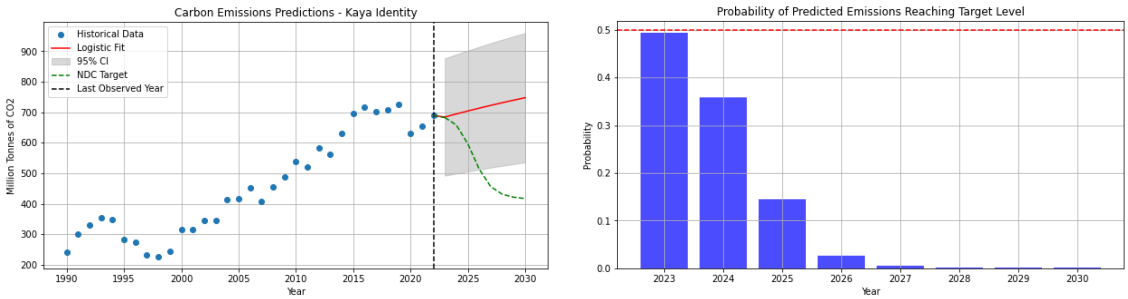
Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	0.3231	1.0000		
CI	0.2032	0.6094	1.0000	
EI	0.4567	-0.1816	-0.1017	1.0000

The table shows us that there is generally a weak relationship among the considered factors, with only carbon intensity and GDP per-capita having a strong positive relationship. This indicates that carbon emissions increase together with the country's economic output, which could be a result of the country's strong reliance on its petroleum sector.

Once we determined that the logistic model can be considered a good fit for the data, and that there is generally a low correlation between the analysed variables, we proceeded to verify if Saudi Arabia could be expected to reach its ambitious emission target.

By applying the CO-STIRPAT model to the country's data, we determined that Saudi Arabia will most likely increase the amount of CO_2 that it releases in the atmosphere by about 8% compared to present quantities (Figure 4.24).

Figure 4.24. *Saudi Arabia's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



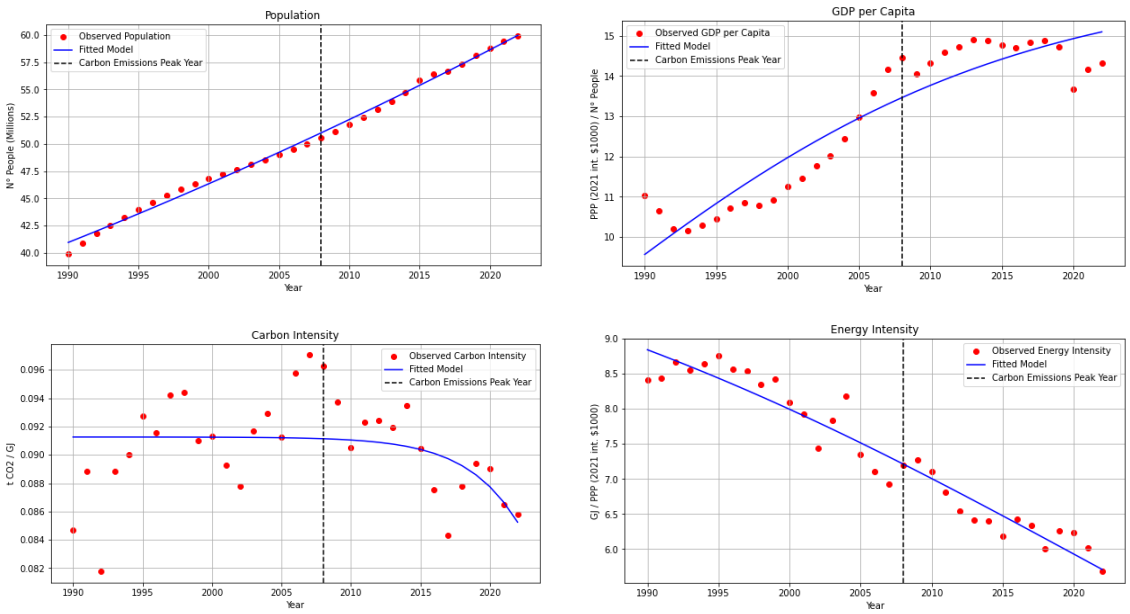
These results negatively affect the country's probability of achieving its 2030 goal, which falls from 49.8% in 2023 to only 0.1% in 2030. Thus, it seems very unlikely that Saudi Arabia will be able to achieve the 40.3% reduction it has committed itself to in its NDC.

4.13. South Africa

The South African government has submitted an updated NDC in which has determined an absolute level of emissions that it aims not to exceed by the target year 2030. If achieved, this objective would result in in a reduction in emissions of about 90 Mt CO_2 compared to those produced by the country in 2022.

To assess whether South Africa will be able to reach its ambitious carbon reduction goal, we first had to verify if our logistic model could be considered appropriate to represent the country's data.

Figure 4.25. *South Africa's Fitted Kaya Identity Components*



Visually, Figure 4.25. shows that South Africa's population and GDP per-capita have followed a growing trajectory, while its energy intensity has progressively decreased and reached its lowest point in the last observed year. Additionally, the figure allows to assess that the country's carbon intensity has varied greatly across the years, which has resulted in a fitted line that evidences a slowly decreasing pathway that only accelerates in the latest part of the observed period.

Nevertheless, the logistic model seems to be providing a solid representation of the pathway that has been followed by each variable, as is confirmed by the p-values of the Jarque-Bera statistic shown below (Table 4.26). Since each p-value exceeds 0.05, we

cannot reject the null hypothesis of the J.B. test, which assumes that the residuals of our variables are normally distributed, and thus conclude that the logistic model is a good fit.

Table 4.26. *South Africa's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	-0.0001	0.4048	-0.3498	-0.1729	0.7140	0.6998
GDPPC	0.0016	0.6570	0.1583	-0.8102	1.0405	0.5944
CI	0.0000	0.0032	-0.8122	1.1902	5.5758	0.0616
EI	0.0002	0.2449	0.0353	-0.6984	0.6776	0.7126

Table 4.27. represents the correlations among the analysed Kaya Identity components.

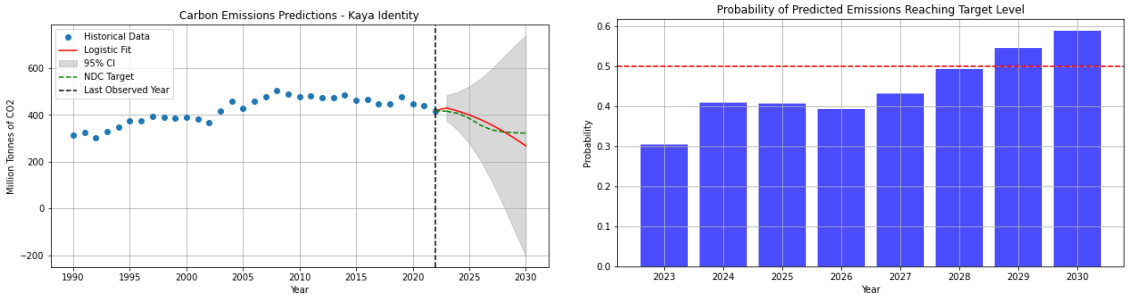
Table. 4.27. *South Africa's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.7611	1.0000		
CI	0.1017	0.0031	1.0000	
EI	0.5249	-0.6425	0.1222	1.0000

The strong negative correlation between GDP per capita and population implies that there are periods where economic output decreases as population increases. This could indicate that the economy is not generating enough jobs to support the growing population, leading to decreases in GDP per capita. Additionally, the strong negative correlation between energy intensity and GDP per capita suggests that increases in the economic output are generally accompanied by more efficient energy use.

Taking all of this information into consideration, we proceeded to verify how South Africa's emissions will change in the future by applying the CO-STIRPAT framework. The model provided us with a decreasing emission pathway for the country's CO_2 emissions, which are expected to decline by 36% from 2022. However, as can be viewed in Figure 4.28., although the prospected emission levels stand below those implied by the country's NDC, the probability of reaching the target in 2030 stands at 58.9%, mainly due to the increasing uncertainty of the predictions in time.

Figure 4.26. *South Africa's Forecasted CO_2 emissions and Probability of Meeting NDC Target*

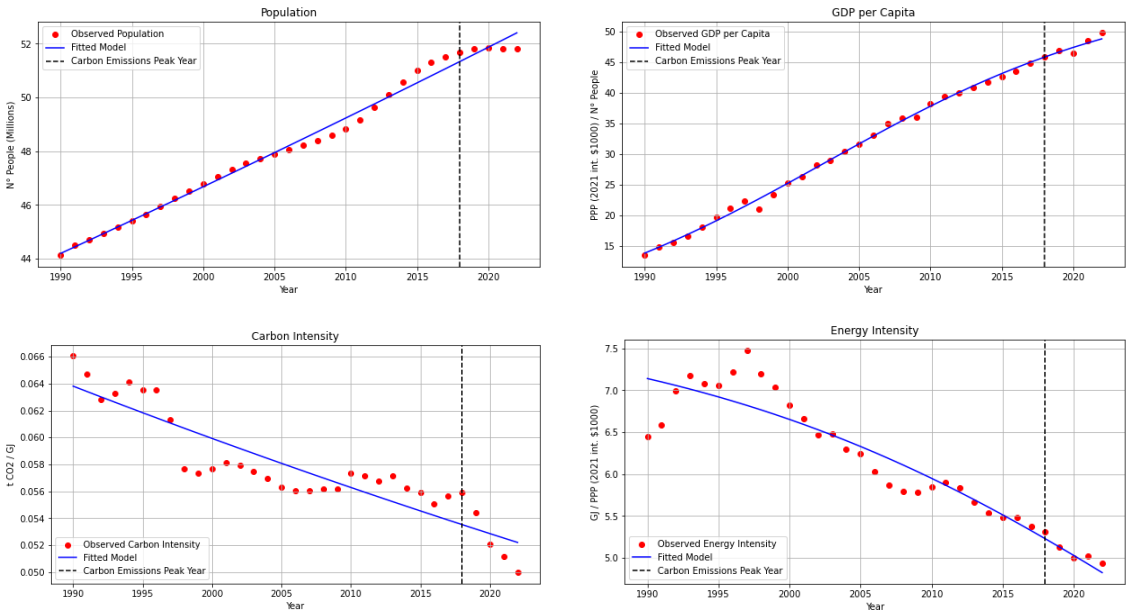


4.14. South Korea

In its 2021 NDC submissions, South Korea has set an unconditional absolute emission reduction target that would produce a 40.0% reduction in the country's emissions in 2030 compared to what they currently are.

The initial step of our CO-STIRPAT model involved fitting each Kaya Identity component with a logistic function, which was later be utilised to define project future values for each of the four factors. The observed and fitted values for the variables can be viewed in Figure 4.27 for the period spanning between 1990 and 2022.

Figure 4.27. *South Korea's Fitted Kaya Identity Components*



The plotted data shows that there has South Korea's population and GDP per-capita have experienced a steady increase in the past 32 year, while its carbon intensity and energy

intensity have progressively decreased through the same time period. This could indicate an improvement in the technological factors that influence the country's energy and carbon efficiencies.

The fitted lines that can be in the figure seem to provide a good representation of the change in the observed data points for this country. This is re-affirmed by the statistics that have been calculated on the residuals of our logistic model. In particular, Table 4.28. provides us with the results of the Jarque-Bera test, which verifies whether the skewness and the kurtosis of a variable are similar to those that can be expected in a normal distribution. The p-value of said statistic, which surpasses 0.05 for all factors, indicates that the null hypothesis of normality cannot be rejected, thus implying that our model can be considered a good fit for the data.

Table 4.28. *South Korea's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0000	0.2534	-0.1438	-0.0753	0.1216	0.9410
GDPPC	-0.0024	0.5581	-0.5555	0.8542	2.7009	0.2591
CI	0.0000	0.0017	-0.2178	-1.3084	2.6146	0.2705
EI	0.0002	0.2543	-0.2268	1.4028	2.9887	0.2244

South Korea's correlation matrix, presented in Table 4.29., provides information on the relationships that occur between the country's Kaya factors. The weak relationships among the variables allows us to affirm that they do not influence each other in any particular way. This means that movements in one variable will generally be independent from the direction which the other ones will change.

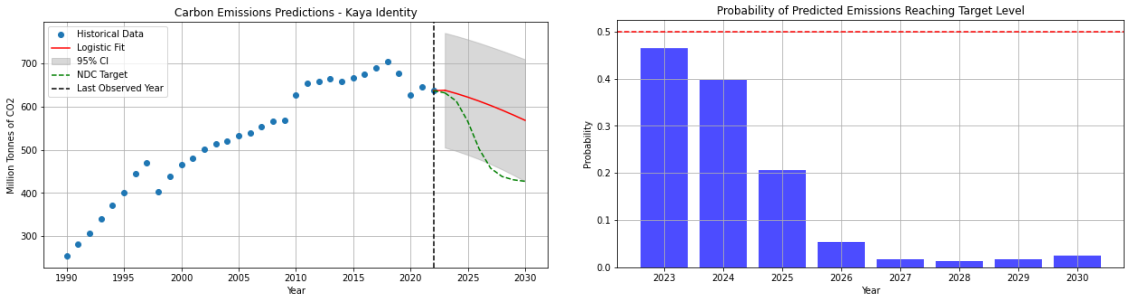
Table. 4.29. *South Korea's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.4152	1.0000		
CI	0.2776	0.1486	1.0000	
EI	0.2018	0.0304	-0.1637	1.0000

After fitting each Kaya factor with the logistic model, we proceeded to use our CO-STIRPAT framework to create their projected future values and then calculated both the historical and future Kaya Identity carbon emissions for the country.

The resulting values, which are graphically represented in Figure 4.28, have allowed us to determine that South Korea is expected to decrease its CO_2 emissions by 11% in 2030 compared to 2022. However, while this is an improvement on current trends, this translates to a 0.6% probability of achieving the level of emissions that has been pledged within the latest NDC submission.

Figure 4.28. *South Korea's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



The assessment of South Korea's probability of achieving its NDC target was particularly relevant for determining the accuracy of out CO-STIRPAT model replication, since it was this country on which the original framework was applied to by Jin Ick in "*Probability of Achieving NDC and Implications for Climate Policy: CO-STIRPAT Approach*".

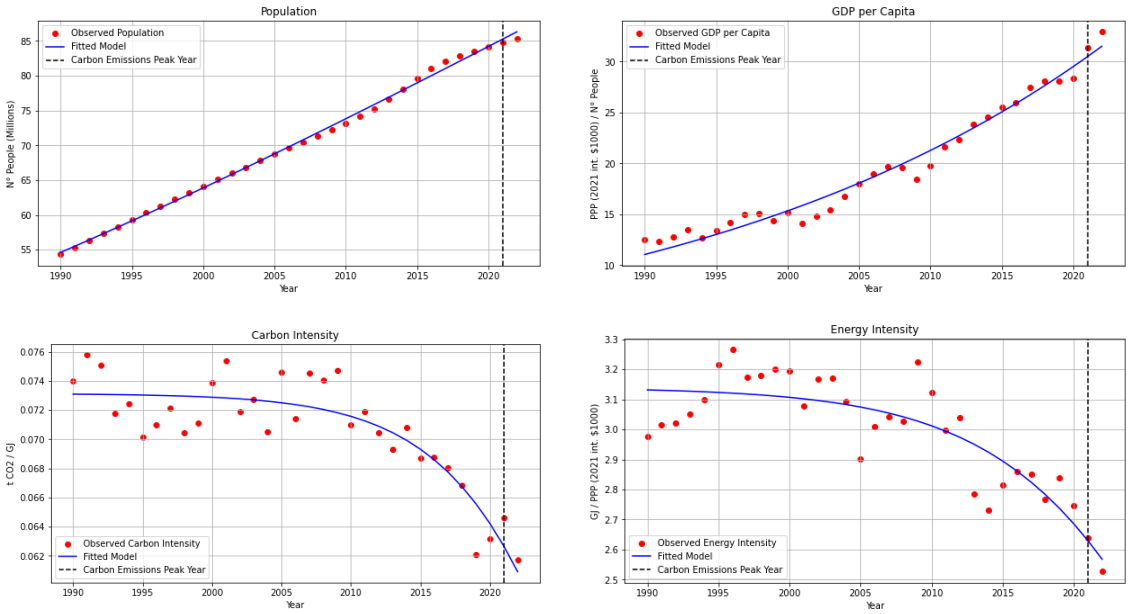
We decided to verify whether our model could be considered an accurate reproduction of the original framework by comparing our results to those obtained by Jin Ick. We found that the models present slightly different values for the Kaya Identity factors, and the resulting descriptive statistics and correlation matrix, which can be explained by the different data sources that have been used. However, we have also found that both result in similar conclusions regarding South Korea's likelihood of achieving its 2030 emission objectives, which leads us to conclude that our model provides a valid representation of the original framework developed by Jin Ick.

4.15. Turkey

The Turkish government has submitted a first update to its NDC in 2023, where it commits itself to reducing GHG emissions to 695 Mt CO_2e by 2030. However, this goal actually allows the country to increase its emissions by 1.1% in the target year compared to those produced in 2022, the year for which data is last available.

To verify whether the country will meet its unambitious emission target, we proceeded to fit its historical data with our logistic function. The results of this fitting process, shown in Figure 4.29, showcase a steady increase through time in the country's population and GDP per-capita, and a more variable decrease in its carbon and energy intensities, which seem to be adequately captured by our logistic model.

Figure 4.29. *Turkey's Fitted Kaya Identity Components*



The goodness of fit of the model to the analysed data is confirmed by the high p-values of the J.B. statistic, presented in Table 4.30., which indicate that the residuals of our variables follow a normal distribution, and thus that the model is able to capture their movement well.

Table 4.31. shows the correlation matrix between Turkey's Kaya Identity components. The table highlights that there are generally weak relationships among the analysed variables, meaning that they tend to move independently from one another, and that significant changes in one factor tend to have very little effect on the others.

Table 4.30. *Turkey's Descriptive Statistic and Normality Test*

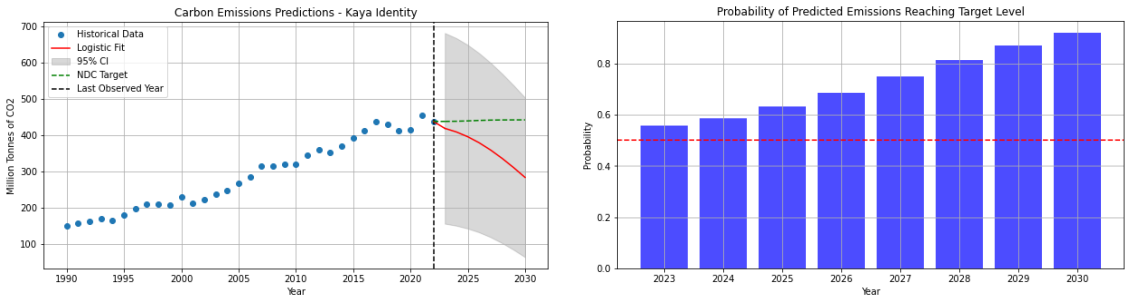
Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0000	0.4634	0.2913	0.0041	0.4667	0.7919
GDPPC	0.0239	0.9611	-0.5811	-0.5035	2.2055	0.3320
CI	0.0000	0.0017	-0.0344	-0.8473	0.9937	0.6085
EI	0.0000	0.0960	-0.2846	-0.5522	0.8648	0.6489

Table. 4.31. *Turkey's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	0.0797	1.0000		
CI	-0.3069	-0.0397	1.0000	
EI	0.0439	-0.4954	-0.3371	1.0000

Lastly, Figure 4.30 gives a graphical representation of the carbon emission forecasts that have been obtained for Turkey through the application of the CO-STIRPAT.

Figure 4.30. *Turkey's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



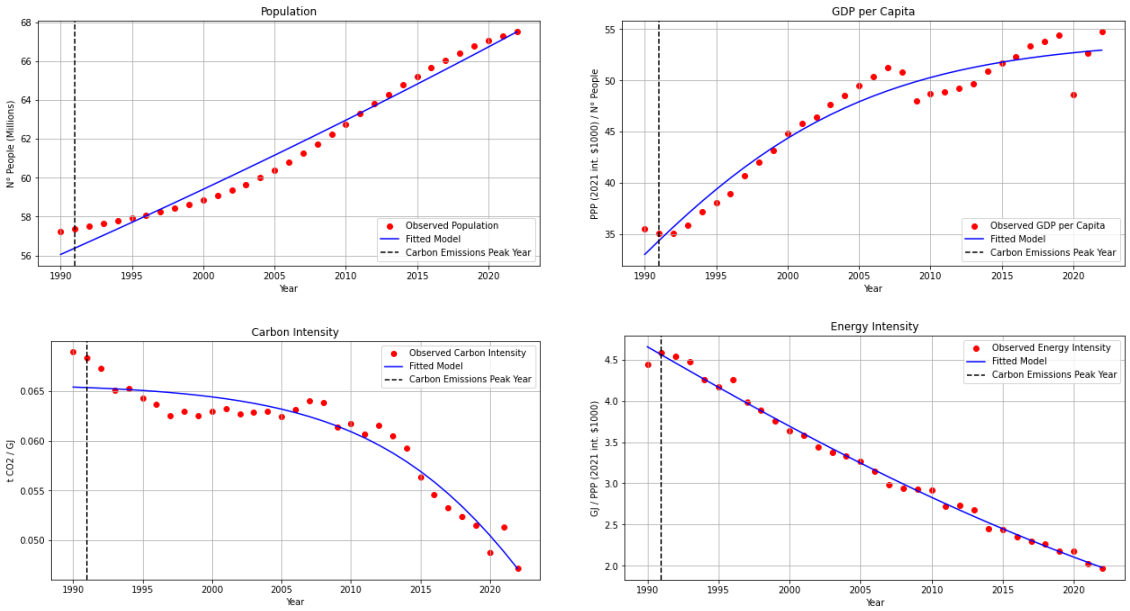
While the country's NDC implies an increase in emissions in the future, our forecasts prospect a substantial decrease of 35% in the country's CO_2 emissions in the future. Although the predictions are affected by significant uncertainty, represented by the 95% confidence intervals, there is a 92.2% probability that Turkey will be able to achieve its updated NDC objective.

4.16. United Kingdom

The United Kingdom has committed itself to reducing the amount of GHG emitted in the atmosphere by 68% below 1990, which effectively translates to 41.0% less emissions compared to 2022 levels.

Assuming that the country will reduce its carbon emissions by the same percentage amount, we proceeded to fit the Kaya Identity components of the United Kingdom with the logistic model of the CO-STIRPAT framework. The results of our fitting process, shown in Figure 4.31., tell us that there has been a consistent increase in the country's population and GDP per-capita, as well as consistent decreases in the intensity of its energy production and that of its carbon emissions.

Figure 4.31. *UK's Fitted Kaya Identity Components*



The ability of the fitted model to accurately capture the movements in the analysed variables is determined by the descriptive statistics presented below (Table 4.32.).

The information contained in the table tells us that the model can be considered a good fit for population, GDP per-capita and carbon intensity, but that the same cannot be said for energy intensity. The low p-value of the variable's J.B. statistic indicated that its residuals do not follow a normal distribution, and that thus the model is unable to fully capture its movements.

Table 4.32. *UK's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0006	0.5491	0.1168	-0.9170	1.2313	0.5403
GDPPC	0.0018	1.5125	-0.3809	-0.1418	0.8258	0.6617
CI	0.0000	0.0015	0.6072	-0.6494	2.6078	0.2715
EI	0.0001	0.0705	-0.1580	2.3720	7.8734	0.0195

To verify how the poor fit of our model for this variable could affect the final results of our analysis, we first decided to calculate a correlation matrix (Table 4.33.) to see the relationship that energy intensity has with the other Kaya components.

Table. 4.33. *UK's Correlation Matrix*

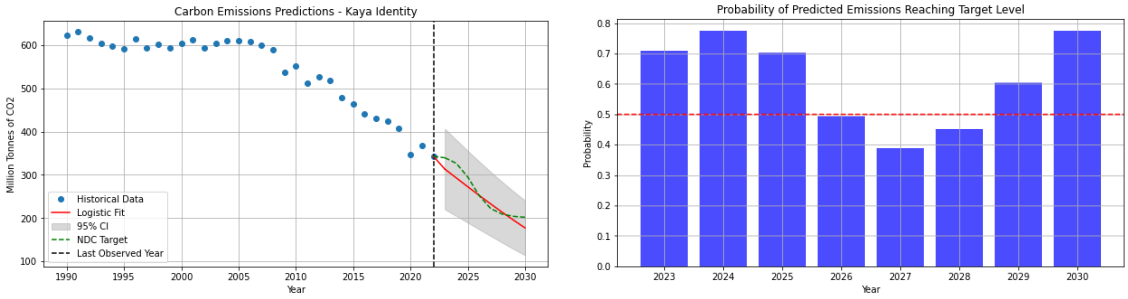
Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.1584	1.0000		
CI	0.3921	0.1567	1.0000	
EI	0.0971	-0.5846	-0.2169	1.0000

The matrix highlights weak to moderate correlations among variables. Thus, as can be observed, there are no strong correlations between said factor and the other Kaya components, which suggests that they move independently from each other, and that changes in energy intensity do not cause by significant changes in other variables.

Once we determined that energy intensity does not have a strong relationship with the other variables, we proceeded to perform an OLS regression analysis to assess how this factor impacts the calculation of the Kaya Identity's carbon emissions. The regression highlighted that, while energy intensity does provide a considerable contribution to the determination of carbon emissions, its impact and that of the other variables is extremely less significant than that provided by carbon emissions, which are well fitted by our model.

Thus, we have concluded that the effect of energy intensity on final carbon emissions is minimal, and have proceeded to apply our logistic function to produce estimates on the future values of the country's carbon emissions.

Figure 4.32. *UK's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



As can be seen in Figure 4.32., the United Kingdom is expected to decrease its CO_2 emissions by 48% in 2030 compared to current observed levels. Since this reduction surpasses the one that has been determined in the country's NDC, it translates to a 77.5% probability of reaching the target quantity of emissions in 2030.

4.17. United States

After re-entering the Paris Agreement in 2021, the United States submitted an updated NDC target which, if achieved, would translate in a 41.0% reduction in emissions compared to their 2022 levels.

In order to determine whether the country will be able to reach its goal, the CO-STIRPAT fits the observed data of the Kaya Identity components with a logistic model. The observed and fitted data, presented in Figure 4.33, show that the US's population and GDP per-capita have followed an increasing pathway through the years, while carbon intensity and energy intensity have decreased in the same time frame, suggesting that there have been significant improvements in the country's technological factors.

The ability of the CO-STIRPAT's logistic model to realistically represent the path followed by the considered variables can be assessed through the Jarque-Bera test. The p-values of the J.B. statistic, represented in Tabel 4.34., tell us that the logistic function can be considered a good fit for the data of GDP per-capita, carbon intensity and energy intensity, but that it does not provide an accurate depiction for the population component.

Figure 4.33. *US's Fitted Kaya Identity Components*

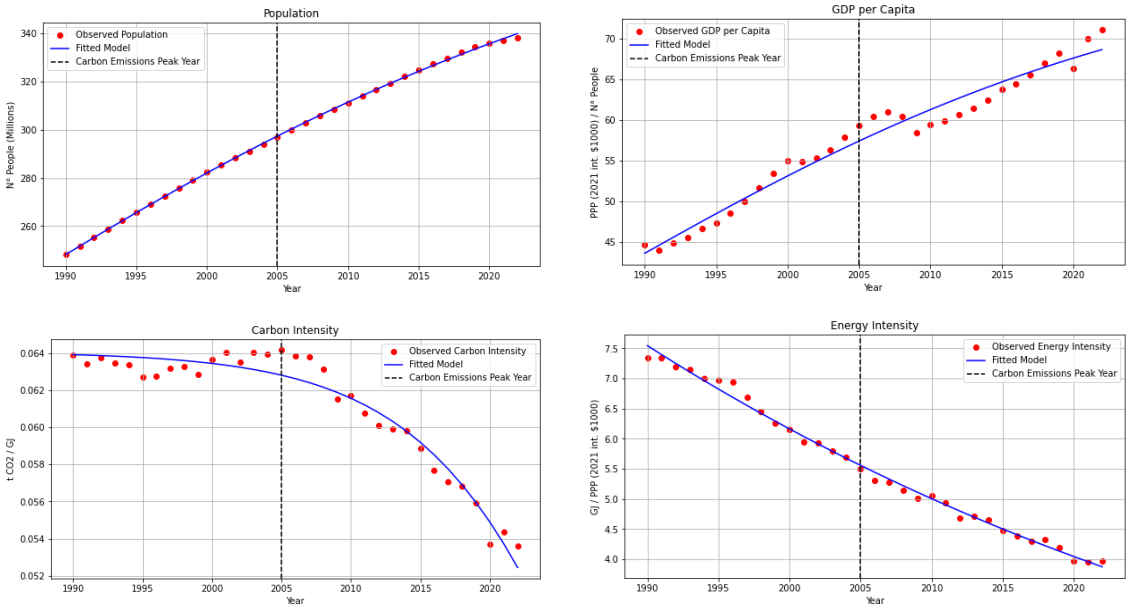


Table 4.34. *US's Descriptive Statistic and Normality Test*

Variable	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J.B. Statistic*	*J.B. P-value*
P	0.0001	0.4926	-0.7164	1.8547	7.5527	0.0229
GDPPC	-0.0012	1.4132	0.1006	-1.2412	2.1739	0.3372
CI	0.0000	0.0007	0.4490	-0.8754	2.1624	0.3392
EI	0.0001	0.0887	0.4580	0.9042	2.2781	0.3201

Before proceeding to investigate the effect that population has on the carbon emissions achieved through the Kaya Identity, we decided to measure the relationship that occur between it and the other variables through a correlation matrix (Table 4.35).

Table. 4.35. *US's Correlation Matrix*

Variable	*P*	*GDPPC*	*CI*	*EI*
P	1.0000			
GDPPC	-0.3246	1.0000		
CI	-0.5914	0.7301	1.0000	
EI	0.1119	-0.1768	-0.2787	1.0000

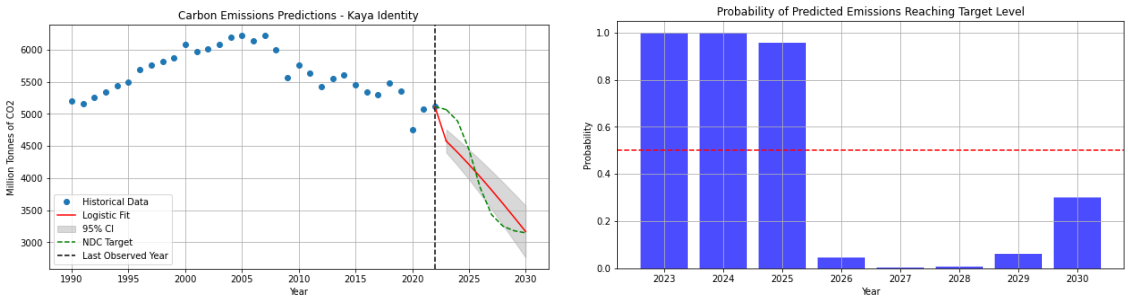
The matrix does not indicate any significant relationships between population and the other Kaya components. It does however highlight a strong positive relationship between

carbon intensity and GDP per capita, suggesting that there could have been improvements in the adoption of low-carbon technologies within the US.

Next, we determined the overall influence of population on the carbon emissions calculated through the Kaya Identity by performing an OLS regression analysis on them. The analysis showed that population has almost no influence on the overall level of carbon emissions when the impact of the other variables is taken in consideration, thus allowing us to assume that the combination of the factor values projected with our logistic model results in reliable CO_2 emission forecasts.

Thus, we proceeded to use our CO-STIRPAT model to calculate the future value of the United States' carbon emissions. The results, displayed in Figure 4.34., show that the country is expected to sharply reduce its emission levels between 2022 and 2030.

Figure 4.34. *US's Forecasted CO_2 emissions and Probability of Meeting NDC Target*



Even so, the forecasted data indicates that it would only be able to achieve a 38% decrease in its CO_2 emissions, which translates to a 29.5% probability of reaching the pledged quantity of carbon emissions for 2030. Thus, while it is expected to greatly lower its environmental impact, the United States is unlikely to reach its NDC target by 2030.

4.18. Conclusive Remarks

By applying the CO-STIRPAT framework to the G20 members' historical data for the Kaya Identity factors, we were able to produce projections on the future values of their carbon emissions, and calculate the probability that each member has of achieving their NDC target emission level, considering the results of our prediction.

The model has forecasted that the examined countries will collectively achieve a 16% reduction in emissions below 2022 levels by 2030. However, our analysis also finds that

there will be differences in the degree to which each country will contribute to said reduction, as well as in the certainty of the model's forecasts.

The largest absolute reductions in emissions are expected from the United States with a reduction of 1,946 Mt of CO_2, followed by China with 1,609 Mt, and the European Union with 671 Mt. On the other hand, India, Brazil, and Saudi Arabia are projected to see the biggest emissions increases, with India leading at 1,067 Mt, Brazil at 85 Mt, and Saudi Arabia at 58 Mt.

In terms of percentage changes, the United Kingdom and Mexico are expected to achieve the most significant cuts, reducing their emissions by 48% and 47% respectively, while Brazil and India are forecasted to see the largest increases, with emissions being expected to rise by 17% and 38%.

Lastly, the probability of achieving NDC emissions targets varies significantly across countries, with India having an almost 100% likelihood, of reaching its emission goal, followed by Turkey at 92%, and Indonesia at 85%. Contrarily, the European Union, South Korea, and Saudi Arabia show much lower probabilities of success, with the EU having a near-zero chance of meeting its target.

Overall, our model shows that countries with low to moderate ambition levels generally have a higher likelihood of reaching their pledged NDC emission amounts compared to those countries which have shown a relatively high level of ambition, which usually have a lower than 50% probability of achieving their emission objectives.

Chapter 5

Connecting the NDCs of the G20 to the Sustainable Development Goals

Determining the ambition that is embedded in a country's Nationally Determined Contribution's emission reduction target, as well as the probability of achieving said objective, is essential to promote the objectives of the Paris Agreement and increase its effectiveness. These processes increase the comparability of NDC submissions, allowing to evaluate whether climate change mitigation and adaptation pledges are distributed equitably among countries, and provide viable information on the soundness of NDC targets, as they assess whether the identified pathways can be associated to realistic and achievable emission reductions.

However, while these documents are primarily designed to allow participating members to communicate the mitigation and adaptation actions that they were willing to undertake in order to fairly and ambitiously contribute to the achievement of the Agreement's target, their content often goes beyond this purpose, addressing a broader array of sustainability objectives.

The Paris Agreement is intrinsically connected to the 2030 Agenda, as its central aim of limiting global temperature rise to well below 2°C aligns with multiple Sustainable Development Goals. In particular, this objective is inherently related to SDG 13, which calls for urgent global action to combat climate change and its adverse impacts, emphasising the need to strengthen resilience, integrate climate policies into national planning, and mobilise the financial resources needed to support climate action.

Understanding the impacts that climate action can have on the goals of the 2030 Agenda can be crucial for the development of interventions that are able to capture the synergies that exists between the two frameworks, and simultaneously contribute to a multitude of objectives. By increasing the policy coherence in the implementation of the two agendas, countries can increase the efficiency and cost-effectiveness of their interventions, and improve the likelihood of achieving their commitments.

There is a wide body of research that emphasises the connection between the Paris Agreement and the 2030 Agenda for Sustainable Development, and the influence that

climate mitigation action can have on the achievement of the 17 Sustainable Development Goals.

Nerini et al.[16] analyses a wide range of scientific studies concerning the relationship between the Paris Agreement and the 2030 Agenda and use a consensus-based expert elicitation method to determine whether each of the 169 SDG targets can be influenced by climate change, and whether synergies and trade-offs can be identified between the targets and climate action. They find that climate change can negatively impact 16 SDGs, undermining their achievement and exacerbating the challenges faced by sustainable development. Additionally, while the research concludes that climate action can accelerate the progress towards the fulfilment of all 17 SDGs, it also finds that it can negatively influence 12 of them, weakening sustainable development efforts.

Cohen et al.[17] study the interactions between the two frameworks by analysing a selection of NDCs to determine the co-benefits and the adverse impacts that climate mitigation actions can have in different sectors, and mapping the co-impacts to the SDGs of the 2030 Agenda. The authors suggest that applying the co-impacts approach within the context of SDGs could enhance the understanding of both positive and negative impacts of climate action. This would allow stakeholders to develop more ambitious climate policies, that are able to pursue both climate and non-climate objectives, while simultaneously minimising the trade-offs that affect the delivery of broader sustainability goals.

Mantlana, Maoela and Nhamo[18] perform a qualitative analysis that uses four cascading levels of visibility to reflect the extent to which a concept, issue, or theme is contained both in South Africa's NDC and in the 2030 Agenda. Through systematic mapping of the alignment between the country's NDC and the 169 targets of the SDGs, the authors found that the majority of targets are absent in the country's NDC, which can be explicitly linked to only 12% of them, with SDG 7 and SDG 13 having the strongest connection to the document.

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[16] Nerini Fuso Francesco et al., *Connecting climate action with other Sustainable Development Goals*, in *Nature Sustainability*, 2, 674-680, Springer Nature, July 2019.

[17] Cohen Brett et al., *Co-benefits and trade-offs of climate change mitigation actions and the Sustainable Development Goals*, in *Sustainable Production and Consumption*, 26, 805-813, ScienceDirect, December 2020.

[18] Mantlana B. Khanyisa, Maoela A. Malebajoa, Nhamo Godwell, *Mapping South Africa's nationally determined contributions to the targets of the sustainable development goals*, in *Natural Resources Forum*, 45 (1), 3-17, John Wiley & Sons, February 2021.

Lastly, Iacobut et al.[19] explore the synergies between the two frameworks by investigating how climate finance contributes to the achievement of Sustainable Development Goals. After determining how climate-driven Official Development Assistance of donor countries influence the SDGs, the researchers adopt correlation analyses and direct matching to assess the alignment between these financial contributions and the NDC activities of recipient countries. The study finds that Official Development Assistance contributes to several SDGs and that the gap in financing between mitigation and adaptation is narrowing, showing a strong alignment between donor and recipient countries SDG priorities.

Within the scope of our work, we decided to determine how the NDCs of the G20 members can be linked to the broader sustainability-related objectives represented by the 17 Sustainability Development Goals. To do so, our principal reference point was the body of academic research conducted by the Klimalog and the ClimEQ projects that was used for the development of the "NDC-SDG Connections" tool. Our assessment relied on both an analysis of the data available in NDC-SDG Connections, as well as on the use of Artificial Intelligence (AI) to identify connections between the two frameworks for countries whose latest NDCs were not yet included in the tool.

In this chapter, we will first provide an overview of the NDC-SDG Connections project, focusing on how it was developed and the methods that are adopted to link the content of NDCs to the SDGs. Afterwards, we will describe the method we used to analyse the data available in the tool, and then shift our focus on the analysis we performed on the missing NDC submissions, outlining the process that we adopted to develop a tailored GPT model that is capable to identify the relationship between a country's NDC content and the broader targets of the SDGs. Lastly, we will proceed to describe the results of our analysis, focusing on the SDG connections that were identified within each member's Nationally Determined Contribution.

[19] Iacobut Ileana Gabriela et al., *Aligning climate and sustainable development finance through an SDG lens. The role of development assistance in implementing the Paris Agreement*, in *Global Environmental Change*, 74, 102509, Elsevier, May 2022.

5.1. NDC-SDG Connections Tool

The NDC-SDG Connections tool is a joint research and visualization project of the German Institute of Development and Sustainability (IDOS) and the Stockholm Environment Institute (SEI) that allows to visualize and compare SDG connections within and between NDCs. The main goal of the project is to identify the synergies between the Paris Agreement and the 2030 Agenda that can foster the creation of policies that promote fair, sustainable, and climate-resilient development.

The synergies between the two frameworks are identified through a textual analysis of Nationally Determined Contributions. The analysis examines the content of each document to identify concrete activities, intended as "statements that present a strand of future activity, conditional or unconditional"[20]. Once an activity is identified, it is classified across a wide array of categories, which are subsequently organised in four broad sections. These include:

- ***Interpretation***: where activities are evaluated based on their scope (national, regional, local), their nature (mitigation, adaptation, both, or none), and whether they contain quantifiable targets to be reached;
- ***SDG targets***: where activities are firstly linked to one or more SDGs, and then coded across all the targets of the connected SDGs, according to their relevance to that particular sustainable development area;
- ***Climate actions***: where common types of climate actions are identified and associated to with specific SDGs to complement their targets;
- ***Socio-economic themes***: where activities are analysed and linked to broader, cross-cutting themes that allow to detect co-benefits that are relevant across multiple SDGs.

Binary coding is used by the researchers to evaluate the applicability of identified activities to specific categories, SDGs, and SDG targets. Additionally, intercoder reliability is used to guarantee the robustness of the analysis, ensuring that the data is reviewed by at least two independent coders, with a third one providing a final review to enhance consistency. The analysis provides a detailed view of how climate activities

[20] Dzebo Adis et al., *Connections between the Paris Agreement and the 2030 Agenda: the case for policy coherence*, SEI Working Paper, Stockholm Environment Institute, September 2019.

contribute to specific SDG targets, highlighting synergies and co-benefits between climate action and sustainable development.

Identified activities are used as data inputs in the NDC-SDG Connections tool to determine the connections between a country's NDC and the 17 SDGs. The tool currently displays connections for the first NDC of all the 198 parties of the UNFCCC, as well as the results of the analysis of 144 updated submissions.

By categorising climate activities and assessing their relevance between specific SDGs and other socio-economic themes, the tool fosters a more profound understanding of the synergies between the Paris Agreement and the 2030 Agenda, offering valuable insights for all stakeholders and promoting increases in global policy coherence.

5.2. Analysing the G20 through the NDC-SDG Connections Tool

Our methodological approach leverages the data underlying the NDC-SDG Connections tool to explore how the NDCs of each G20 member align themselves to the SDGs of the 2030 Agenda.

The first step of our assessment involved collecting data on the activities that have been identified in the latest NDC submission of each G20 country, along with their connection to the 17 SDGs and their 169 targets. We then proceeded to analyse the extent of these linkages by identifying which SDGs had the strongest connection to each NDC. This was done by calculating the number of activities that could be mapped to each SDG, and determining which goal had the highest number of associated activities. Furthermore, we extended our analysis to the target level by examining how the content of each NDC was found to contribute to specific SDG targets. For this, we identified the share of SDG targets that were linked to NDC activities, and assessed the strength of these connections by calculating the number of activities associated to each target.

Through this process, we were able to evaluate the latest NDC submissions of eight G20 members (Australia, Canada, Indonesia, Japan, Saudi Arabia, South Africa, South Korea, and the United Kingdom), and assess the broader implications of their climate commitments for global sustainability.

However, we were unable to utilise the NDC-SDG Connections data for the remaining G20 members (Argentina, Brazil, China, European Union, India, Mexico, Russia, Turkey,

and the United States of America), as their latest NDC submissions had not yet been analysed and incorporated into the tool at the time of our study.

5.3. Analysing the G20 through the NDC-SDG Analyser Tool

To bridge the gap in data availability, we decided to replicate the methodology adopted by the researchers at IDOS and SEI to construct our own NDC-SDG analysis tool.

We did so by using ChatGPT to create a customised AI model that we trained to connect the content of a country's NDC with the 17 SDGs of the 2030 Agenda, and their 169 targets. This approach allowed us to extend the analysis to all G20 members, enabling a comprehensive assessment of their climate commitments and their alignment with the goals of the 2030 Agenda.

In the following paragraph we will first provide an overview of ChatGPT and the features that allowed us to create our analyser, and then proceed to describe the processes that we followed to build the tool and verify its ability to provide an adequate analysis of the relationships existing between NDCs and SDGs.

5.3.1. ChatGPT and Custom GPTs

ChatGPT is a Large Language Model (LLM), developed by OpenAI, that operates as a text-driven generative artificial intelligence tool. By leveraging an advanced Generative Pre-trained Transformer (GPT) architecture, ChatGPT is capable of understanding natural language and can generate human-like responses to user prompts. The model is built upon a deep neural network and is trained on vast amount of textual data, which allows it to engage in conversations, produce coherent and informative content, answer queries, perform advanced data analysis tasks, and generate images from textual descriptions.

One of the most recent features added to OpenAI's services have been GPTs, customisable versions of ChatGPT that can be tailored to user-specific needs. This feature allows users to integrate the basic capabilities of OpenAI's GPT-4 with their own data to train a GPT and personalise it for the exploration of specific topic or the execution of particular tasks by combining instructions, knowledge, and capabilities.

5.3.2. Building the NDC-SDG Analyser GPT

ChatGPT users can create personalised models through the GPT Editor interface. Within this interface, users can configure their model either by interacting with the GPT Builder, which customises the GPT based on answers given to a series of questions, or by using the Configuration section, which allows users to directly personalise their GPT through a detailed group of settings.

The development of our NDC-SDG Analyser through the GPT Editor involved multiple stages. After naming our GPT and designing a custom image for its display icon, we proceeded to configure it by providing it with topic-specific information, clearly defining its purpose and objectives, and establishing detailed guidelines for task execution.

We initiated the design process of our GPT by providing it with a tailored repository of information through the "Knowledge" feature. This function allows users to upload various forms of domain-specific materials to facilitate the development and customisation of GPTs. It ensures that customised versions of ChatGPT prioritise learning from the data provided by the user, thus leading it to deliver precise and insightful responses to a wide array of queries. Our repository contains a wide body of documents and datasets that were used to both provide our GPT with a solid knowledge basis of the Paris Agreement and the 2030 Agenda, as well as a starting point to train the model and refine its ability to effectively identify the connections between the two frameworks. We uploaded a comprehensive set of materials, including: the full text of the Paris Agreement; the complete list of the Sustainable Development Goals along with their targets; a collection of publications from IDOS and SEI, detailing their NDC-SDG Connections tool and the methodology adopted in its development; the text of the first NDC submissions of all UNFCCC parties, as well as a dataset containing the connection between these documents and the SDGs that we obtained from the NDC-SDG Connections platform. Additionally, we included a detailed list of keywords and example activities for each of the 169 SDG targets, to further support the model's contextual understanding and response accuracy.

After providing our GPT with a comprehensive knowledge on the subjects under examination, we proceeded to establish a detailed set of instructions outlining the purpose and objectives of our analyser, as well as the behaviour it should adopt in performing its functions. As can be observed in Table 5.1., starting from the methods adopted by IDOS

and SEI in their research, the instructions focus on guiding the NDC-SDG Analyser in identifying and mapping specific activities within a country's NDC to the appropriate SDGs and their targets.

Table 5.1. *NDC-SDG Analyser Instructions*

The NDC-SDG Analyser's main purpose is to understand how Nationally Determined Contributions (NDCs) can be connected to Sustainable Development Goals (SDGs), providing insights into the relationship between the Paris Agreement and the 2030 Agenda.
The tool's main objective is to analyse the textual content of a given NDC and identify activities that relate to specific SDG targets, based on both its knowledge and all other information it can retrieve.
The tool leverages the Paris Agreement, a list of SDGs and their Targets, articles and reports that analyse the link between NDCs and SDGs, First NDCs of all participating countries, Excel datasets containing identified activities and their links to SDGs and their targets for First NDCs, as well as a comprehensive set of keywords for SDG targets.

In its analysis process, the tool should:

1. *Read and examine the entire content of the NDC to identify concrete activities, defined as statements presenting a strand of future activity, conditional or unconditional. Activities should be assessed based on their radius of influence, type of climate action, capacity-building measures, technological improvements, quantifiable targets, and policy plans or strategies. Their length should range between one and three sentences.*
2. *Verify if the content of each activity can be matched to any SDGs and link them to specific SDG targets considering the wording of each SDG, its targets, and using the keyword file 'SDG Targets - Keywords.txt' that contains key phrases and terms for each SDG, categorized under each SDG target with contextual examples to illustrate their application, as a reference point for the matching.*
   If activities apply to multiple targets, they should be added to each applicable target. In cases where SDG targets overlap in their definition, an activity should be assigned to only one.
3. *Avoid addressing co-benefits and trade-offs not directly linked to the wording of the NDC climate activity, indicating only the SDGs directly addressed.*
4. *Refine the criteria for identifying actions to better capture specific activities mentioned in NDCs based on additional data provided. Develop a more precise mapping of actions to SDGs and SDG targets to ensure higher accuracy and relevance. Use the provided data*

as a reference to fine-tune the analysis process, ensuring alignment with documented actions and linkages.

5. *Once the analysis is completed, display results in a table of three columns, one for activities, one for the linked SDGs, one for the specific SDG targets that have been linked to the activity. In the activity column, display the entire text of the identified activity from the NDC.*

The process should be performed only after the tool has studied all the information contained in its knowledge and identified how this process was applied to the NDCs uploaded in its knowledge by considering both the methodological documentation and the dataset containing the results of said analysis.

The tool should interact with users in a formal but precise tone, providing detailed descriptions of its results. Adjust the analysis of which NDC actions are related to which SDGs and SDG targets to reflect more closely the type of answers provided by the user when analysing the First_NDC-SDG.xlsx, and any other NDC-SDG.xlsx file provided in the future.

The tool is tasked with examining the entire content of a provided NDC to identify concrete activities and assess them based on their scope, type of climate action, and strategic goals. It is then instructed to match said activities with specific SDG targets using a specific set of keywords and phrases, while also referencing datasets containing the results of the analysis performed by IDOS and SEI on first NDC submissions. After refining its analysis using any additional information provided, the analyser presents the results in a structured table that highlights the links between the identified activities, the 17 SDGs, and their targets.

5.3.3. Testing the NDC-SDG Analyser

Once we configured our custom GPT model, we decided to test both its capacity to process the information provided within its knowledge repository, as well as its ability to use said information to perform the functions described within its guidelines and accurately identify the correlations between a given NDC and the goals of the 2030 Agenda.

To verify whether the NDC-SDG Analyser was able to examine and understand the content of the uploaded documentation, we decided to create a set of 100 sample questions covering all of the provided data, which we presented to our NDC-SDG Analyser. Initial queries focused on verifying its ability to retrieve specific content, such as identifying a particular article of the Paris Agreement, the wording of an SDG target based on its number, a section of the methodological documentation, or detailed information from a country's first NDC submission. Other questions tested the tools' ability to use the provided databases to match NDC activities with their corresponding SDG targets, or to extract activities linked to a specified set of targets. After the tool responded to all 100 questions, we evaluated its performance by comparing its answers to the correct responses using a cosine similarity analysis. This analysis method measures the similarity between two vectors by calculating the cosine of the angle between them in an inner product space. In our case, the application of this method involved vectorising both the answers provided by the GPT and the correct answers we were comparing them to. We did so by representing them as term frequency vectors, single vectors that contain the frequencies of the words that appear in each answer. Lastly, we measured the cosine between the angles of the two vectors to determine the similarity between the two provided answers. After manually reviewing the results of the cosine similarity analysis to differentiate between low similarity scores caused by mere differences in the wording and those resulting from actual misunderstandings by the GPT, we concluded that the tool correctly answered 66% of the questions, using on a similarity threshold of 0.6, which had to be exceeded for answers to be considered similar.

Based on these results, we considered the tool sufficiently capable of recalling and processing its knowledge, and thus we proceeded to test its ability to perform the more complex analytical task of identifying the connections between NDCs and SDGs.

However, before we proceeded to test our GPTs ability to effectively and accurately connect NDCs to relevant SDGs, we decided to train it to refine its analytical abilities. To do so, we used a subset of updated NDC submissions from 28 countries[21], which allowed us to fine-tune our model across a diverse range of geographical locations, socio-

[21] We used the updated NDCs of Armenia, Bahrain, Bangladesh, Bhutan, Central African Republic, Chile, Colombia, Egypt, Ethiopia, Fiji, Ghana, Kazakhstan, Kenya, Lebanon, Maldives, Micronesia, Mongolia, New Zealand, North Macedonia, Norway Panama, Peru, Switzerland, Thailand, Timor-Leste, Tonga, United Kingdom, Vietnam.

economic conditions, climate vulnerabilities, and climate mitigation and adaptation strategies. This process involved feeding the model the content of each updated NDC and tasking it with identifying potential activities and linking them to the relevant SDG targets. After the model generated the results of its analysis, we uploaded a dataset containing the connections identified by IDOS and SEI researchers, instructing it to adjust and enhance its analytical approach based on the content of the verified connections.

Once we refined the model on all 28 updated NDC submissions, we proceeded to test its ability to link the content of Nationally Determined Contributions to the goals of the 2030 Agenda. To do this, we selected the updated NDCs of 18 countries[22] for which we already had analysis results from the NDC-SDG Connections tool. Then we proceeded to ask our NDC-SDG Analyser to examine the content of each updated NDC, identify potential activities, and link them to corresponding SDGs through their targets. Once the GPT created a table of identified activities along with their linked SDGs and SDG targes, we compared its content to the results of the researchers at IDOS and SEI. Since the activities identified by our tool often differed in both number and content from those in the NDC-SDG Connections tool, we conducted a manual assessment to evaluate both sets of results and selected the activities that most closely aligned with the findings of the NDC-SDG Connections project. Then, we performed a cosine similarity analysis to measure the alignment between activities, SDGs, and SDG targets of both tools, using a lower threshold of 0.5 due to the complexity of the analysis process that we were performing. The similarity analysis showed that our NDC-SDG Analyser correctly identified and connected only 45% of compared activities. However, once we manually reviewed the activities identified by out tool that were not included in the cosine similarity analysis to verify whether their content was matched with an appropriate SDG and SDG target, the accuracy of our tool improved, reaching 51%. While there is still much room for improvement in accuracy, we are confident that the NDC-SDG Analyser is capable of identifying activities within Nationally Determined Contributions and connect them to appropriate Sustainable Development Goals.

After configuring, training, and testing our NDC-SDG Analyser, we updated its knowledge by uploading a dataset containing the analysis results of all updated NDCs

[22] Here we used the updated NDCs of Australia, Bolivia, Bosnia and Herzegovina, Canada, Gabon, Georgia, Honduras, Japan, South Korea, Laos, Nauru, Saudi Arabia, Uzbekistan, South Africa.

available within the NDC-SDG Connections tool at the time of our study, providing the GPT with a wider range of information to enhance its capabilities. Then we used it to identify the connections between the NDCs of the remaining G20 members and the SDGs of the 2030 Agenda. Once our GPT provided us with the results of its assessment, we proceeded to analyse its data with the same approach we adopted for the previous G20 members, which allowed us to assess the strength of the identified connections at both the SDG and the SDG target levels.

5.4. Results of G20 NDC-SDG Connection Analysis

Through the use of the NDC-SDG Connections project and our own NDC-SDG Analyser GPT model, we were able to study the latest NDC submissions of all G20 members. In this paragraph, we will describe our results, first by providing an overview of the connections that have been identified across all analysed countries, and then by focusing on how each individual G20 member contributes to the broader sustainability goals of the 2030 agenda through their Nationally Determined Contribution.

As can be observed in Table 5.2, our analysis of the NDCs of the G20 has led us to identify a total of 1,180 connections that cover all the 17 Sustainable Development Goals, as well as 62% of their targets, with 105 out of the 169 targets being connected to at least one activity. However, the distribution of the identified connections varies across the goals, with SDG 13 (Climate Action), SDG 7 (Clean Energy), and SDG 9 (Sustainable Industry) having 602 links to NDC activities, representing 51% of all the identified connections.

The table highlights how each examined country contributes to a specific SDG in relation to other countries. Our analysis identified China to be the leading contributor in nearly half of the Sustainable Development Goals (SDGs 3, 4, 6, 7, 8, 11, 12, and 13), followed by Brazil, which has been found to plays a significant role in the advancement of SDGs 1, 16, and 17 relative to other G20 members, and Indonesia, which has provides a significant support to the achievement of SDGs 2, 14, and 15 in relation to the other examined countries. Overall, our analysis has highlighted an uneven distribution in the contributions of G20 countries to the goals of the 2030 agenda, with areas such as climate action and energy transition being the most frequently identified within NDCs.

Table 5.2. *Connections Between G20 NDCs and the 17 Sustainable Development Goals*

	SDG 1 *No Poverty*	**SDG 2** *Zero Hunger*	**SDG 3** *Good Health*	**SDG 4** *Quality Education*	**SDG 5** *Gender Equality*	**SGD 6** *Clean Water*	**SDG 7** *Clean Energy*	**SDG 8** *Decent Work*	**SDG 9** *Sustainable* Industry	**SDG 10** *Reduced Inequalities*	**SDG 11** *Sustainable Cities*	**SDG 12** *Sustainable Consumption*	**SDG 13** *Climate Action*	**SDG 14** *Life Below Water*	**SDG 15** *Life on Land*	**SDG 16** *Peace & Justice*	**SDG 17** *Partnerships for Goals*	Total Country
Argentina																		38
Australia																		30
Brazil																		62
Canada																		77
China																		235
EU																		47
India																		63
Indonesia																		148
Japan																		34
Mexico																		81
Russia																		25
Saudi Arabia																		25
South Africa																		40
South Korea																		55
Turkey																		126
UK																		51
USA																		43
Total SDG	23	47	14	17	24	55	193	28	119	16	69	77	290	27	93	28	60	1180

Table 5.3. *Intensity of NDC-SDG connections of each G20 member*

	Argentina	Australia	Brazil	Canada	China	EU	India	Indonesia	Japan	Mexico	Russia	Saudi Arabia	South Africa	South Korea	Turkey	UK	USA	Total SDG
SDG 1																		23
SDG 2																		47
SDG 3																		14
SDG 4																		17
SDG 5																		24
SDG 6																		55
SDG 7																		193
SDG 8																		28
SDG 9																		119
SDG 10																		16
SDG 11																		69
SDG 12																		77
SDG 13																		290
SDG 14																		27
SDG 15																		93
SDG 16																		28
SDG 17																		60
Total Country	38	30	62	77	235	47	63	148	34	81	25	25	40	55	126	51	43	1180

Additionally, table 5.3. showcases the differences among the NDC-SDG connections that have been identified through our analysis. It allows to determine how much each country's NDC contributes to each one of the 17 SDGs. The results of this analysis will be discussed for each country in the following sections of this paragraph.

5.4.1. Argentina

The NDC-SDG Analyser identified 38 activities in Argentina's latest NDC update, linking them to 15 out of the 17 SDGs, with only SDG 4 (Quality Education) and SDG 11 (Sustainable Cities) not being connected to any activities. Additionally, our customised GPT model mapped the identified activities to 25 of the 169 SDG targets. In particular, the strongest connections were found with targets 13.2, 13.1, 7.2, 7.1, and 1.5, highlighting Argentina's focus on enhancing its resilience and adaptive capacity to, integrating climate change measures into national policies and strategies, expanding access to affordable, reliable, and renewable energy sources, and reducing the vulnerability of the poorest sections of its population.

5.4.2. Australia

The NDC-SDG Connections project found 30 activities within Australia's last NDC submission. These were linked to 9 out of the 17 Sustainable Development Goals, with SDG 9 (Sustainable Industry) and SDG 13 (Climate Action) having the strongest link to the content of the country's document with 8 connections each. The identified activities were also associated with 16 out of the 169, representing only 13% of the total. Out of these, the strongest correlations were observed with targets 9.5, 7.2, and 13.1, which reflects that, during the development of its NDC update, Australia put a particular emphasis on enhancing scientific research and innovation, increasing the share of renewables in its energy mix, and strengthening its ability to face climate-related hazards.

5.4.3. Brazil

Brazil's most recent NDC was examined with our NDC-SDG Analyser GPT to recognise possible activities and connect them with relevant SDGs. The analyser identified 43 activities within the country's document, which it linked to 12 SDGs and 25 of their targets. Overall, 62 connections were found by our tool, with several activities being

associated to multiple SDG targets. While the connections resulted fairly distributed across the diverse targets of the 2030 Agenda's goals, they were particularly present with targets 10.2, 1.5, 13.a, 11.a, and 15.2. The wide range of addressed targets highlights the country's focus on multiple areas of sustainable development, such as promoting increased inclusion, increasing the resilience of the most vulnerable parts of the population to adverse climate impacts, increasing climate financing for developing countries, strengthening national and regional development planning, and promoting the sustainable management of forests by stopping deforestation and increasing reforestation efforts.

5.4.4. Canada

The analysis of the researchers at the NDC-SDG Connections project identified 77 different activities within Canada's updated NDC submission, and linked them with 12 out of the 17 Sustainable Development Goals and with 23 SDG targets. The content of the country's NDC related in particular to SDG 7 (Clean Energy), SDG 9 (Sustainable Industry) and SDG 13 (Climate Action), with targets 9.4, 7.2, 7.3, and 13.2 being connected to 57% of the identified activities. Thus, the analysis suggests that the climate-related goals in Canada's NDC document can impact a broader set of sustainability objectives, particularly those related to improving industrial infrastructure, increasing energy efficiency, and expanding renewable energy use.

5.5.5. China

By using our NDC-SDG Analyser, we were able to extract 123 activities from China's updated NDC and identified 235 connections with 13 different SDGs. Among these, SDG 13 (Climate Action) and SDG 7 (Clean Energy) emerged as the most strongly linked goals, accounting for 57% of the connections. Our tool was also able to associate 14 of the 169 targets with China's activities, with targets 13.2, 7.1, 12.1, and 6.1 covering 76% of identified activities. This underscores the China's commitment to integrating climate change into its national policies and strategies, expanding access to affordable and reliable energy services, promoting sustainable consumption and production patterns, and ensuring universal access to safe and affordable drinking water.

5.5.6. European Union

Through the application of our personalised GPT model, we identified 42 activities in the European Union's updated NDC document, covering 12 SDGs and 17 specific SDG targets, resulting in 48 connections between activities and targets. Overall, the NDC submissions was found to highly contribute SDG 13 (Climate Action) and SDG 6 (Clean Water), which accounted for over 70% of connections. Additionally, we found that targets 13.2, 13.1, 5.5, and 16.7 represented more than 63% of identified activities. This reflects the EU's commitment to incorporate climate change into policy-making process and increases resilience against climate-related risks, as well as fostering inclusive, participatory, and representative decision-making processes at all levels.

5.5.7. India

The assessment of India's latest NDC version through the use of our NDC-SDG Analyser tool has enabled us to extract 51 activities and identify 65 connections with 26 targets spanning across 12 out of the 17 SDGs. With over 70% of total connections, the strongest links were found with SDG 7 (Clean Energy), SDG 13 (Climate Action), and SDG 9 (Sustainable Industry). Additionally, when analysed at the target level, 50% of the identified activities were tied to targets 7.2, 13.2, 9.4, and 15.2. These targets showcase the country's focus on increasing the adoption of renewable alternatives in energy production, developing national policies and strategies that fully integrate climate change measures, supporting the upgrading of industry infrastructure to increase resource-use efficiency and the adoption of environmentally sound technologies and processes, and implement sustainable practices in forest management.

5.5.8. Indonesia

Indonesia's latest NDC submission has been linked to 15 goals of the 2030 Agenda for Sustainable Development by the researchers at the NDC-SDG Connections project, with only SDG 1 (End Poverty) and SDG 8 (Decent Work) not being covered by the content of the country's document. Within the tool, 148 activities have been associated to 37 SDG targets, which represents a coverage of 29% of the total amount.

The strongest connections between Indonesia's NDC and the goals of the Agenda were identified with SDG 15 (Life on Land), which alone accounted for 24% of total connections, followed by SDG 13 (Climate Action) and SDG 7 (Clean Energy), which respectively accounted for 15% and 10% of the identified links. On a target level, the country was found to substantially contribute to a wide variety of targets, with targets 9.4, 7.2, 7.3, 13.2, 13.1, 2.4, and 15.2 only representing 37% of total connections. This wide range of covered targets highlights the country's commitment to several areas of sustainable development, such as upgrading industrial infrastructure, increasing renewable energy and energy efficiency, integrating climate change into national policies, promoting climate resilience, ensuring sustainable food production, and conserving forests and biodiversity.

5.5.9. Japan

The NDC-SDG Connections project found 34 activities within Japan's last NDC submission. These were linked to 10 out of the 17 Sustainable Development Goals, with SDG 9 (Sustainable Industry) and SDG 7 (Clean Energy) having the strongest link to the content of the country's document, representing 47% of total connections. The identified activities were also associated with 18 out of the 169. Out of these, the strongest correlations were observed with targets 9.4, 7.3, and 9.2, which account for 43% of total connected activities. This reflects that, in addition to purely climate-related objectives, the country's NDC also includes goals that can benefit several areas of sustainability, such as such as improving industrial efficiency, enhancing energy conservation, and promoting resilient infrastructure development.

5.5.10. Mexico

We examined Mexico's most recent NDC with our NDC-SDG Analyser to recognise activities and connect them with the appropriate SDGs. The analyser identified 73 activities within the country's document, which it linked to 16 SDGs and 45 of their 169 targets. Altogether, 82 connections were found by our tool, with several activities being associated to multiple SDG targets. While the connections were fairly distributed across the different SDG targets, they were particularly concentrated with targets 13.2, 13.1, 2.4, 7.2, and 15.1, which accounted for 36% of total connections. This variety demonstrates

the country's commitment to advancing multiple aspects of sustainable development, including incorporating climate action into policy frameworks, enhancing resilience to climate impacts, ensuring sustainable food production, expanding the use renewable energy, and conserving terrestrial ecosystems.

5.5.11. Russia

The NDC-SDG Analyser found 25 activities in Russia's NDC, linking them to 7 of the 17 SDGs. These activities were also mapped to 11 SDG targets. A total of 26 connections were identified between activities and targets, with targets 13.2, 13.a, 17.6, 4.4, and 13.1 accounting for 76% of the total. This analysis underscores that Russia's NDC puts a substantial emphasis on climate change mitigation and adaptation objectives, while also covering other areas of sustainability, such as enhancing the development of both technical and vocational skills to increase employability and entrepreneurship, and improving international cooperation with regards to scientifical and technological knowledge sharing.

5.5.12 Saudi Arabia

Through the NDC-SDG Connections project, 25 activities were identified in Saudi Arabia's latest NDC, which were linked to 7 out of the 17 SDGs, with the strongest association emerging with SDG 7 (Clean Energy) and SDG 6 (Clean Water), to which 40% and 24% of total activities were respectively connected. The tool also highlighted that the identified activities could be connected to 12 of the specific SDG targets, allowing us to assess that target 7.2, 6.4, 7.3, and 9.5 were those most strongly correlated to the NDC document, representing 63% of total target connections. These findings highlight Saudi Arabia's efforts to align national climate policies with the broader goals of sustainable development such as promoting renewable and efficient energy options, optimising the use of water resources, and fostering sustainable innovation in industry and infrastructure.

5.5.13. South Africa

South Africa's latest NDC submission has been linked to 11 goals of the 2030 Agenda by the NDC-SDG Connections analysis, Within the connections tool, 40 activities have been associated to 26 SDG targets, which represents a coverage of 21% of the total amount.

The content of the country's NDC has been found to contribute mostly to SDG 13 (Climate Action), which accounts for 40% of total connections, followed by and SDG 17 (Partnership for Goals), SDG 9 (Sustainable Industry) and SDG 7 (Clean Energy), which collectively account for another 40% of the identified links. On a target level, the country was found to substantially contribute to targets 13.1, 13.2, 13.3, 17.2, and 17.3, which represent 50% of total connections. These targets highlight the South Africa's NDC is concentrated on implementing climate mitigation and adaptation actions and fostering international cooperation for the achievement of the SDGs, with particular focus on with particular focus on increasing resilience to climate-related hazards, integrating climate policies into national strategies, enhancing climate education and capacity-building, mobilizing international financial resources, and strengthening multi-stakeholder partnerships to advance sustainability goals.

5.5.14. South Korea

The NDC-SDG Connections tool mapped 55 activities in South Korea's updated NDC submission to 13 of the 17 SDGs, with a total of 32 SDG targets being associated to the contents of the document. The strongest relationships were found with SDG 13 (Climate Action), SDG 9 (Sustainable Industry), SDG 11 (Sustainable Cities), and SDG 1 (No Poverty), with 29 out of the 55 activities being linked to these goals, representing 53% of the total. In addition, while we found the connections to be evenly distribute across the identified targets, we can affirm that targets 13.2, 1.5, 7.2, 9.4, and 13.3 covered an important part of these connections. These findings reflect that South Korea's NDC does not merely contribute to climate-related goals, but also focuses on supporting other areas of sustainable development through activities that aim to reduce poverty, promote clean energy, and advance sustainable industrial practices.

5.5.15 Turkey

By using our NDC-SDG Analyser, we were able to extract 117 activities from Turkey's updated NDC submission, identifying 126 connections with 14 different SDGs. Among these, SDG 13 (Climate Action), SDG 7 (Clean Energy), SDG 11 (Sustainable Cities), and SDG 2 (Zero Hunger), emerged as the most strongly linked goals, accounting for 61% of connections. Our tool was also able to associate 34 of the 169 SDG targets with Turkey's activities, with targets 13.2, 2.4, 13.3, 7.2, and 7.3 covering 48% of identified activities. This underscores that Turkey's NDC commitment covers a broad range of sustainable-related themes, focusing on climate resilience, sustainable agriculture, renewable energy, and enhancing energy efficiency in urban and rural areas.

5.5.16. United Kingdom

The analysis of the researchers of the NDC-SDG Connections project identified 51 different activities within the UK's latest NDC submission, linking them with 12 out of the 17 Sustainable Development Goals and 31 out of the 169 specific SDG targets. The content of the country's NDC related particularly to SDG 12 (Sustainable Consumption), SDG 5 (Gender Equality) and SDG 14 (Life Below Water). The identified connections fairly distributed across the associated targets, with targets 12.4, 14.2, and 15.9 presenting the most notable number of linkages with the activities of the country's NDC. This suggests that the United Kingdom has incorporated a broader set of sustainable objectives within the climate actions of its NDC, with activities covering topics such as sustainable chemical waste management, coastal and marine ecosystem protection and restoration, and the integration of biodiversity considerations into national policies.

5.5.17. United States

We examined most recent NDC of the United States with our NDC-SDG Analyser to identify activities and connect them with the appropriate SDGs. The analyser extracted 35 activities from the country's document, and linked them to 10 SDGs and 19 of their 169 targets. Altogether, 43 connections were found by our tool, with several activities being associated to multiple SDG targets. While the connections were fairly distributed across the different SDG targets, they were particularly concentrated with targets 13.2, 7.2, 7.3, 7.b, 13.b, and 15.1, which accounted for 63% of total connections. This

demonstrates the country's NDC content supports the progress of multiple aspects of sustainable development, with activities covering areas such as promoting the integration of climate change measures into national policies, increasing the share of renewable energy, improving energy efficiency, enhancing infrastructure for clean energy technology, supporting efforts to raise capacity in addressing climate change, and fostering the sustainable management of forests and ecosystems.

5.6. Discussion

The alignment between Nationally Determined Contributions and the Sustainable Development Goals is critical for achieving the dual goals of climate action and sustainable development. Our analysis of the NDCs of G20 members revealed 1,180 connections across 105 SDG targets, spanning all 17 SDGs and highlighting a substantial overlap between climate activities and global sustainability efforts. The most frequently connected goals were SDG 13 (Climate Action), SDG 7 (Clean Energy), and SDG 9 (Sustainable Industry), which reflect that a strong emphasis has been put towards decarbonisation and energy transition. However, other goals, such as SDG 3 (Good Health), SDG 4 (Quality Education), SDG 10 (Reduced Inequalities), and SDG 14 (Life Below Water) remain underrepresented in the analysed NDCs, revealing gaps in policy integration and the possibility for further alignment between the two agendas.

The strong connection between most country's NDCs and SDG 13 highlights the centrality of climate mitigation and adaptation strategies. However, the weak connection to SDG 3 suggests that climate policies tend to overlook the public health impacts of climate changes, even though these can have great consequences, particularly in disadvantaged communities.

Similarly, SDG 4, which is essential for building the knowledge and skills needed for climate adaptation, is insufficiently addressed in NDCs. Increasing the focus on education could empower communities to actively engage in sustainable practices and enhance their resilience to climate impacts. Likewise, the weak alignment with SDG 10 underlines the need for more inclusive climate policies that address inequality, ensuring that vulnerable populations benefit from climate action and are not disproportionately impacted by climate-related risks.

From an environmental perspective, the underrepresentation of SDG 14 reflects an important gap in addressing ocean conservation, despite their essential role in regulating the climate. Incorporating marine ecosystem protection into NDCs would support both climate mitigation and biodiversity conservation effort, creating synergies that benefit both climate and environmental goals.

Additionally, our analysis has highlighted an uneven distribution in the identified connections, with countries like Brazil and China contributing mostly to a selected number of SDGs, and others like Indonesia and Mexico showing strong commitments to several sustainability themes. Countries that primarily focus on a limited number of SDGs may benefit from more holistic frameworks that encourage broader integration of sustainability objectives, helping them address overlooked issues.

In conclusion, countries should prioritise the integration of climate policies with broader sustainable development objectives to enhance their effectiveness. This involves adopting holistic approaches that incorporate environmental, social, and economic dimensions, ensuring that climate actions create co-benefits across multiple SDGs, thus contributing meaningfully to both the Paris Agreement and the 2030 Agenda.

Conclusion

The primary aim of this thesis was to explore the relationship between country ambition and the probability of achieving climate action targets, as well as its alignment with the broader scope of the Sustainable Development Goals, by analysing the Nationally Determined Contributions of 17 G20 members.

To do so, we firstly had to determine the ambition level that was contained within the NDC targets of each G20 member. Through the normalisation climate objectives, we were able to determine the emission levels that each G20 member was aspiring to achieve by the 2030 target year, and calculate the percentage changes in GHG emissions that these would generate. Our analysis found that 11 out of the 17 analysed members exhibited moderate to high ambition levels, with projected reductions of at least 17% in greenhouse gas emissions compared to 2022. Leading this group are Australia, Saudi Arabia, the United Kingdom, and the United States, each having targets that exceed a 40% reduction. On the other hand, we also found that six countries displayed low ambition levels, with reductions below 10%, and that three of these (India, Indonesia, and Turkey) set NDC targets that would allow them to increase their emissions by 2030. Despite the high ambition levels shown by most of the analysed countries, the average reduction across the G20 was calculated to be only 14%. This is largely due to the targets set by India and Indonesia, which would see these countries increasing their emissions by 114% and 57% respectively by 2030. Given the fact that these two economies collectively account for 10% of global greenhouse gases emissions, their targets could seriously undermine the global efforts to mitigating climate change.

Once we established the target level of emission set by each G20 member in their Nationally Determined Contribution, we used CO2 as a proxy for overall GHG emissions, and applied the CO-STIRPAT framework to predict the possible pathway that will be followed by each member's carbon emissions and calculate the probability that they had of achieving their NDC objective by comparing them to their target pathway.

The CO-STIRPAT model forecasted a reduction in carbon emissions for 14 out of the 17 analysed G20 members, with only Brazil, India and Saudi Arabia expected to see an increase in their emissions. The United Kingdom is projected to achieve the largest percentage reduction, with a 48% decrease in CO2 emissions by 2030 compared to 2022,

while the largest increase has been forecasted for India, with emissions predicted to rise by 38% in the same timeframe.

However, predicted changes in emissions do not necessarily align with NDC targets. The model forecasts suggest that the emissions of 10 members will fall short of their pledged target, while the remaining 7 are predicted to exceed their target level. Notably, Indonesia is expected to reduce its emissions by 26% despite its NDC target allowing for a 57% increase, and Saudi Arabia is predicted to increase emissions by 8% compared to a target reduction of 40%.

The discrepancies between target and predicted emissions have resulted in varying probabilities of achieving NDC goals. Countries such as India, Turkey, Indonesia, the United Kingdom, and Mexico have a high likelihood of meeting their targets, with probabilities exceeding 75%. Conversely, several G20 members have are projected to likely be unable to uphold their pledges, with countries such as Australia, Brazil, Canada, and South Korea all having probabilities below 30%, and Saudi Arabia and the EU having a near-zero chance of meeting their NDC targets. It is worthwhile noting, however, that a higher probability of achieving NDC targets does not necessarily equate to higher absolute emission reductions. The United States, despite its lower probability of meeting its NDC target, is predicted to make the largest contribution to global emissions reductions, with a projected decrease of 1,947 Mt CO2e by 2030. In contrast, India, with a near 100% probability of achieving its target, is expected to be the biggest driver of emission growth, leading to an increase of 1,067 Mt CO2e in the same time frame. This underscores the complexity of global emissions dynamics, where both significant reductions and increases can stem from countries with varying levels of ambition and target achievement probabilities.

Lastly, we set out to ascertain how the Nationally Determined Contributions of the G20 related to the broader objectives of the 2030 Agenda for Sustainable Development, by identifying potential connections between their content and the 17 Sustainable Development Goals. By analysing the data provided by researchers of the NDC-SDG Connections project and adopting our AI-driven NDC-SDG Analyser model, we were able to identify a total of 1180 connections, encompassing all 17 SDGs, as well as 105 out of their 169 targets.

Further analysis has revealed that China has the strongest relationship with the SDGs with 235 connections, representing 20% of the total, followed by Indonesia with 148 connections (13%) and Turkey with 126 connections (11%). Canada and Mexico also showed significant integration, with 77 and 81 connections respectively, each accounting for 7% of the total.

Out findings show that the NDCs of the G20 encompass a broad spectrum of the Sustainable Development Goals, with 14 of these being linked to the contributions of over half of the analysed members. The SDGs most frequently associated with NDCs include SDG 7 (Clean Energy), connected by 94% of the countries, followed by SDG 9 (Sustainable Industry) at 88%. Furthermore, SDGs 11 (Sustainable Cities), 12 (Responsible Consumption), and 13 (Climate Action) are each tied to 82% of the countries. Our results show that the themes represented within these goals are considered essential by the majority of analysed countries.

Among the 17 goals of the 2030 Agenda for Sustainable Development, SDG 13 (Climate Action) was found to be the most featured one in the Nationally Determined Contributions of the G20 with 290 connections, accounting for 25% of the total. It is followed by SDG 7 (Clean Energy) with 193 connections (16%), and SDG 9 (Sustainable Industry). Additionally, SDG 15 (Life on Land) and SDG 12 (Responsible Consumption) also showed notable engagement, with 93 connections (8%) and 77 connections (7%), respectively.

These figures illustrate the diverse and interconnected nature of the themes addressed by Nationally Determined Contributions. While environmental goals connected to climate action continue to dominate these contributions, our analysis highlights that economic and social objectives are also integral to the climate strategies of the G20, reflecting the commitment of its members to advancing multiple aspects of sustainable development.

Although our three different analysis frameworks allowed us to determine the ambition of G20 NDCs, evaluate the probability that each member had of achieving its pledged emission target, and assess how these documents can be connected to the wider scope of the SDGs, they still present some limitations.

The CO-STIRPAT model is subject to significant uncertainty associated with the Kaya Identity factors, which make it challenging to produce accurate long-term projections. Additionally, although the model allows for some interaction between factors through

correlated error terms, it does not fully capture the complex, non-linear dynamics between these variables over time, which limits its ability to fully model the influence of their interactions on emissions. Another limitation is represented by the fact that our replication of the framework relied on the content of the original publication where the model was described for the first time, which may be affected by lacks in the specification of the adopted methodology.

Our NDC-SDG connection framework presents limitations related multiple aspects. One key limitation of the adopted methodology is represented by the fact that it focuses exclusively on identifying direct links between NDC climate activities and SDGs, without addressing the co-benefits and trade-offs that may arise indirectly. This leads it to overlook the broader range of co-impacts that a climate activity could have on other SDGs. Another limitation is directly related to the AI-driven NDC-SDG Analyser tool that was used within our framework. The model was constructed using a corpus of information provided by the NDC-SDG Connections project, which means its accuracy can be affected by gaps in the available data. For instance, the lack of detailed descriptions of the methods used to categorize activities into broader categories, as well as the specific keywords adopted for analysis, could influence the model's performance. Moreover, the NDC-SDG Analyser was trained on a subset of the total submitted NDCs, which may limit its overall reliability. Enhancing the model's accuracy would require further training and fine-tuning on a more comprehensive dataset.

Nevertheless, these frameworks allowed us to gain some precious insights on how ambition can both affect a country's likelihood of achieving its NDC emission reduction targets, and be associated to the implementation of a wider range of sustainability goals.

When all of the areas of our analysis are compared, we are able to determine that the ambition of the NDC targets of the G20 is inversely related to their probability of achieving said targets, with higher ambition levels resulting in a lower likelihood of reaching the desired levels of GHG emissions, and a lower ambition leading to more consistent chances of meeting climate objectives. Additionally, our analysis also exposed that higher degrees of connections between NDCs and SDGs are associated to lower ambition levels, and that higher ambition levels are usually correlated to low or moderate degrees of contentions.

These results lead us to conclude that while each country's NDC should reflect the highest possible level of ambition, this ambition must be matched with sufficient action and policy implementation across a broad scope of development targets. Only by doing so can countries fairly and effectively contribute to achieving the goals of the Paris Agreement, while also harnessing the synergies between climate action and the Sustainable Development Goals of the 2030 Agenda for Sustainable Development.

Appendices

Appendix I: Exponential Smoothing Code

```
import pandas as pd
from statsmodels.tsa.holtwinters import ExponentialSmoothing
import matplotlib.pyplot as plt
import os


def main():
    file_path = #INSERT FILEPATH
    data = pd.read_csv(file_path, delimiter=';')

    data['LULUCF Emissions'] = data['LULUCF Emissions'].str.replace(',', '.').astype(float)

    years = data['Year']
    emissions = data['LULUCF Emissions']

    model = ExponentialSmoothing(emissions, trend='add', seasonal=None, damped_trend=False)
    fit = model.fit()

    forecast_years = pd.Series(range(1990, 2031))
    forecast = fit.forecast(len(forecast_years) - len(years))

    forecast_data = pd.Series(emissions.tolist() + forecast.tolist(), index=forecast_years)

    plt.figure(figsize=(12, 6))
    plt.plot(years, emissions, label='Historical LULUCF Emissions', color='blue')
    plt.plot(forecast_years, forecast_data, label='Forecasted LULUCF Emissions', linestyle='--',
    color='blue')
    plt.xlabel('Year')
    plt.ylabel('Mt CO2e')
    plt.title('LULUCF Emissions')
    plt.legend()
    plt.grid(True)
    plt.show()
```

```
    output_directory = #INSERT FILEPATH
    output_filepath = os.path.join(output_directory, 'LULUCF_Forecast_2030.csv')
    forecast_data.to_csv(output_filepath, header=['Carbon Emissions'])
    print(f"LULUCF data has been saved to {output_filepath}")

if __name__ == "__main__":
    main()
```

Appendix II: CO-STIRPAT Code

Code 1: Logistic Model and Residual Statistics for Kaya Components

```
import pandas as pd
import numpy as np
from scipy.optimize import curve_fit
from scipy import stats
import matplotlib.pyplot as plt
import os

def load_and_clean_data(filepath):

    data = pd.read_csv(filepath, delimiter=';')

    data['Year'] = pd.to_numeric(data['Year'], errors='coerce')
    data['Population'] = pd.to_numeric(data['Population'], errors='coerce')
    data['GDP'] = pd.to_numeric(data['GDP'], errors='coerce')
    data['Energy Consumption'] = pd.to_numeric(data['Energy Consumption'], errors='coerce')
    data['Carbon Emissions'] = pd.to_numeric(data['Carbon Emissions'], errors='coerce')

    data.fillna(data.median(), inplace=True)

    data['Population']=(data['Population'])/1000000
    data['GDP per Capita'] = data['GDP'] / (data['Population']*1000000)
    data['Carbon Intensity'] = data['Carbon Emissions'] / (data['Energy Consumption'])
    data['Energy Intensity'] = data['Energy Consumption'] / data['GDP']
    return data
```

```
def logistic(x, L, k, x0):
    return L / (1 + np.exp(-k * (x - x0)))


def fit_logistic_model(xdata, ydata):
    p0 = [max(ydata) * 1.1, 1 / (max(xdata) - min(xdata)), np.median(xdata)]
    try:
        params, cov = curve_fit(logistic, xdata, ydata, p0=p0, maxfev=25000)
        return params

    except RuntimeError as e:
        print(f"Error fitting model: {e}")
        return None


def plot_fitted_curve(data, column_name, fitted_params, peak_year, y_label):
    xdata = data['Year'].values
    ydata = data[column_name].values

    plt.figure(figsize=(10, 5))
    plt.scatter(xdata, ydata, color='red', label=f'Observed {column_name}')
    plt.plot(xdata, logistic(xdata, *fitted_params), label='Fitted Model', color='blue')
    plt.axvline(x=peak_year, color='black', linestyle='--', label='Carbon Emissions Peak Year')
    plt.xlabel('Year')
    plt.ylabel(y_label)
    plt.title(f'{column_name}')
    plt.legend()
    plt.grid(True)
    plt.show()
```

```
def calculate_residuals_statistics(ydata, predictions):
    residuals = ydata - predictions
    mean_res = np.mean(residuals)
    std_res = np.std(residuals, ddof=1)
    skew_res = stats.skew(residuals)
    kurt_res = stats.kurtosis(residuals, fisher=True)
    jb_stat, jb_p_value = stats.jarque_bera(residuals)
    t_stat, t_p_value = stats.ttest_1samp(residuals, 0)
    stats_dict = {
        "Component": "",
        "Mean": mean_res,
        "Std Dev": std_res,
        "Skewness": skew_res,
        "Kurtosis": kurt_res,
        "Jarque-Bera Statistic": jb_stat,
        "Jarque-Bera P-value": jb_p_value,
    }

    return residuals, stats_dict


def compute_correlations(dataframe):
    correlation_matrix = dataframe.corr()
    return correlation_matrix


def main():
    filepath =    # INSERT FILEPATH
    output_directory # INSERT FILEPATH

    data = load_and_clean_data(filepath)
    print(data.head())

    peak_year = data['Year'].values[np.argmax(data['Carbon Emissions'].values)]

    columns_to_model = ['Population', 'GDP per Capita', 'Carbon Intensity', 'Energy Intensity']
```

```
    y_labels = {
        'Population': 'N° People',
        'GDP per Capita': 'PPP (2021 int. $1000) / N° People',
        'Energy Intensity': 'GJ / PPP (2021 int. $1000)',
        'Carbon Intensity': 't CO2 / GJ'
    }

    residuals_df = pd.DataFrame()
    stats_list = []

    for column in columns_to_model:
        xdata = data['Year'].values
        ydata = data[column].values
        fitted_params = fit_logistic_model(xdata, ydata)
        if fitted_params is not None:
            predictions = logistic(xdata, *fitted_params)
            residuals, stats_dict = calculate_residuals_statistics(ydata, predictions)
            stats_dict["Component"] = column
            residuals_df[column + 'Residuals'] = residuals
            stats_list.append(stats_dict)
            plot_fitted_curve(data, column, fitted_params, peak_year, y_labels[column])

    stats_df = pd.DataFrame(stats_list)
    correlation_matrix = compute_correlations(residuals_df)

    stats_df.to_csv(os.path.join(output_directory, 'descriptive_statistics.csv'), index=False)
    correlation_matrix.to_csv(os.path.join(output_directory, 'correlation_matrix.csv'))

    print("Descriptive statistics and correlation matrix have been saved to CSV files.")

if __name__ == '__main__':
    main()
```

Code 2: Probability of Achieving NDC Target Emissions

```
import pandas as pd
import numpy as np
from scipy.optimize import curve_fit
from scipy.special import erf
```

```
import matplotlib.pyplot as plt
from sympy import symbols, diff, exp, lambdify
import os


def load_and_clean_data(filepath):

    data = pd.read_csv(filepath, delimiter=';')
    data['Year'] = pd.to_numeric(data['Year'], errors='coerce')
    data['Population'] = pd.to_numeric(data['Population'], errors='coerce')
    data['GDP'] = pd.to_numeric(data['GDP'], errors='coerce')
    data['Energy Consumption'] = pd.to_numeric(data['Energy Consumption'], errors='coerce')
    data['Carbon Emissions'] = pd.to_numeric(data['Carbon Emissions'], errors='coerce')

    data.fillna(data.median(), inplace=True)

    data['Population']=data['Population']
    data['GDP per Capita'] = data['GDP'] / data['Population']
    data['Carbon Intensity'] = data['Carbon Emissions'] / (data['Energy Consumption'])
    data['Energy Intensity'] = data['Energy Consumption'] / data['GDP']

    data['Kaya Identity'] = (data['Population'] *
                             data['GDP per Capita'] *
                             data['Energy Intensity'] *
                             data['Carbon Intensity']) / 1000000
        return data
    except Exception as e:
        print(f"Error loading data: {e}")
        return None


def logistic(x, L, k, x0):
    return L / (1 + np.exp(-k * (x - x0)))
```

```
def fit_logistic_model(xdata, ydata):
    p0 = [max(ydata) * 1.1, 1 / (max(xdata) - min(xdata)), np.median(xdata)]
    try:
        params, cov = curve_fit(logistic, xdata, ydata, p0=p0, maxfev=25000)
        return params
    except RuntimeError as e:
        print(f"Error fitting model: {e}")
        return None


def predict_logistic(params, x):
    L, k, x0 = params
    return logistic(x, L, k, x0)


def calculate_jacobian(x, params):
    L, k, x0 = params
    x_sym, L_sym, k_sym, x0_sym = symbols('x L k x0')
    logistic_expr = L_sym / (1 + exp(-k_sym * (x_sym - x0_sym)))
    partials = [diff(logistic_expr, var) for var in (L_sym, k_sym, x0_sym)]
    jacobian_func = lambdify((x_sym, L_sym, k_sym, x0_sym), partials, 'numpy')
    return np.array([jacobian_func(x_val, L, k, x0) for x_val in x])


def predict_with_confidence(params, cov, x):
    predictions = predict_logistic(params, x)
    J = calculate_jacobian(x, params)
    variance = np.dot(J, np.dot(cov, J.T))
    std_error = np.sqrt(np.diag(variance))
    return predictions, std_error


def calculate_kaya_identity_std(params_dict, cov_dict, future_years):
    predicted_components = {}
    relative_uncertainties = {}
```

```
    for component, params in params_dict.items():
        predictions, std_error = predict_with_confidence(params, cov_dict[component], future_years)
        predicted_components[component] = predictions
        relative_uncertainties[component] = std_error / predictions

    kaya_identity_predictions = (predicted_components['Population'] *
                                 predicted_components['GDP per Capita'] *
                                 predicted_components['Energy Intensity'] *
                                 predicted_components['Carbon Intensity']) / 1000000

    relative_uncertainty_kaya = np.sqrt((
        (relative_uncertainties['Population']**2 +
        relative_uncertainties['GDP per Capita']**2 +
        relative_uncertainties['Energy Intensity']**2 +
        relative_uncertainties['Carbon Intensity']**2)
    ))

    std_kaya = kaya_identity_predictions * relative_uncertainty_kaya
    return kaya_identity_predictions, relative_uncertainty_kaya, std_kaya, relative_uncertainties


def save_results_to_excel(output_directory, future_years, kaya_identity_predictions,
    relative_uncertainty_kaya, std_kaya, relative_uncertainties):
    output_filepath = os.path.join(output_directory, 'Kaya_Identity_Results.xlsx')

    results_df = pd.DataFrame({
        'Year': future_years,
        'Kaya Identity Prediction': kaya_identity_predictions,
        'Relative Uncertainty (Kaya)': relative_uncertainty_kaya,
        'Standard Deviation (Kaya)': std_kaya
    })

    for component, uncertainties in relative_uncertainties.items():
        results_df[f'Relative Uncertainty ({component})'] = uncertainties
```

```
    with pd.ExcelWriter(output_filepath) as writer:
        results_df.to_excel(writer, index=False, sheet_name='Kaya Identity Predictions')

    print(f"Results have been saved to {output_filepath}")


def plot_predictions(data, kaya_identity_predictions, std_kaya, ndc_emissions, probabilities,
    output_directory='.'):
    last_observed_year = data['Year'].max()
    future_years = np.arange(last_observed_year + 1, 2031)
    ci_lower = kaya_identity_predictions - 1.96 * std_kaya
    ci_upper = kaya_identity_predictions + 1.96 * std_kaya
    df = pd.DataFrame({
        'Year': np.concatenate((data['Year'], future_years)),
        'Kaya Identity (Observed)': np.concatenate((data['Kaya Identity'], [np.nan] * len(future_years))),
        'Kaya Identity (Predicted)': np.concatenate(([np.nan] * len(data['Year']),
        kaya_identity_predictions)),
        'Kaya Identity (Target)': np.concatenate(([np.nan] * len(data['Year']), ndc_emissions)),
        'Probability': np.concatenate(([np.nan] * len(data['Year']), probabilities))
    })
    output_filepath = os.path.join(output_directory, 'Jacobian_predictions.csv')
    df.to_csv(output_filepath, index=False)
    print(f"Kaya Identity data has been saved to {output_filepath}")

    plt.figure(figsize=(10, 5))
    plt.plot(data['Year'], data['Kaya Identity'], 'o', label='Historical Data')
    plt.plot(future_years, kaya_identity_predictions, 'r-', label='Logistic Fit')
    plt.fill_between(future_years, ci_lower, ci_upper, color='gray', alpha=0.3, label='95% CI')
    plt.plot(future_years, ndc_emissions, 'g--', label='NDC Target')
    plt.axvline(x=last_observed_year, color='black', linestyle='--', label='Last Observed Year')

    plt.plot([last_observed_year, future_years[0]], [data['Kaya Identity'].iloc[-1],
    kaya_identity_predictions[0]], 'r-')
    plt.plot([last_observed_year, future_years[0]], [data['Kaya Identity'].iloc[-1], ndc_emissions[0]],
    'g--')
```

```
    plt.title('Carbon Emissions Predictions - Kaya Identity')
    plt.xlabel('Year')
    plt.ylabel('Million Tonnes of CO2')
    plt.legend()
    plt.grid(True)
    plt.show()

    plt.figure(figsize=(10, 5))
    plt.bar(future_years, probabilities, color='blue', alpha=0.7)
    plt.axhline(y=0.5, color='r', linestyle='--')
    plt.title('Probability of Predicted Emissions Reaching Target Level')
    plt.xlabel('Year')
    plt.ylabel('Probability')
    plt.grid(True)
    plt.show()


def main():
  filepath # INSERT FILEPATH
  output_directory =   # INSERT FILEPATH

  data = load_and_clean_data(filepath)
  if data is not None and not data.empty:
    xdata = data['Year'].values

    params_dict = {}
    cov_dict = {}
    for component in ['Population', 'GDP per Capita', 'Energy Intensity', 'Carbon Intensity']:
      params, cov = fit_logistic_model(xdata, data[component].values)
      params_dict[component] = params
      cov_dict[component] = cov

    future_years = np.arange(data['Year'].max() + 1, 2031)

    kaya_identity_predictions, relative_uncertainty_kaya, std_kaya, relative_uncertainties =
    calculate_kaya_identity_std(params_dict, cov_dict, future_years)
```

```
        save_results_to_excel(output_directory, future_years, kaya_identity_predictions,
        relative_uncertainty_kaya, std_kaya, relative_uncertainties)
        basis_year_emissions = data[data['Year'] == #INSERT BASE YEAR ]['Kaya Identity'].values[0]
        ndc_percentage = # INSERT % REDUCTION BETWEEN BASE AND TARGET EMISSIONS
        ndc_target_emissions = basis_year_emissions * (ndc_percentage / 100.0)
        last_emissions = data['Kaya Identity'].iloc[-1]
        tau = 2
        k = 1
        x0 = (data['Year'].max() + 2030) / 2
        modulating_factor = logistic(future_years, 1, k, x0)
        ndc_emissions = ndc_target_emissions +
                        (last_emissions - ndc_target_emissions) *
                        np.exp(-modulating_factor *
                        (future_years - data['Year'].max()) / tau)

        probabilities = 1 - 0.5 * (1 + erf((kaya_identity_predictions - ndc_emissions) /
                       (std_kaya *np.sqrt(2))))

        plot_predictions(data, kaya_identity_predictions, std_kaya, ndc_emissions, probabilities,
        output_directory=output_directory)
    else:
        print("Data file is empty or invalid.")
if __name__ == "__main__":
    main()
```

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