Leveraging Data Science and Artificial Intelligence to Monitor and Predict Progress on United Nations Sustainable Development Goal 7

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ABSTRACT

This Ph.D. dissertation examines the impact of Data Science and Artificial Intelligence in tracking and forecasting developments associated with the United Nations' Sustainable Development Goal 7 – Affordable Clean Energy. The study provides a clear understanding of how modern technologies can streamline progress assessments, identify prevalent challenges, and devise data-backed strategies for advancing sustainable, affordable energy solutions. Through Python and its comprehensive libraries, the research emphasizes the tangible, real-world applications of Data Science and Artificial Intelligence. By bridging the gap between sustainable development and technological methodologies, this research offers critical insights valuable to policymakers, researchers, and a broad spectrum of stakeholders in the sustainable energy domain.

LIST OF ABBREVIATIONS

AI	:	Artificial intelligence
DS	:	Data Science
GBM	:	Gradient Boosting Machines
GDP	:	Gross Domestic Product
GNIPC	:	Gross National Income Per Capita
IEA	:	International Energy Agency
kW	:	Kilowatt
LR	:	Linear Regression
LSTM	:	Long Short-Term Memory Networks
ML	:	Machine Learning
MW	:	Megawatt
OECD	:	Organization for Economic Cooperation and Development
RF	:	Random Forest
RNN	:	Recurrent Neural Networks
SDG	:	Sustainable Development Goal
SDG 7	:	Sustainable Development Goal 7
SDGs	:	United Nations Sustainable Development Goals
UN	:	United Nations
USD	:	United States Dollar

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CHAPTER 1

INTRODUCTION

The pursuit of achieving the United Nations Sustainable Development Goals (UN SDGs) is a global imperative that aims to address a broad range of challenges, from poverty alleviation to environmental conservation. This dissertation focuses on harnessing the capabilities of Data Science and Artificial Intelligence to enhance the monitoring and forecasting of progress towards Sustainable Development Goal 7 (SDG 7): Affordable Clean Energy. The primary objective of this research is to demonstrate that the incorporation of Data Science and Artificial Science not only improves the accuracy and effectiveness of monitoring efforts but also offers crucial predictive analytics that can inform and shape policy decisions.

This chapter is divided into two parts. Part A outlines the Problem Statement, Focus of the Dissertation, and Contribution of the Dissertation. Part B is dedicated to an in-depth exploration of the UN SDGs and discusses the role of Data Science and Artificial Intelligence in advancing sustainable development.

The rationale for this division is to present the dissertation's core themes in a structured manner, enabling the reader to understand the research's significance and objectives. The Problem Statement, Focus, and Contribution section establish a clear foundation, and the subsequent section delves into the UN SDGs and the pivotal role played by Data Science and Artificial Intelligence, allowing for a more comprehensive examination of the topic.

The division of the chapter into two parts simplifies the presentation while providing a clear understanding of the dissertation's focus, significance, and context before delving into the research's finer details.

Part A

1.1 Problem Statement

The Sustainable Development Goals (SDGs), which were adopted by the United Nations in 2015, aim to improve various domains such as poverty, health, education, and climate change by 2030. However, tracking progress towards these goals has been hindered by the vast amount and complexity of relevant data.

Data Science is an interdisciplinary field that uses scientific methods, algorithms, and tools to extract actionable insights from both structured and unstructured data. It encompasses techniques such as machine learning and frequently employs Python for data manipulation and visualization. Artificial Intelligence, on the other hand, focuses on the development of information technology systems that can perform tasks typically reserved for human cognition, such as problem-solving, learning, and decision-making. Artificial Intelligence utilizes sophisticated algorithms and data-driven techniques to analyze large data sets, enabling automated pattern recognition and adaptive learning.

By combining Data Science and Artificial Intelligence, there is significant potential to revolutionize the way we monitor and predict progress towards the SDGs. These technologies can analyze vast data sets to identify trends, provide valuable insights, and contribute significantly to the formulation of informed policies and the evaluation of developmental progress. This technological fusion enables policymakers to make data-informed decisions, prioritize necessary interventions, and allocate resources more efficiently, thereby accelerating progress towards the SDGs.

1.2 Focus of the Dissertation

The focus of this dissertation is on SDG 7, which aims to ensure access to affordable, reliable, sustainable, and modern energy for all. By utilizing the power of Data Science and Artificial Intelligence for monitoring and predictive analytics, this study seeks to explore how these technologies can enhance progress tracking, identify bottlenecks, and propose data-driven strategies to accelerate the attainment of clean and affordable energy solutions.

Python, a versatile and widely used programming language, will serve as the foundation for computational analyses in this research. Specialized Python libraries, such as NumPy, Pandas, and Scikit-learn, will be employed to perform rigorous statistical analyses on data relevant to SDG 7. This approach will demonstrate the practicality and potential of Python-driven DS and AI in progress monitoring and forecasting.

1.3 Contribution of this Dissertation

This dissertation aims to make a significant contribution across multiple disciplines —sustainable development, data science, and artificial intelligence — by evaluating the practicality of Data Science and Artificial Intelligence in monitoring and predictive analysis of SDGs, with a particular focus on Affordable Clean Energy (SDG 7). The research outcomes are expected to provide valuable insights for policymakers, academics, and other stakeholders, highlighting the transformative potential of data science and artificial intelligence in facilitating evidence-based decision-making and accelerating progress towards a more sustainable and equitable future. Through empirical case studies and Python-based applications, this dissertation aims to demonstrate the far-reaching impact of these technologies on the attainment of SDGs and to inspire further research into their applicability across other sectors of development.

Part B

1.4 United Nations Sustainable Development Goals

This dissertation is focused on SDG 7, which is one of the 17 SDGs established by the United Nations in 2015 as part of its 2030 Agenda for Sustainable Development. SDG 7 is aimed at ensuring universal access to affordable, reliable, sustainable, and modern energy for all. This research will explore the various targets and indicators of SDG 7 and highlight its significance in promoting clean energy, enhancing energy efficiency, and achieving equitable energy access for a more sustainable and resilient future.

Figure 1.1 Sustainable Development Goals

Source: Wikimedia

Figure 1.3 illustrates the broad range of global challenges that the SDGs encompass, and SDG 7 plays a critical role in addressing these challenges. By advancing sustainable energy practices, SDG 7 can help mitigate the impacts of climate change and foster an inclusive and resilient future for all.

1.5 Sustainable Development Goal 7

The United Nations' 2030 Agenda for Sustainable Development includes SDG 7, which aims to ensure access to affordable, reliable, sustainable, and modern energy for all. Access to energy is crucial for economic development, poverty eradication, and improving the quality of life for billions of people worldwide. SDG 7 calls for a transition from conventional fossil fuels to cleaner and renewable energy sources, reduced greenhouse gas emissions, and increased energy efficiency to mitigate the impacts of climate change. As shown in Figure 1.5, SDG 7 has several targets and indicators that guide its implementation.

Figure 1.2 SDG 7 Targets and Indicators

Targets	Indicators
7.1 By 2030, ensure universal access to affordable, reliable and modern energy services	**7.1.1** Proportion of population with access to electricity **7.1.2** Proportion of population with primary reliance on clean fuels and technology
7.2 By 2030, increase sustainability the share of renewable energy in the global energy mix	**7.2.1** Renewable energy share in the total final energy consumption
7.3 By 2030, double the global rate of improvement in energy efficiency	**7.3.1** Energy intensity measured in terms of primary energy and GDP
7.a By 2030, enhance international cooperation to facilitate access to clean energy research and technology, including renewable energy, energy efficiency and advanced and cleaner fossil-fuel technology, and promote investment in energy infrastructure and clean energy technology	**7.a.1** International financial flows to developing countries in support of clean energy research and development and renewable energy production, including in hybrid systems
7.b By 2030, expand infrastructure and upgrade technology for supplying modern and sustainable energy services for all in developing countries, in particular least developed countries, small island developing States, and land-locked developing countries, in accordance with their respective programs of support	**7.b.1** Installed renewable energy-generating capacity in developing countries (in watts per capita)

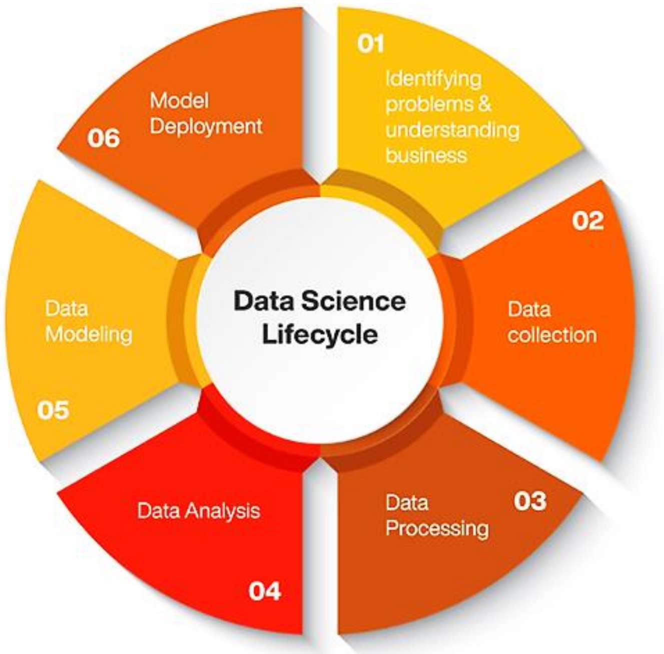
Source: United Nations

1.6 Data Science & Artificial Intelligence in Sustainable Development

1.6.1 Understanding Data Science

Data Science (DS) is a multidisciplinary field that utilizes mathematical models, algorithms, and statistical methods to extract insights from data, both structured and unstructured. The ultimate objective is to convert these insights into actionable knowledge that can be used to address real-world problems. In the context of sustainable development, DS plays a critical role in data aggregation, cleansing, visualization, and interpretation. By analyzing diverse sets of data related to climate, energy usage, social behavior, and economic indicators, among others, DS can offer a comprehensive view of current challenges and possible solutions.

Figure 1.3 Data Science Lifecycle

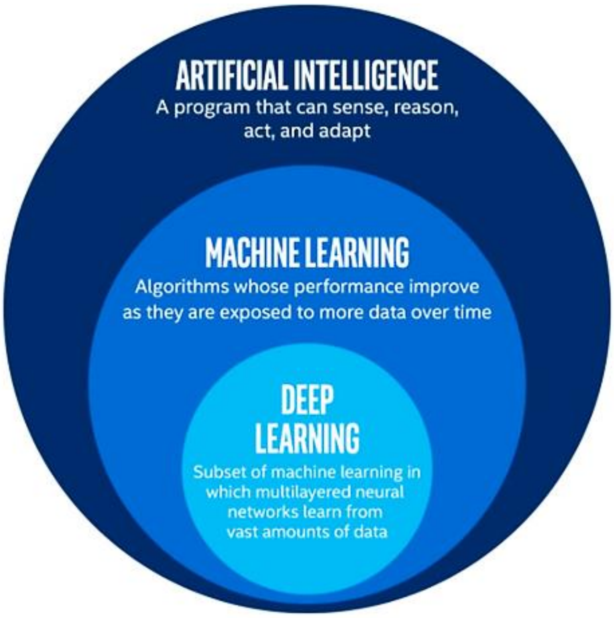


Source: www.onlinemanipal.com

1.6.2 Defining Artificial Intelligence

Artificial Intelligence (AI) is focused on developing systems that can perform tasks requiring human-like cognitive functions, such as understanding, reasoning, learning, and decision-making. AI technologies, including machine learning, deep learning, neural networks, and natural language processing, enable the creation of adaptive systems that can learn from data and improve over time. These AI systems are particularly adept at tasks that are time-consuming or virtually impossible for humans to accomplish, such as sifting through vast volumes of data at incredible speeds.

Figure 1.4 Artificial Intelligence Classification



Source: Atria Institute of Technology

1.6.3 Synergy between DS and AI

DS and AI offer a powerful combination for tackling complex, multi-faceted challenges, such as the UNSDGs. DS provides the methodology for collecting and structuring large volumes of data relevant to these goals, while AI supplies the computational power needed to identify patterns, make predictions, and automate decision-making processes. This symbiotic relationship enables DS to serve as the foundational architecture upon which AI algorithms can operate effectively and efficiently.

The application of DS and AI to the SDGs is of relevance to monitoring and forecasting progress towards these goals. The process of monitoring progress involves dealing with a range of complexities, such as the availability of high-quality data, potential biases within these data, and the need to interpret them across social, economic, and cultural contexts. By utilizing DS, this research aims to establish a structured framework for collecting and processing diverse data sets. Once this framework is in place, AI technologies can be deployed to uncover deeper insights.

For example, machine learning (ML) models can be trained to predict energy consumption patterns or to optimize renewable energy generation based on historical data. These predictive capabilities provide policymakers with concrete data points to design more effective and targeted interventions. In other words, AI can predict future scenarios based on existing data, enabling preemptive actions rather than reactive measures.

The integration of DS and AI has significant implications for policy decisions and resource allocation. This technology can provide a comprehensive understanding of regions that are lagging in the adoption of clean energy, the social and economic factors contributing to this lag, and the most effective methods for rectifying the situation. The use of predictive analytics can support policy decisions with data-driven evidence, leading to more equitable and efficient resource distribution. For instance, if AI algorithms identify a correlation between a lack of access to clean energy and high poverty rates in specific regions, policymakers can prioritize investment in these areas to address both SDG 7 (Affordable Clean Energy) and SDG 1 (No Poverty).

CHAPTER 2

LITERATURE REVIEW

Preamble

The pursuit of sustainable development has become a global imperative in response to the escalating environmental, social, and economic challenges facing humanity in the 21st century. At the forefront of this global agenda are the SDGs, a set of 17 interconnected objectives aimed at addressing global issues and ensuring a more equitable and sustainable future. Among these goals, SDG 7 stands out as it calls for universal access to affordable, reliable, sustainable, and modern energy for all by 2030.

Clean and sustainable energy is central to SDG 7, playing a pivotal role in promoting economic growth, reducing inequality, mitigating climate change, and enhancing human well-being. The global energy landscape is undergoing a profound transformation, driven by increased awareness of the environmental consequences of fossil fuels and the need to transition to clean and renewable energy sources. This transformation is being facilitated and accelerated by advances in DS and AI technologies, offering unprecedented opportunities to monitor, analyze, and predict progress towards SDG 7's ambitious targets.

This literature review explores the connections between clean energy, SDG 7, and the application of DS and AI methodologies. It aims to illuminate the current state of knowledge and provide insights into how data-driven approaches can contribute to achieving SDG 7 objectives. Understanding the existing literature is crucial, as it informs the theoretical foundation of our research and underpins our analytical framework and methodology.

This literature review sets the stage for the subsequent chapters of this dissertation. In these chapters, DS and AI methodologies will be leveraged to enhance our understanding of the pivotal role of clean energy in achieving SDG 7, assess progress, and predict future developments.

2.1. Clean Energy

Clean energy serves as a cornerstone in the global mission for sustainable development. The escalating threats of climate change, dwindling fossil fuel reserves, and surging energy demand make a compelling case for a transition to renewable energy sources like solar, wind, hydro, and geothermal power. These renewable options are essential in mitigating the environmental impact, reducing greenhouse gas emissions, and ensuring energy security (Carvalho, Luis, & Antunes, 2021). Concurrently, advancements in DS and AI are creating a transformative ripple effect across various sectors, including energy. The melding of DS and AI with clean energy offers promising avenues for optimizing renewable energy systems, increasing efficiency, and accelerating the shift towards sustainable energy solutions.

2.1.1 Significance

The global urgency for clean energy adoption is palpable. While fossil fuels have historically powered our civilizations, their adverse environmental impact is pushing the world towards sustainable alternatives (Ajayi, Oyedepo, & Alabi, 2020). Clean energy provides an ecologically responsible alternative that lowers greenhouse gas emissions and mitigates environmental degradation.

2.1.2 Mitigating Climate Change

Renewable energy technologies are vital in climate change mitigation. Shifting from fossil fuels to renewable energy sources can significantly reduce carbon dioxide emissions and other pollutants, thereby helping countries meet their obligations under international agreements like the Paris Agreement (United Nations Framework Convention on Climate Change [UNFCCC], 2015).

2.1.3 Ensuring Energy Security and Independence

Investing in renewable energy technologies enhances energy security by diversifying the energy portfolio. This diminishes dependency on finite fossil fuels, which in turn reduces susceptibility to volatile prices and geopolitical tensions (International Energy Agency [IEA] & World Bank, 2021).

2.1.4 Nurturing Economic Growth with Sustainability in Mind

The renewable energy sector is emerging as a catalyst for sustainable economic growth. This sector promotes innovation, job creation, and research and development investments, contributing to a future-oriented green economy (Ketterer, Boeters, Madlener, & Rosellón, 2020).

2.1.5 Advantages and Trends of DS and AI in Clean Energy

The intersection of DS, AI, and renewable energy is forging a paradigm shift with transformative possibilities. Leveraging these technologies can significantly bolster the adoption and optimization of clean energy systems (Lu, Ai, Li, Yan, & Wu, 2021).

2.1.6 Utilizing Data for Informed Decision Making

DS and AI technologies empower stakeholders with data-driven decision-making capabilities. These technologies analyze large datasets encompassing energy production, consumption patterns, weather forecasts, and grid operations, yielding actionable insights (Liu et al., 2019).

2.1.7 Advancing Grid Optimization and Energy Management

AI and DS can significantly improve energy management systems, enabling intelligent grid optimization. AI-driven smart grids utilize data analytics to balance supply and demand, maximize energy efficiency, and stabilize the grid (Alleyne et al., 2021).

2.1.8 Enhanced Renewable Energy Forecasting

The application of DS and AI dramatically refines renewable energy forecasting. Advanced AI models can predict solar and wind energy generation fluctuations with high accuracy, facilitating efficient grid management (Diagne et al., 2020).

2.1.9 Autonomous Energy Systems

The synergy between DS, AI, and clean energy technologies enables the development of autonomous energy systems. These systems leverage self-learning algorithms to adapt to fluctuating conditions and consumer behaviors, optimizing energy usage and minimizing waste (Kusiak, 2018).

2.1.10 Accelerating Research and Development

AI and DS technologies streamline the R&D process in the clean energy sector by facilitating data analysis and simulations. These technologies accelerate innovation, paving the way for the discovery of new renewable energy technologies and materials (Zhang et al., 2021).

2.1.11 Conclusion

The imperatives of climate change mitigation and sustainable development highlight the critical role of clean energy. DS and AI are emerging as invaluable tools for advancing clean energy adoption, policy formulation, and project management. Their capabilities in data-driven decision-making, grid optimization, forecasting, and autonomous energy systems underscore their transformative potential (Schmidt & Cohen, 2019). As global efforts intensify to achieve a sustainable future, the role of DS and AI in catalyzing a transition to a resilient, low-carbon energy landscape will be increasingly pivotal.

2.2 Sustainable Development Goal 7

Sustainable Development Goal 7 (SDG 7) - Affordable Clean Energy, occupies a central role in the United Nations' 2030 Agenda for Sustainable Development. This goal aims to ensure universal access to energy services that are not only affordable and reliable but also sustainable and modern (United Nations, 2015). The significance of SDG 7 extends beyond energy, impacting various facets of sustainable development including poverty alleviation, climate action, and more. This section provides a comprehensive overview of SDG 7, examining its importance, the progress made, international policy frameworks, current trends, and the effectiveness and constraints of existing efforts.

2.2.1 Importance

SDG 7 is critical due to its synergistic relationship with other SDGs such as poverty reduction, health, education, and gender equality. The promotion of clean energy technologies like solar, wind, and hydroelectric power offers renewable alternatives that are instrumental in climate change mitigation and emission reduction (Carvalho et al., 2021).

2.2.2 Progress

As of the latest data, progress towards achieving SDG 7 has been uneven. Despite gains in electrification, significant gaps remain, particularly in clean cooking solutions and the pace of transition to renewable energy sources (International Energy Agency [IEA] & World Bank, 2021).

2.2.3 International Policies

Global policy frameworks have been pivotal in driving the SDG 7 agenda. The Paris Agreement has been a major catalyst, encouraging nations to transition to low-carbon, sustainable energy systems (United Nations Framework Convention on Climate Change [UNFCCC], 2015). The United Nations' Sustainable Energy for All (SEforALL) initiative further amplifies these efforts by encouraging investments in clean energy (SEforALL, n.d.).

2.2.4 Emerging Trends

Several promising trends are shaping the SDG 7 landscape:

a. Decentralized Energy Solutions: Decentralized energy systems, including mini-grids and off-grid solutions, are increasingly recognized as effective means for extending energy access to remote areas (Kansal et al., 2020).

b. Digitalization and Smart Technologies: The incorporation of digital technologies like smart grids and IoT is enhancing energy efficiency and sustainability (Lu et al., 2021).

c. Renewable Energy Innovation: Technological innovations are making renewable energy sources like solar PV and wind more cost-competitive (Ketterer et al., 2020).

Climate Finance and Investment: Financial mechanisms, such as the Green Climate Fund, are facilitating the scale-up of clean energy projects globally (GCF, n.d.).

2.2.5 Effectiveness and Limitations

While SDG 7 has seen substantial progress, several challenges persist:

a. Energy Poverty and Affordability: The high cost of clean energy technologies often limits their adoption, especially in resource-constrained settings (Ajayi et al., 2020).

b. Policy and Regulatory Barriers: Inconsistent or unclear policy frameworks can deter investments and slow down the deployment of renewable energy technologies (Sovacool, 2020).

c. Infrastructure and Technological Gaps: Lack of adequate infrastructure and technological readiness can impede the integration of renewable energy sources into existing systems (Carvalho et al., 2021).

d. Global Energy Inequalities: Developed and developing nations face unequal access to clean energy solutions, often due to financial constraints and technological limitations (Masera et al., 2020).

2.2 Conclusion

The attainment of SDG 7 is indispensable to the accomplishment of broader sustainability and equity objectives. Although commendable progress has been made in certain areas, substantial obstacles persist that demand coordinated international cooperation, policy reforms, and innovative financing mechanisms. By addressing these constraints and leveraging emerging trends, we can accelerate global efforts to achieve affordable, reliable, and sustainable energy for all.

CHAPTER 3

ANALYTICAL FRAMEWORK

Preamble

In this chapter, an analytical framework is presented for use in this dissertation. The overarching goal of this framework is to assess and forecast progress towards SDG 7, which focuses on ensuring access to affordable, reliable, sustainable, and modern energy for all. To achieve this objective, the pertinent indicators associated with SDG 7 are examined. These indicators play a pivotal role in evaluating the extent to which the targets of SDG 7 are being met and are crucial in understanding the overall importance of achieving SDG 7.

Indicators, in the context of SDG 7, are utilized as measurable parameters that provide valuable insights into the various facets of energy access, sustainability, and affordability. These indicators encompass dimensions such as electricity access, renewable energy adoption, energy efficiency, and affordability, among others. Their significance lies in their ability to quantify progress, identify disparities, and inform policymaking to foster sustainable energy practices globally.

To facilitate this analysis, relevant data pertaining to each of these indicators will be meticulously collected from reputable sources, including but not limited to, the World Bank and the IEA. These data sources are renowned for their credibility and comprehensiveness, ensuring the reliability of the information used in our research.

To provide a structured and insightful analysis, our approach involves categorizing all countries into four distinct groups. Additionally, the performance of these countries will be compared against two benchmark classifications: the global average represented by the World and the advanced economies within the OECD. This categorization and benchmarking strategy will enable regional and global trends to be discerned, disparities to be pinpointed, and the progress of both developing and developed nations in relation to SDG 7 to be evaluated.

The data obtained from this categorization will be subjected to rigorous processing and analysis, leveraging the power of Python programming and its associated libraries. Furthermore, AI algorithms will be employed to extract meaningful insights and patterns from the data. These analytical results will subsequently be discussed comprehensively and, if deemed appropriate, utilized for forecasting future trends and developments in the context of SDG 7.

Ultimately, the findings derived from this comprehensive analysis will be synthesized to offer valuable insights and recommendations. These insights will not only contribute to a deeper understanding of the progress towards SDG 7 but will also serve as a guide for future research initiatives and policy formulation in the pursuit of sustainable energy access for all.

This chapter is organized into two sections to provide a structured approach to our analytical framework. In Section 3.1, the rationale behind the global country categorization and the selection of the two benchmark classifications is elucidated. In Section 3.2, an in-depth description of the six key indicators that underpin our analysis is presented, forming the foundation for our analyses in the subsequent chapters.

3.1 Country Categorization and Benchmarking

The initial phase of the analysis of SDG 7 focuses on the first three targets, namely 7.1, 7.2, and 7.3, utilizing SDG indicators 7.1.1, 7.1.2, 7.2.1, and 7.3.1. This analysis commenced by examining a diversity of countries. However, given the practical constraints associated with conducting extensive analyses on nearly 200 countries globally, a more structured approach has been adopted within this dissertation. As a result, countries are categorized into four distinct groups: "Low-Income," "Lower-Middle-Income," "Upper-Middle-Income," and "High-Income," as well as two benchmark classifications: "OECD Members" and "World." As of May 2021, the Organization for Economic Co-operation and Development (OECD) comprises 38 member nations. OECD countries typically represent advanced economies characterized by high standards of living, well-developed infrastructure, and a strong commitment to democratic governance and market-oriented economies. A comprehensive list of OECD countries is provided in Appendix 1.

According to the World Bank, the Gross National Income Per Capita (GNIPC) thresholds for each group and category as of 2022 are as follows:

Figure 3.1 Categorization of Economies

Economy	Gross National Income Per Capita (USD)
Low-Income	Below $1,085
Lower-Middle-Income	$1,085 - $4,255
Upper-Middle-Income	$4,256 - $13,205
High-Income	Exceed $13,205
OECD Members	$43,261
World	$12,804

Source: World Bank

This dissertation will concentrate on two specific sub-categories within the broader "Middle-Income" category, namely "Upper-Middle-Income" and "Lower-Middle-Income" countries. The rationale for this selection is that these sub-categories provide a more comprehensive and nuanced understanding of the challenges and opportunities related to their economies, societies, and development. By analyzing these sub-categories and comparing them with the averages of OECD Member countries and the rest of the world, the data can be examined in a manner that more accurately reflects the unique characteristics and needs of each group, leading to more reliable recommendations.

In Section 3.2, the analyses of the GDP of the six income groups and classifications will be conducted to provide a comprehensive overview of the economies represented within these diverse categories. This preliminary assessment serves as a foundation for the subsequent analysis of the SDG indicators.

By conducting a two-step analysis that examines both how economies are grouped and how specific sustainable development goals are performing, our goal is to demonstrate a clear and helpful connection between these goals and the economies of various income groups.

3.2 SDG 7 Targets and Indicators

3.2.1 SDG Target 7.1

The aim of Target 7.1 of the SDGs is to ensure universal access to affordable, reliable, and modern energy services by 2030. This target highlights the need to achieve universal access to modern energy and demonstrates a commitment to ensuring that people worldwide have access to reliable and affordable energy sources. Progress towards this objective is monitored using Indicators 7.1.1 and 7.1.2.

"Access to Electricity" (Indicator 7.1.1) is a crucial metric used to evaluate the proportion of the population that has access to electric services, both from the grid and off-grid renewable sources. This indicator recognizes the importance of electricity as a cornerstone of development, as it not only affects economic productivity but also plays a crucial role in enhancing health, education, and overall well-being. By assessing the percentage of households and individuals that are connected, the strides made towards the UN's SDGs, primarily the SDG 7.1 target of affordable and clean energy for all, can be determined.

"Access to Clean Fuels for Cooking" (Indicator 7.1.2) is an essential indicator in addressing energy-related challenges, particularly concerning health and environmental sustainability. This indicator aims to gauge the proportion of households provided with clean and efficient cooking technologies, such as clean-burning stoves or electric cookers. These technologies mitigate indoor air pollution, reduce dependence on traditional biomass fuels, improve air quality, reduce respiratory illnesses, and foster a healthier living environment, particularly for communities in low-income settings. The alignment of achieving this indicator with the broader SDG 7.1 target is also observed, contributing to the evolution of sustainable and inclusive energy systems.

By examining SDG indicators 7.1.1 and 7.1.2, the dissertation not only reflects the progress made towards universal energy access but also highlights the multifaceted dimensions of development and sustainability that depend on reliable and clean energy availability for all. The analysis contributes to a deeper understanding of the complex interplay between energy access, economic growth, and social well-being within diverse income groups.

3.2.2 SDG Target 7.2

SDG Target 7.2, which states that "by 2030, increase substantially the share of renewable energy in the global energy mix," emphasizes the need for a shift from the current dominant fossil fuels to more sustainable sources, such as wind, solar, and hydroelectric power. This shift is crucial due to the escalating climate change threats caused by the burning of fossil fuels, which emit greenhouse gases (GHGs) like carbon dioxide (CO2) that intensify global warming. Adopting renewable energy can not only reduce GHG emissions but also alleviate other environmental hazards associated with fossil fuel utilization, such as air and water pollution.

SDG Indicator 7.2.1, also known as the "Renewable energy share in the total final energy consumption," plays a crucial role in measuring the world's energy originating from renewable sources. This indicator is essential for achieving SDG Target 7.2, as it offers several benefits:

- Quantifiability: It provides a numerical value, which enables countries and organizations to establish benchmarks, monitor progress, and compare developments across regions.

- Focus on 'Final Energy Consumption': By focusing on final energy consumption, the evaluated energy more accurately reflects actual end-user consumption, providing a more accurate depiction of renewable energy use in homes, businesses, and transportation.

- Accountability Boost: The presence of a tangible metric leads to heightened accountability at the country level, discouraging evasive commitments and requiring evident progress.

- Policy Guidance: The indicator can guide policymakers' decisions. A country with a small renewable energy share may need to invest in renewable infrastructure or incentivize private sector participation in the renewable energy sector.

- Inclusive Coverage: By encompassing all forms of renewable energy, it provides a comprehensive outlook on renewable energy use.

The SDG Indicator 7.2.1 is more than just a statistical measure; it serves as a crucial link between Target 7.2's aspirations and its actualization. This indicator plays a vital role in the global shift towards a sustainable energy pathway, aligning with the broader objectives of SDG 7 and the overarching SDG framework. The momentum towards renewable energy, as outlined in SDG Target 7.2 and monitored by Indicator 7.2.1, is the foundation of global efforts against climate change and for a sustainable future. This transition requires global collaboration, substantial financial resources, and robust policy frameworks, but the potential rewards for the world and future generations are immeasurable.

3.2.3 SDG Target 7.3.

SDG Target 7.3 aims to promote energy sustainability by doubling the global rate of improvement in energy efficiency by 2030. This target encompasses several key elements necessary for achieving energy sustainability, including universal access to energy, affordable energy services, reliable energy, sustainable energy practices, and the transition to cleaner and more efficient energy sources and technologies. These elements are crucial for improving living standards, eliminating energy poverty, reducing disparities, supporting economic growth, and building resilience against climate change and disasters.

The SDG Indicator 7.3.1, which measures the "Percentage of population with access to electricity," serves as a crucial tool for monitoring progress towards the target of universal energy access outlined in SDG Target 7.3. This metric provides a clear and quantifiable measure that enables comparisons across regions and over time, promoting transparency and accountability by motivating governments to uphold their energy access pledges. Furthermore, accurate data on electricity access supports evidence-based decision-making, directing resources where they are most needed, and highlighting the interdependence of various development facets such as health, education, and the economy.

In conclusion, SDG Target 7.3, and its associated indicator 7.3.1 are integral in driving efforts towards comprehensive energy access and environmental sustainability, reflecting the global commitment to creating a just and sustainable future for all.

3.2.4 SDG Target 7.A.

The main objective of SDG Target 7.A is to enhance international cooperation to facilitate access to clean energy research and technology, including renewable energy, energy efficiency, and advanced and cleaner fossil-fuel technology, as well as to promote investment in energy infrastructure and clean energy technology. This target recognizes the importance of shared research and adaptable, scalable technologies across borders, as well as the need for cooperation that enables rapid technological transfer and financial resource mobilization. Furthermore, the alignment between Target 7.A and the overarching ethos of SDG 7 is observed, with a strategic emphasis on the research, development, and investment pathways that will drive the outcomes.

The specific goal associated with Target 7.A is SDG Indicator 7.A.1, which measures international financial support for clean energy research and development, as well as renewable energy production in developing countries. This indicator provides a tangible representation of international cooperation, allowing stakeholders to track progress and identify areas for improvement. The importance of this indicator lies in several aspects:

- Quantitative Analysis: It offers a numeric value, making it easier to visualize progress and identify gaps.

- Emphasis on Developing Nations: The focus on tracking financial flows to developing countries, rich in renewable energy potential, ensures that the SDG's promise of inclusivity and cooperation is upheld.

- Innovation Promotion: By highlighting R&D, the indicator emphasizes the importance of future solutions, not just immediate fixes.

- Stimulating Investment: The potential for attracting further investments can be increased by tracking and showcasing these financial flows.

The broader goal of sustainable and universal energy access, as part of SDG 7, is supported by Target 7.A's emphasis on technology exchange and international collaboration. Indicator 7.A.1, with its actionable and quantifiable metric, ensures accountability, transparency, and engagement by the global community. The SDGs' structured, collaborative, and comprehensive approach to addressing global challenges is exemplified by their collective efforts.

3.2.5 SDG Target 7.B

The essence of SDG Target 7.B stems from recognizing renewable energy as a fundamental human right and a linchpin for sustainable development. It also understands the distinct challenges developing countries face in transitioning to such energy, due to resource constraints, technological hurdles, and infrastructure deficits.

SDG Target 7.B focuses on enhancing infrastructure to promote clean and sustainable energy in developing countries, as part of the broader goal of achieving universal access to affordable, sustainable, and modern energy by 2030. This specific target aims to boost the availability of renewable energy in these countries, by improving energy efficiency and fostering eco-friendly energy infrastructure. The rationale behind Target 7.B lies in the belief that access to renewable energy is a fundamental human right and a crucial element of sustainable development, while also acknowledging the challenges that developing countries face in transitioning to such energy sources, due to limited resources, technological obstacles, and infrastructure deficits.

A crucial tool in achieving SDG Target 7.B's objectives is SDG Indicator 7.B.1, which measures the extent to which a country's renewable energy consumption accounts for its total energy use. This indicator's significance lies in its ability to:

- Track Progress: It provides a tangible measure of a nation's shift towards renewable energy sources.
- Encourage Investment: It motivates countries to invest in renewable energy technologies like wind, solar, and hydro, which helps mitigate climate change.

- Evaluate Policies: It serves as a benchmark for assessing the success of renewable energy policies and initiatives.

- Identify Regional Disparities: This metric highlights differences in renewable energy usage across countries, guiding targeted interventions.

- Ensure Accountability: Nations' public reporting on this metric demonstrates their commitment to achieving SDG Target 7.B's goals.

In summary, SDG Indicator 7.B.1 plays a central role in SDG Target 7's focus on increasing clean energy access in developing regions. This indicator is vital in quantifying progress, promoting renewable energy, refining policies, identifying regional gaps, and ensuring accountability. Together, these efforts drive the global push towards sustainable energy access and environmental preservation.

CHAPTER 4

METHODOLOGY

Preamble

This chapter serves as an exposition of the methodology employed in the present dissertation. The research framework applied in this study revolves around the SDG indicators, where Python programming language and its associated libraries are harnessed as pivotal tools for conducting comprehensive analyses. Furthermore, ML models come into play when deemed suitable to generate forecasts, thus augmenting the depth of the examination.

In the pursuit of rigor and precision, historical data pertinent to the SDG indicators is meticulously curated and subjected to rigorous scrutiny. The primary sources of data for this research are The World Bank and the IEA. This meticulous approach ensures that only data meeting the requisite criteria are utilized in the forecasting process, reinforcing the reliability of the results.

To enhance the accessibility and interpretability of the analytical findings, a diverse set of data visualization techniques is employed. Line charts, bar charts, heat maps, and donut charts are strategically chosen based on their appropriateness in conveying specific insights derived from the data analysis. Additionally, the data for the charts and Python code are available on GitHub at this link: https://github.com/BlockQuant18/SU-PHD-TM. Furthermore, when deemed appropriate, forecast results are presented in tabular form to complement the graphical analysis. These visualizations are instrumental in facilitating a more comprehensive understanding of the complex interplay among various SDG indicators.

Importantly, the use of Python and ML models offers several advantages to this research. Firstly, it allows for the automation of data processing tasks, ensuring efficiency and reproducibility in the analysis. Secondly, it facilitates the handling of large and diverse datasets, which is essential for conducting in-depth investigations into the multifaceted nature of the SDGs. Additionally, the employment of ML models facilitates the extraction of concealed patterns and trends within the data, thus enhancing our comprehension of the dynamics within the SDG framework. This, in turn, establishes a robust foundation for the forecasting process.

In conclusion, the methodological approach outlined in this chapter underscores the commitment to conducting a rigorous and data-driven exploration of the SDG indicators. Consequently, this chapter approach lays a solid foundation for the subsequent chapters of the dissertation, setting the stage for in-depth analyses and critical discussions of SDG 7 and the associated indicators.

4.1 GDP Per Capita

4.1.1 Historical Data Analysis

The GDP per capita, a measure of a country's economic output per person, is calculated by dividing the GDP by the total population of a country. It serves as an important proxy indicator for energy sustainability and access, and higher GDP per capita usually translates to more resources and technology available for sustainable energy solutions. The study of GDP per capita across various economies used data visualization techniques such as line charts and heat maps to depict the temporal shifts in GDP per capita across different income groups and regions. The data extraction and preprocessing process were focused on groups such as "Low-Income," "Lower-Middle-Income," "Upper-Middle-Income," "High-Income," "OECD Members," and the global "World" average, using Python, a versatile programming language, for its proficiency in data analysis and ML. The dataset, comprising GDP per capita figures from 1990 to 2022, was sourced from a World Bank CSV file and processed using Python's pandas library.

The line chart titled "GDP per capita from 1990 to 2022" was used to show trends over time and help understand economic patterns. A heatmap was also used to display GDP values in a different way, making it easier to compare different years and groups. The heatmap was particularly useful for identifying patterns and anomalies in large datasets.

For the forecasting section, several ML algorithms were considered, including Linear Regression (LR), Random Forest (RF), Gradient Boosting Machines (GBM), Long Short-Term Memory Networks (LSTM), and Recurrent Neural Networks (RNN). The selection of algorithms was based on their unique advantages and challenges. Random Forest and GBM were chosen because they are robust, interpretable, efficient, and resistant to data irregularities.

After undergoing processing with Python, a Line Chart and a Heat Map are generated for further analysis.

4.1.2 Forecast

Various ML algorithms can be employed for time-series forecasting, each with its own set of advantages and drawbacks:

- Linear Regression (LR): A simple yet effective algorithm for making numerical predictions. It assumes a linear relationship between the input and output variables.

- Random Forest (RF): An ensemble learning algorithm that leverages multiple decision trees for prediction, offering higher accuracy and robustness.

- Gradient Boosting Machines (GBM): Another ensemble method that builds trees sequentially, each one correcting the errors of its predecessor.

- Long Short-Term Memory Networks (LSTM): A type of recurrent neural network designed to remember past information, making it suitable for sequence prediction tasks.

- Recurrent Neural Networks (RNN): A neural network architecture designed for sequence prediction but often less effective at capturing long-term dependencies compared to LSTM.

Given the characteristics of the dataset and specifics of this analysis, RF and GBM were selected to forecast the 2023 GDP per capita for the following reasons:

- Data Sparsity: The dataset under examination is relatively small, comprising 33 years of data for each income group. Random Forest and GBM can generate robust predictions from such limited datasets.

- Interpretability: Both Random Forest and GBM offer insights into feature importance, thereby allowing for a more nuanced understanding of how the years influence GDP per capita—a crucial asset in the academic context.

- Computational Efficiency: These algorithms are computationally less demanding than LSTM and RNN, providing quicker results without the need for extensive computational resources.

- Resilience to Data Irregularities: Economic datasets often come with outliers or missing values, which these algorithms can handle effectively.

The steps for the RF and GBM analyses are outlined below:

1. Data Extraction: Acquire the historical time-series data for each income group and isolate the relevant information.

2. Feature-Target Definition: Utilize years as features and GDP per capita as the target variable.

3. Model Training: Employ the Random Forest and GBM algorithms and train them on the extracted data.

4. Prediction: Utilize the trained models to forecast GDP per capita for 2023.

5. Evaluation: Calculate the percentage change in GDP per capita for the future years, relative to 2022.

After undergoing processing with Python, two Line Charts and two Tables that show the forecast values in 2023 are generated for further analysis.

The Python program corresponding to section 4.1 is provided in Appendix 3.

4.2 SDG Indicator 7.1.1

4.2.1 Historical Data Analysis

An investigation was carried out on SDG Indicator 7.1.1, with a focus on electricity access, and data was sourced from The World Bank, a renowned international organization that provides substantial financial and technical support to developing countries. The data set, which comprises information on the percentage of the population with electricity access from 2000 to 2021, was meticulously segmented into economic tiers ranging from 'High-Income' to 'Low-Income'. Additionally, a comprehensive 'World' average was presented, encompassing global electricity accessibility trends.

The dataset was carefully curated with the aim of addressing two critical issues: the disparities in electricity access across various economic backgrounds and the recognition of electricity access as a fundamental aspect of national development. The study highlighted the significance of electricity access as a catalyst for multiple sectors, including healthcare, education, and technology.

The SDG Indicator 7.1.1 was analyzed within the context of the United Nations' Sustainable Development Goals (SDGs). The significance of this indicator extends beyond mere statistical analysis, as it highlights the proportion of the global population with access to electricity. This metric is crucial in supporting health, education, and societal well-being. The provision of electricity access to a community is essential for promoting economic growth, improving health, enhancing education, and improving the overall quality of life.

The Line Chart was chosen for Indicator 7.1.2 due to its effectiveness in presenting time-series data, allowing for a clear comparison of energy intensity trends across various economic categories throughout the years. By employing different colors and line styles, it aids in distinguishing and interpreting the progress of these groups.

To conduct a comprehensive analysis, a Python-based approach was utilized. The steps for the Line Chart analysis are outlined below:

1. Data Extraction and Library Utilization:

- The Pandas library, a powerful toolset in Python for data analysis and manipulation, was employed for the extraction and manipulation of data from the source.

- The dataset was ingested and converted into a DataFrame using the read csv function from pandas. This data structure facilitates easy data manipulation and analysis due to its tabular nature, with rows and columns mimicking the structure of a spreadsheet or SQL table.

2. Python Libraries:

- Pandas: A premier library, indispensable for sophisticated data manipulation and analytical tasks.

- Matplotlib.pyplot: A versatile visualization toolkit that enabled the generation of illustrative bar charts.

3. Data Preprocessing:

- Time Frame Isolation: Given the vastness of the dataset, it was imperative to narrow down the focus to a specific time frame. The dataset was filtered to retain only the years 2000 through 2021, which are of primary interest for this study.

- Filtering Mechanism: The pandas DataFrame provides a seamless mechanism for filtering using conditional statements. The data corresponding to the years of interest was isolated using logical conditions, and a copy was made to ensure the original dataset remained unaltered and to prevent any inadvertent data manipulation warnings.

4. Visualization:

The matplotlib library was the visualization tool of choice due to its versatility and capability to generate a wide array of charts and graphs. Three line charts were generated to provide insights into electricity access trends, disparities, and a comparison of urban versus rural access in 2021:

- Chart 1: Access to electricity in urban areas (2000-2021)
- Chart 2: Access to electricity in rural areas (2000-2021)
- Chart 3: Difference in urban and rural access to electricity over time

4.2.2 Forecast

The data available extends only up to the year 2021, as a result, forecasts for the year 2022 were made using the five ML algorithms outlined in section 4.1.2. Given the characteristics of the dataset and specifics of this analysis, RF and GBM were selected for the projection of values in the year 2022.

The steps for the RF and GBM analyses are outlined below:

1. Data Extraction: Acquire the historical time-series data for each income group and isolate the relevant information.

2. Feature-Target Definition: Utilize years as features and GDP per capita as the target variable.

3. Model Training: Employ the Random Forest and GBM algorithms and train them on the extracted data.

4. Prediction: Utilize the trained models to forecast GDP per capita for 2023.

5. Evaluation: Calculate the percentage change in GDP per capita for the future years, relative to 2022.

After undergoing processing with Python, two tables are generated for further analysis.

The Python program corresponding to section 4.2 is provided in Appendix 4.

4.3 SDG Indictor 7.1.2

4.3.1 Historical Data Analysis

For SDG Indicator 7.1.2, rather than focusing on a specific economic group, a country-specific analysis is included for all countries. This approach is driven by the need for:

- Data Granularity: Due to variations in urban development, infrastructure, and policies, a detailed, country-specific analysis is necessary to understand each country's unique circumstances, which aids policymakers and stakeholders.

- Comparative Analysis: The inclusion of all countries permits a comparative study, highlighting best practices and areas for enhancement.

The heatmap methodology was chosen for Indicator 7.1.2 based on the dataset characteristics:

- Spatial Representation: The data, which is geographically oriented, benefits from a heatmap's visual spatial comparisons, elucidating geographic disparities.

- Visual Clarity: Through color gradients, heatmaps simplify the recognition of patterns. Countries with varying access to clean fuels can be promptly discerned.

- Scalability: Global datasets like this one are well-suited to heatmaps due to their scalability.

- Integration with Geospatial Data: Integration with geospatial data, such as country boundaries, is easily achieved, ensuring accurate portrayal.

The steps to create a detailed Heatmap showing the accessibility of clean fuels across countries are outlined below:

1. Load the dataset using specific libraries like pandas. Inspect the dataset's structure to identify crucial columns.

2. Identify the target variable, such as access to clean fuels in urban areas for 2021, and relevant features like country names and codes.

3. Use Python libraries like pandas, geopandas, matplotlib, and matplotlib.colors for data analysis, geospatial data processing, and custom colormap creation.

4. Remove metadata and rename columns as necessary. Convert data types, such as changing percentage access to a float.

5. Merge geospatial data representing country boundaries with the dataset using common identifiers like country codes.

6. Plot the heatmap, apply the custom colormap, and add labels and legends for clarity.

After undergoing processing with Python, two Heatmaps are generated for further analysis.

4.3.2 Forecast

The forecast is not provided for SDG Indicator 7.1.2 as the data deemed appropriate for this purpose is not currently available.

The Python program corresponding to section 4.3 is provided in Appendix 5.

4.4 SDG Indictor 7.2.1

4.4.1 Historical Data Analysis

The data used in this analysis was sourced from The World Bank. The dataset covers the percentage of the population with access to electricity from renewable sources across various economic categories of countries, from 2000 to 2021. The countries in this dataset are categorized as 'High-Income', 'Higher-Middle-Income', 'Lower-Middle-Income', 'Low-Income', and overall averages for 'OECD Members' and the 'World'. The intention behind this dataset is multifaceted:

- Comparative Analysis: Categorizing countries into economic groups enables a comparative analysis between nations of similar economic status. This helps in understanding disparities or commonalities in energy transition efforts.

- Trend Identification: Spanning over two decades, the data can be used to identify trends in the adoption of renewable electricity sources. This highlights progress or stagnation in different economic groups over time.

- Policy Implications: By determining which groups are lagging in renewable energy adoption, policymakers can devise strategies to promote green energy in those specific areas.

The Line Chart, Heatmap and Area Chart have been selected for Indicator 7.2.1 for the following reasons:

- Line Chart: A line chart is effective in showing trends over time, providing clarity on the trajectory of data points, making it easier to identify patterns, progressions, or regressions over the years.

- Heatmap: A heatmap allows for a visual representation of data magnitude through color variations, making it ideal for comparing the relative strength of values across two categorical dimensions, such as years and economic categories. This helps to quickly spot years or categories with high or low renewable electricity percentages.

- Area Chart: An area chart emphasizes the quantity beneath a line, representing the cumulative effect. In the context of this data, it visually communicates the magnitude of renewable electricity adoption for each economic category over time, while also allowing for comparisons between them.

The steps for the Line Chart analysis are outlined below:

1. Data Extraction: The data was obtained from a CSV file using Pandas, a powerful Python library for data manipulation.

2. Feature-Target Definition: The primary features of interest are 'Year' and 'Entity', with the target variable being 'Renewables (% electricity)'.

3. Python Libraries: Pandas, Matplotlib, and Seaborn were utilized for data manipulation, visualization, and enhanced visualization capabilities, respectively.

4. Data Preprocessing: The data was filtered based on specific groups of interest and then further filtered to include only the years 2000 to 2021.

5. Visualization: A line chart was plotted for each economic category, representing the percentage of renewable electricity from 2000 to 2021.

The following are the steps for the Heatmap analysis:

1. Data extraction: Utilized the preprocessed data from the line chart analysis.

2. Feature-Target Definition: Same as the Line Chart.

3. Python Libraries: Same as the Line Chart.

4. Data Preprocessing: The data was pivoted to create a matrix of 'Entity' against 'Year'.
5. Visualization: A heatmap was created using Seaborn, where color intensity represents the percentage of renewable electricity.

The steps for the Area Chart analysis are outlined below:

1. Data extraction: Utilized the preprocessed data from the previous analyses.

2. Feature-Target Definition: Same as the previous charts.

3. Python Libraries: Same as the previous charts.

4. Data Preprocessing: The data was pivoted to create a matrix of 'Year' against 'Entity'.

5. Visualization: An unstacked area chart was plotted for each economic category, showcasing the evolution of renewable electricity percentages from 2000 to 2021.

After undergoing processing with Python, a Line Chart, Heatmap and Area Chart are generated for further analysis.

4.4.2 Forecast

For the forecast section, the LR, RF, and GBM algorithms, which were chosen due to the unique characteristics of the dataset. The following are the steps for the 2022 forecast:

The steps for the LR, RF and GBM analyses are outlined below:

1. Data Extraction: The data was sourced from a CSV file containing information on the percentage of electricity sourced from renewables for different entities. The process involved using Python's pandas library to read the CSV file and extract relevant data.

2. Feature-Target Definition: The feature (independent variable) is Year, representing the time series nature of the data. The target (dependent variable) is Renewables (% electricity), which is the metric we aim to predict for 2022.

3. Python Libraries: The following libraries were used for the analyses: pandas for data manipulation and analysis, sklearn.linear_model for LinearRegression, sklearn.ensemble for RandomForestRegressor and GradientBoostingRegressor, and sklearn.model_selection for train_test_split.

4. Model Training: Three models (LR, RF, and GB) are trained on historical data (2003-2021) to forecast 2022 values.

5. Prediction: Once the models were trained, they were used to predict the target variable's values for the year 2022, resulting in a forecast of the percentage of electricity expected to be sourced from renewables for each entity in 2022.

After undergoing processing with Python, a table with the forecast values in 2022 from the LR, RF, and GBM algorithms are generated for further analysis.

The Python program corresponding to section 4.4 is provided in Appendix 6.

4.5 SDG Indictor 7.3.1

4.5.1 Historical Data Analysis

The data utilized in the analysis was sourced from The World Bank. This dataset provides energy intensity indicators across various economic categories of countries from the year 2000 to 2020. Energy intensity refers to the energy required to generate a single unit of economic yield. A lower value indicates greater energy efficiency. The dataset classifies countries into 'High-Income', 'Upper-Middle-Income', 'Lower-Middle-Income', 'Low-Income', and provides averages for 'OECD Members' and the 'World'.

The objective of this information is to elucidate how resources are apportioned and allocated towards energy-efficient practices over time by various economies. By analyzing these categories, the pace at which sustainable energy practices are embraced by diverse income groups can be discerned, the impact of international policies on energy efficiency can be assessed, and progress towards global sustainability targets can be evaluated. This data is considered of paramount importance to policymakers, energy consultants, and researchers as it allows them to comprehend the current trend and plan for forthcoming energy-efficient initiatives.

The Line Chart and Area Chart have been selected for Indicator 7.3.1 for the following reasons:

- Line Chart: A line chart is an effective means of displaying time-series data, enabling straightforward comparison of energy intensity trends across different economic categories over the years. The use of different colors and line styles facilitates the distinction and interpretation of the groups and their progress.

- Area Chart: Stacked area charts provide a comprehensive view of the combined energy intensity indicators of all categories over time. They highlight the relative contributions of each group and how these evolve annually. The use of semi-transparent colors aids in discerning overlapping trends.

The steps for the Line Chart analysis are outlined below:

1. Data Extraction: The data was imported from a CSV file using the pandas library. The file was read into a DataFrame, and the initial rows were skipped to align with the actual data.

2. Feature-Target Definition: Features include the years from 2000 to 2020, and the target is the energy efficiency indicator value for each year.

3. Python Libraries: The primary libraries used for this analysis include pandas for data manipulation, matplotlib for visualization, and scikit-learn for linear regression.

4. Data Preprocessing: The dataset was filtered to include only the groups of interest. The columns were also filtered to represent years from 2000 to 2020.

5. Visualization: Using matplotlib, a line chart was plotted displaying the energy intensity indicator for each group over the specified period.

The following are the steps for the Area Chart analysis:

1. Data extraction: The data was already extracted in the line chart analysis and can be reused.

2. Feature-Target Definition: The target remains the cumulative energy efficiency indicator value for each year across groups, while the features continue to be the years from 2000 to 2020.

3. Python Libraries: Pandas and matplotlib were primarily used for this analysis.

4. Data Preprocessing: The data was prepared for a stacked area chart by setting the 'Country Name' as the index and transposing the dataset to have years as rows.

5. Visualization: A stacked area chart was plotted using matplotlib, which showcases the energy intensity indicators of each group over time. The alpha parameter was adjusted to ensure transparency and better visualization of overlapping areas.

After undergoing processing with Python, a Line Chart and Area Chart are generated for further analysis.

4.5.2 Forecast

The data available extends only up to 2020. As a result, forecasts for the years 2021, 2022, and 2023 were made using the five ML algorithms outlined in section 4.1.2. Given the dataset's specific characteristics, the LR algorithm is selected for the prediction of values in 2021, 2022, and 2023. The steps for the forecast are outlined below:

1. Data Extraction: The data in the CSV file was extracted using a formal process that involved reading the file into a pandas DataFrame, and skipping the first four rows as they were determined to be irrelevant.

2. Feature-Target Definition: The features (X) in the analysis are represented by the years from 2000 to 2020, which were converted into a numerical range. The target variable (y) represents the 'Energy Efficiency Indicator' values for the corresponding years. Additionally, the data was filtered to focus on specific groups of interest: Low-Income, Lower-Middle-Income, Upper-Middle-Income, High income, OECD Members, and World.

3. Python Libraries: The following libraries were utilized in this analysis: pandas for data manipulation and analysis, numpy for numerical operations, matplotlib.pyplot for visualizing the data, sklearn.linear_model for the Linear Regression class, and specifically the LinearRegression class for creating the linear regression model.

4. Model Training: For each group of interest, a Linear Regression model was trained using the years as the feature and the corresponding 'Energy Efficiency Indicator' as the target. The models were trained on the historical data to be used for future predictions.

5. Prediction: Once trained, each model predicted the 'Energy Efficiency Indicator' values for the years 2021, 2022, and 2023. These predictions were then consolidated in a new DataFrame.

6. Evaluation: The percentage changes for the predicted years (2021, 2022, and 2023) were calculated relative to the actual value of 2020. This provides a sense of how much the indicator is expected to change over the next three years compared to the most recent known value.

After undergoing processing with Python, a Line Chart and a Table are generated to show the forecast values in 2022 and 2023.

The Python program corresponding to section 4.5 is provided in Appendix 7.

4.6 SDG Indicator 7.A.1

4.6.1 Historical Data Analysis

Two prominent datasets sourced from the IEA have been employed to shed light on the progress made towards SDG Indicator 7.A.1. This specific indicator emphasizes the "International financial flows to developing countries in support of clean energy research and development and renewable energy production, including in hybrid systems." Consequently, evaluating datasets that capture the nuances of global investments and funding mechanisms becomes paramount.

4.6.1.1 Global Investment in Energy Sources (2015-2023)

The first dataset, detailing global investments in diverse energy sources from 2015 to 2022, with forecasts extending into 2023, offers a comprehensive overview of the evolving energy landscape. By categorizing investments into sectors such as "Renewable power," "Energy efficiency," "Grids," "Electric vehicles," "Battery storage," "Nuclear," "Low-emission fuels and carbon capture," and "Fossil energy," a multifaceted understanding of the world's energy priorities can be acquired. The importance of each category within the framework of SDG Indicator 7.A.1. is shown as follows:

- Renewable Power: As previously noted, investments in this sector directly align with the emphasis of 7.A.1 on renewable energy production. Observing fluctuations in this investment over time offers a gauge on global commitments to cleaner energy sources.

- Energy Efficiency: Investment in optimization indicates a global movement towards not just generating energy but ensuring its efficient consumption, vital for a sustainable energy ecosystem.

- Grids: Infrastructural advancements are crucial, especially for harnessing and distributing renewable energy, especially in areas lacking robust infrastructure.

- Electric Vehicles (EVs): The transportation sector is one of the major contributors to greenhouse gas emissions globally. Therefore, investments in EVs represent a direct effort to mitigate carbon footprints. Rising investments here can demonstrate a global pivot from traditional vehicular modes to cleaner transportation, in line with sustainable energy goals.

- Battery Storage: As renewable sources like solar and wind are intermittent, effective storage solutions become pivotal. Increased investments in battery storage technology indicate preparedness for a future where renewables play a more dominant role.

- Nuclear: Although controversial, nuclear energy remains a significant low-carbon source. Tracking investments here can provide insights into how nations are balancing their energy portfolios in the quest for low-emission solutions.
- Low-emission Fuels and Carbon Capture: These represent transitional or complementary solutions as the world gradually shifts away from high-emission sources. Significant investments in these

technologies signify a commitment to reduce carbon footprints even while relying on traditional energy sources.

- Fossil Energy: This category is especially crucial for comparative analysis. By contrasting investments in fossil fuels against those in clean and renewable sources, insights can be driven into the pace and commitment of the global shift towards sustainable energy. A decline in these investments might suggest a progressive shift towards cleaner alternatives.

In essence, this expanded dataset from the IEA provides a holistic perspective on global energy investments. Each category, from renewables to fossil fuels, offers insights into the world's energy transition, helping assess the genuine commitment and pace towards achieving the goals encapsulated in SDG Indicator 7.A.1.

The steps for the Bar Chart analysis are outlined below:

1. Data Extraction
    - Data from a CSV file provided by the IEA was imported into a DataFrame using Python's pandas library.

2. Feature-Target Definition
    The dataset features were categorized into two groups:
    - Absolute Investments: Raw values for energy sectors like 'Renewable power' were identified.
    - Relative Investments: Percentages representing proportional investments were recognized. The 'Year' column served as the key temporal dimension.

3. Python Libraries
    The following libraries were utilized:
    - pandas: This library was deemed indispensable for advanced data manipulation and analytical tasks.
    - matplotlib.pyplot: A versatile visualization toolkit was employed, enabling the generation of illustrative bar charts.

4. Data Preprocessing
    - Percentage columns underwent cleansing by removing the '%' symbol and converting them into floating-point numbers.
    - Columns were grouped into 'columns' (absolute values) and 'columns_percentage' (relative values) for visualization.

5. Visualization
    Two stacked bar charts were created:
    - Absolute Investments: Investments from 2015 to 2023 were displayed with distinct colors from a color dictionary. Data labels were added to 'Fossil energy' and 'Renewable power.'

- Relative Investments: Percentage investments were showcased with consistent colors. Labels were affixed to 'Fossil energy %' and 'Renewable power %'.

After undergoing processing with Python, two Bar Charts are generated for “Global Investment in Energy Sources”.

4.6.1.2 Global Sustainable Debt Issuance (2016-2022)

The second dataset delves into the realm of sustainable debt issuance from 2016 to 2022. By detailing the sources of funding—from corporates to sovereign entities—it unveils the multifaceted channels through which sustainable energy projects receive backing.

For SDG Indicator 7.A.1, the selected dataset from the IEA becomes particularly salient because:

- Diverse Funding Sources: Recognizing the diversity of funding sources, from sovereigns to supranational, provides a comprehensive view of global engagement and commitment towards clean energy projects. Such diverse investments indicate a universal consensus and shared responsibility towards a sustainable energy future.

- Sustainability Focus: The very term "sustainable debt issuance" underlines that the financing isn't just about debt but about sustainable goals. It is an indicator of the global financial sector's alignment with long-term environmental and socio-economic objectives encapsulated in the SDGs.

In summary, these datasets from the IEA, with their detailed categories and broad coverage, serve as invaluable tools for assessing the progress made towards SDG Indicator 7.A.1. Through them, one can gauge not just the quantum of investments but also the global intent and commitment towards a sustainable energy future.

The following steps outline the analysis process:

1. Data Extraction: In the realm of sustainable finance, understanding debt issuance patterns is pivotal. This section delineates the methodology employed to visualize the trajectory of sustainable debt issuance from 2016 to 2022. To ingest the dataset from the CSV file, the pandas library was employed.

2. Feature-Target Definition: To enhance the clarity and usability of the dataset, several steps were taken. First, the aggregate row marked "Total" was removed, ensuring that the focus remained on individual issuance categories. Additionally, the initial column was renamed as 'Category' to improve its interpretability.
3. Python Libraries: to achieve the objectives of the research, various Python libraries were employed. The pandas library served as a crucial foundation for data manipulation and analysis. Meanwhile, matplotlib was utilized as a proficient resource for designing both static and interactive visualizations. Finally, numpy was employed as a linchpin for executing mathematical computations on arrays.

4. Data Processing: The preprocessing of the dataset involved a series of methodical steps. Firstly, the dataset was meticulously rearranged according to a predetermined category nomenclature. Following this, the data matrix underwent a transformation, positioning years as row indices and setting issuance categories as columns. To further refine the dataset, indices that represented years were converted to integer types. One of the salient features of this preprocessing was the computation of relative percentages for the year 2022 data, which subsequently provided insightful annotations for the bar chart.

5. Visualization: The culmination of the research was captured in its visual representations. A bar chart was crafted, offering insights into sustainable debt issuance across different years, with each category represented in unique colors. Notably, the 2022 data segment was enriched with percentage annotations, providing a clearer perspective. In parallel, a donut chart was designed, offering a concise overview of the sustainable debt issuer landscape for the year 2022. Each sector within this chart was distinctly colored and labeled for instant recognition. To ensure a seamless viewing experience, the plot_charts() function was employed, adeptly integrating and presenting both charts. For enthusiasts and further inquiries, the origins of the dataset and the specific Python code for the charts can be referenced in Appendix 7.

After being processed with Python, a Bar Chart and a Donut Chart are generated for “Global Sustainable Debt Issuance”.

4.6.2 Forecast

The forecast is not provided for SDG Indicator 7.A.1 as the data deemed appropriate for this purpose is not currently available.

The Python program corresponding to section 4.6 is provided in Appendix 8.

4.7 SDG Indicator 7.B.1

4.7.1 Historical Data Analysis

The SDG Indicator 7.B.1 is analyzed through a multifaceted approach. A benchmark is established by comparing the installed renewable energy capacity in what is designated as "Developing Countries" against countries of the OECD and the global average. It should be noted that a universal definition for "Developing Countries" is not provided. Therefore, data from "Low-Income countries" and "Low-Middle-Income countries", based on the World Bank classification, are aggregated, and utilized as a proxy for "Developing Countries" in this examination. Detailed criteria for this income classification are provided in Section 3.1, and a comprehensive list of countries categorized as "Developing Countries" is included in Appendix 2.

The IEA and World Bank data have been integrated to provide a comprehensive understanding of renewable energy access and its intricacies. The IEA dataset offers information on installed renewable energy capacity by economy group, while the World Bank dataset provides population statistics, enabling a more nuanced analysis than simple aggregate comparisons. Through the utilization of these datasets, two objectives are achieved: firstly, to offer a comprehensive perspective on the progress of Developing Countries in relation to SDG Indicator 7.B.1, comparing their advancements to those of Developed Countries and the global average; and secondly, to conduct per capita analyses that account for demographic variations. By merging the renewable energy capacity data from the IEA with population figures from the World Bank, per capita renewable energy access is computed. This method facilitates fairer comparisons among diverse economic groups and delves deeper into individual-level renewable energy access, shedding light on the effectiveness of relevant policies.

This comprehensive analysis of SDG Indicator 7.B.1, utilizing the chosen datasets and methodology, is intended to provide a thorough examination of renewable energy access in Developing Countries in relation to OECD nations and the global average. By employing both aggregate and per capita metrics, valuable insights into the intricate and complex nature of renewable energy access are revealed, offering guidance for the development of effective policy directions aimed at improving renewable energy access in Developing Countries.

The following steps provide a framework for conducting a comprehensive analysis.

1. Data Extraction: The process commences with the extraction of data from a CSV file utilizing the pandas library. The dataset is then subjected to transposition to enable easy extraction of columns as series suitable for plotting. The extraction of features such as world population, OECD population, and installed renewable capacity, followed by their conversion to suitable units, is crucial for comprehensive analysis.
2. Feature-Target Definition: The dataset comprises an array of features, including World Population, Developing Country Population, OECD Population, Installed Renewable Capacity (measured in

MW), and kW per Capita, which play a crucial role in crafting the various charts and discerning the intricate trends in population growth and the development of renewable energy capacity.

3. Python Libraries: To facilitate analysis and visualization, certain Python libraries are employed, notably pandas for its efficiency in data manipulation and analysis, and matplotlib.pyplot for its expertise in plotting the charts to present the data in a visually appealing and comprehensible manner.

4. Data Preprocessing: Before analyzing the data, it undergoes a series of preprocessing steps to enhance clarity and relevance. These steps include converting population figures from individual counts to billions, adjusting the renewable capacity from MW to billions of MW, and transforming percentages into float values. Additionally, the charts are formatted with custom annotations to highlight the latest data points, ensuring up-to-date insights are easily discernible.

5. Visualization: The Python code serves as a powerful tool for generating informative visual representations from the dataset. By integrating the steps of data extraction, transformation, and plotting, it produces six distinct charts that offer unique perspectives on the evolution of population and renewable energy capacity from 2000 to 2022.

After undergoing processing with Python, six Line Charts are generated for further analysis:

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- World, Developing Country, and OECD Population (2000-2022): This line chart visualizes the population growth in billions across the world, developing countries, and OECD countries. Each line represents a different group, and the latest data points are annotated.

- Developing Country and OECD Population as % of World Population (2000-2022): This line chart represents the population of developing countries and OECD countries as a percentage of the world population over the years. The Y-axis is formatted to show percentages up to two decimal points.

- World, OECD, and Developing Country Renewable MW (2000-2022): This chart displays the installed renewable energy capacity in MegaWatts (MW) across the world, OECD, and developing countries. Data are converted to billions for easy interpretation.

- World, OECD, and Developing Country kW per Capita (2000-2022): This line chart shows the per capita installed renewable energy capacity in kiloWatts (kW) for the world, OECD countries, and developing countries.
- OECD and Developing Country Renewable MW as % of World Renewable MW (2000-2022): This chart shows the renewable energy capacity of OECD and developing countries as a percentage of the world's renewable energy capacity. The Y-axis shows percentages.

- Developing Country kW per Capita as a Percentage of World and OECD kW per Capita (2000-2022): This chart visualizes the per capita installed renewable energy capacity of developing countries as a percentage of the world and OECD countries.

4.7.2 Forecast

The forecast is not provided for SDG Indicator 7.B.1 as the data deemed appropriate for this purpose is not currently available.

The Python program corresponding to section 4.7 is provided in Appendix 9.

CHAPTER 5

RESULTS AND DISCUSSION

Preamble

In this chapter, a deep exploration of the analytical findings, which have been drawn from the comprehensive framework presented in Chapter 3 and the detailed methodology outlined in Chapter 4, is undertaken. The goal is not merely to have the data presented, but for insightful analysis to be offered, in-depth discussions to be fostered, and informed forecasts to be made. All these efforts are directed towards a better understanding of SDG 7 and its wider implications being achieved.

To enhance the accessibility and interpretability of the analytical findings, a diverse set of data visualization techniques is employed. Line charts, bar charts, heat maps, and donut charts are strategically chosen based on their appropriateness in conveying specific insights derived from the data analysis. Importantly, the data for these charts and the Python code utilized in the analyses are available on GitHub at this link: https://github.com/BlockQuant18/SU-PHD-TM.
Furthermore, when deemed appropriate, forecast results are presented in tabular form to complement the graphical analysis. These visualizations are instrumental in facilitating a more comprehensive understanding of the complex interplay among various SDG indicators.

For clarity and systematic presentation, the chapter is divided into two main sections.

In Section 5.1, an examination of GDP per capita trends is conducted. In this section, the economic landscape is thoroughly examined, with specific patterns and shifts in the GDP per capita data being spotlighted. By this section, a stage is set, ensuring that a backdrop for understanding the broader environment in which the SDGs function is provided.

In the subsequent sections, a focus is placed on the indicators related to SDG 7. A close look at each relevant indicator is taken, with an aim to reveal its various facets and its ties to the wider sustainable development goals.

Through this structured approach, it is ensured that the information is presented in a logical flow, making it easier for the rich tapestry of data and insights to be navigated by readers. By having the GDP per capita trends presented at the beginning, a foundation is laid, paving the way for a more detailed exploration of the SDG 7 indicators to be undertaken. Through this step-by-step progression, not only is clarity improved, but the relationship between economic factors and sustainable development goals is also highlighted.

5.1 GDP Per Capita

While GDP per capita data does not directly measure energy access or sustainability, it provides valuable insights for several reasons:

- Economic Perspective: GDP per capita, which represents the average economic output per person, is a widely recognized proxy for a country's standard of living. A higher GDP per capita generally suggests better access to basic services, including energy. Therefore, when reviewing SDG Target 7, which focuses on affordable and clean energy, it is essential to consider the economic context in which energy policies and initiatives are implemented.

- Interrelation with Energy Access: Economies with higher GDP per capita tend to have more developed infrastructure, which can influence the accessibility and reliability of energy sources. A country's capacity to generate, distribute, and effectively use energy often correlates with its GDP per capita, indicating a symbiotic relationship between economic prosperity and energy access.

- Energy Intensity of the Economy: By comparing GDP per capita data with energy consumption data, one can gain insights into the energy intensity of an economy. In essence, it indicates how much energy is used to produce a unit of economic output. This information provides crucial clues regarding the efficiency and sustainability of energy usage in different economies.

- Influencing Policy Decisions: Policymakers frequently utilize GDP per capita as a benchmark to allocate resources and establish developmental agendas. Comprehending the relationship between a nation's economic status and its energy goals can aid in the formulation of more focused and effective policies, particularly those aimed at expanding access to sustainable energy.

- Indirect Socio-Economic Indicators: GDP per capita can also shed light on other socio-economic factors such as education, health, and general well-being, which can have indirect implications on energy consumption patterns. For example, a well-educated population might be more inclined towards sustainable energy practices, thereby influencing the overall metrics related to SDG Target 7.

- Diversity in Energy Sources: Economically prosperous nations often have the means to invest in diverse energy sources. Exploring GDP per capita alongside SDG Target 7 indicators can reveal whether wealthier nations are actively diversifying their energy portfolio and investing in cleaner, more sustainable sources.

In conclusion, while GDP per capita does not directly measure energy access or sustainability, it offers a broader context that can enrich our understanding of a country's energy landscape. This context is critical when striving to achieve a comprehensive perspective on SDG Target 7 and its related indicators.

5.1.1 Results

The line chart (Chart 5.1) presented herein displays temporal fluctuations in GDP per capita for various income groups, with the aim of highlighting economic growth or decline. The heatmap (Chart 5.2) serves to depict the monetary values of GDP, facilitating the simultaneous comparison of diverse years and income groups.

Chart 5.1: GDP Per Capita Line Chart (1990-2022)

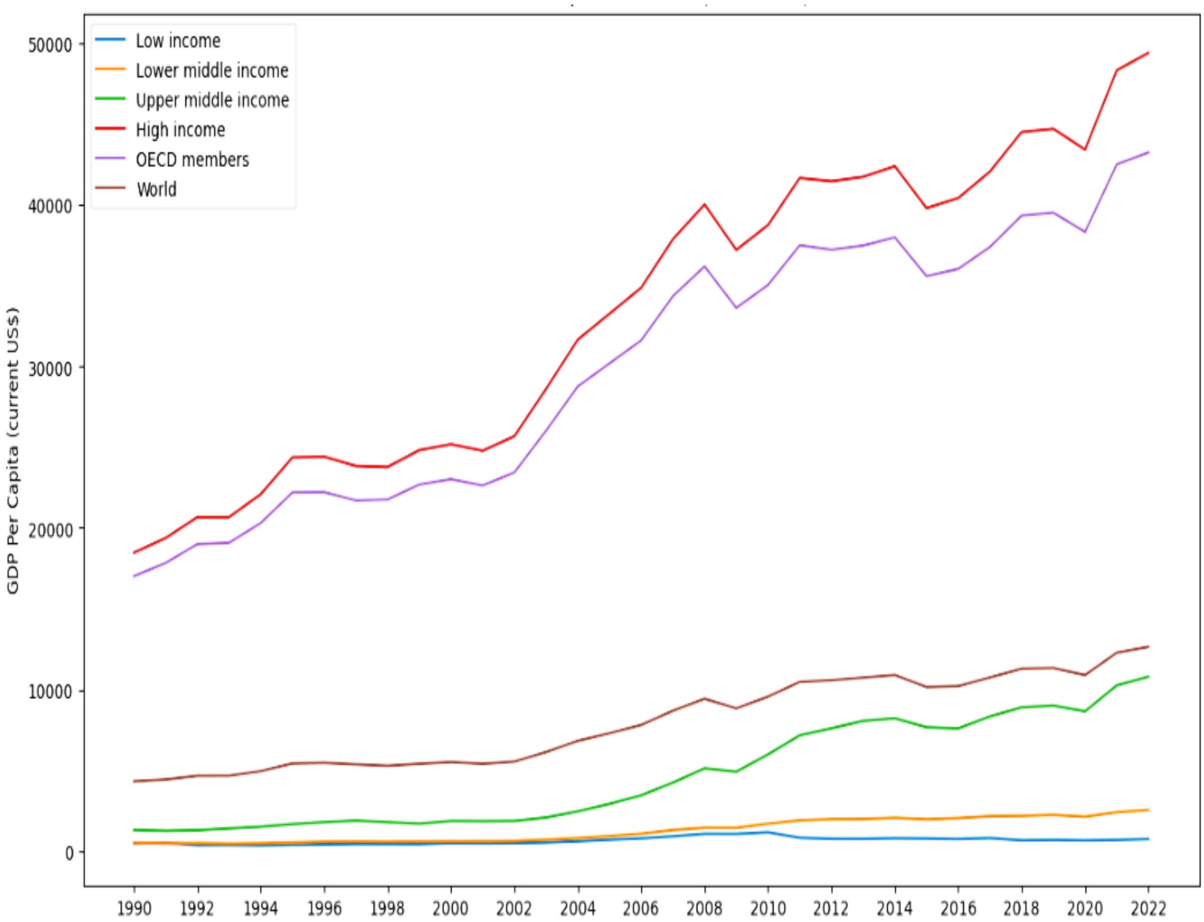
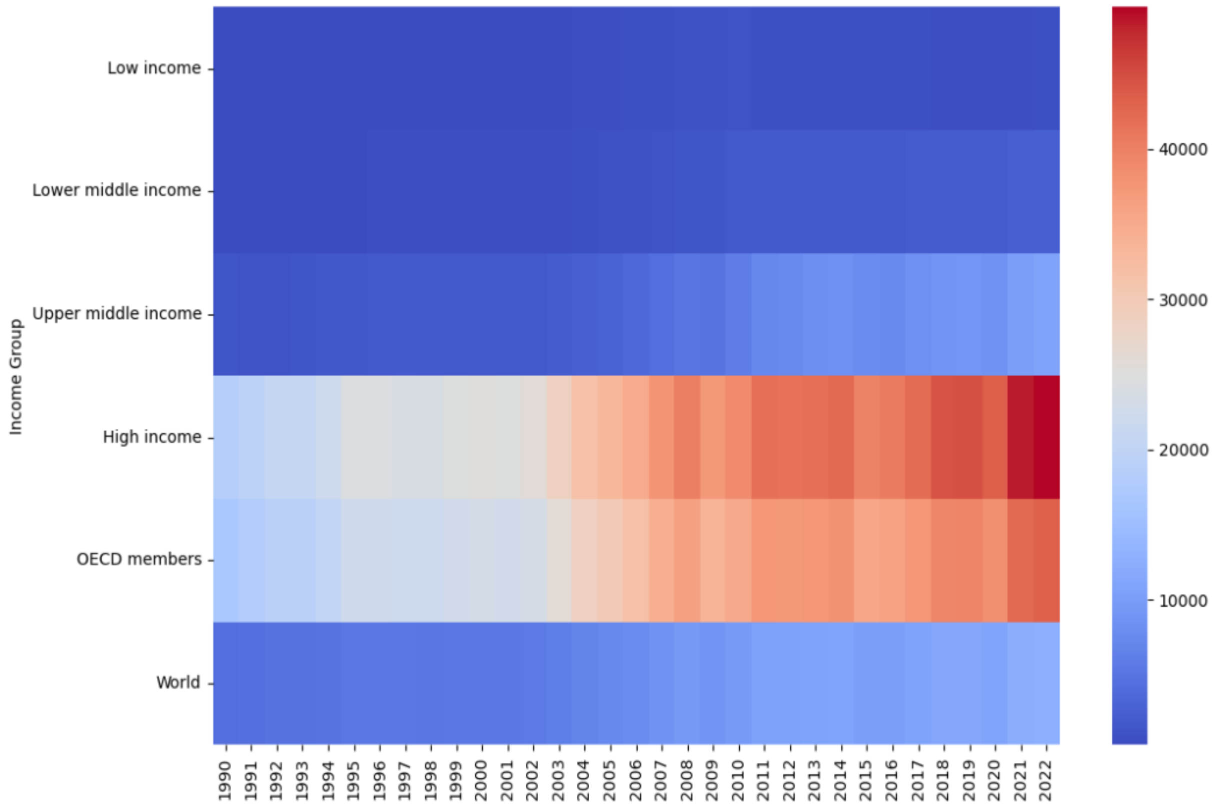


Chart 5.2: GDP Per Capita Heat Map (1990-2022)



The following points summarize the analysis results from Charts 5.1 and 5.2:

High Growth in Upper-Middle-Income Countries: Rapid economic expansion in Upper-Middle countries is linked to factors like aggressive economic reforms, substantial technology and infrastructure investments, and effective integration into the global economy. These elements underscore the success of these nations in advancing development and elevating their citizens' living standards.

Low-Income Countries Facing Challenges: The modest GDP per capita growth in Low-Income countries implies challenges such as economic volatility, infrastructure gaps, or restrictive policies. This highlights the ongoing need for development support, economic restructuring, and growth-promoting strategies in these regions.

Consistent Growth in High-Income and OECD Countries: Despite starting with a substantial GDP per capita base in 1990, High-Income and OECD countries have managed consistent growth, albeit more gradual.

Convergence Trends: The faster growth in Upper-Middle-Income countries compared to High-Income countries indicates a possible narrowing of income disparities if current trends continue.
Global Improvement in Living Standards: A notable rise in the World GDP per capita from 1990 to 2022 shows an overall enhancement in global living standards.

It's crucial to note that while GDP per capita is a valuable metric for assessing economic performance and living standards, it doesn't encompass other critical aspects of economic health, like income disparities or ecological viability.

The Python program corresponding to Charts 5.1 and 5.2 is provided in Appendix 3.

5.1.2 Discussion

A comparative analysis of the GDP per capita from 1990 to 2022 for specified groups reveals the following insights:

- Low-Income: The GDP per capita has experienced a moderate increase from $461.12 in 1990 to $741.24 in 2022, with an average annual growth rate of 1.49% and a total growth of 60.75% over the period.

- Lower-Middle-Income: This group has seen a considerable increase in GDP per capita, growing from $514.02 in 1990 to $2542.20 in 2022. The average annual growth rate stands at 5.12%, and the total growth reached 394.57%.

- Upper-Middle-Income: These countries have experienced the most significant growth in GDP per capita, rising from $1304.73 in 1990 to $10794.93 in 2022. The average annual growth rate is 6.83%, and the total growth during this period is 727.37%.

- High-Income: High-income countries have seen a steady growth in GDP per capita, increasing from $18476.89 in 1990 to $49430.33 in 2022. The average annual growth rate is 3.12%, and the total growth over this period is 167.53%.

- OECD: The GDP per capita of OECD countries has grown from $17019.74 in 1990 to $43260.70 in 2022, with an average annual growth rate of 2.96% and total growth of 154.18%.

- World: The world's GDP per capita has seen a significant increase, growing from $4318.91 in 1990 to $12647.48 in 2022. The average annual growth rate is 3.41%, and the total growth during this period is 192.84%.

5.1.3 Forecast

Various ML algorithms can be employed for time-series forecasting, each with its own set of advantages and drawbacks:

- Linear Regression (LR): A simple yet effective algorithm for making numerical predictions. It assumes a linear relationship between the input and output variables.

- Random Forest (RF): An ensemble learning algorithm that leverages multiple decision trees for prediction, offering higher accuracy and robustness.

- Gradient Boosting Machines (GBM): Another ensemble method that builds trees sequentially, each one correcting the errors of its predecessor.

- Long Short-Term Memory Networks (LSTM): A type of recurrent neural network designed to remember past information, making it suitable for sequence prediction tasks.

- Recurrent Neural Networks (RNN): A neural network architecture designed for sequence prediction but often less effective at capturing long-term dependencies compared to LSTM.

Given the characteristics of the dataset and specifics of this analysis, RF and GBM were selected for several compelling reasons:

- Data Sparsity: The dataset under examination is relatively small, comprising 33 years of data for each income group. Random Forest and GBM can generate robust predictions from such limited datasets.

- Interpretability: Both Random Forest and GBM offer insights into feature importance, thereby allowing for a more nuanced understanding of how the years influence GDP per capita—a crucial asset in the academic context.

- Computational Efficiency: These algorithms are computationally less demanding than LSTM and RNN, providing quicker results without the need for extensive computational resources.

- Resilience to Data Irregularities: Economic datasets often come with outliers or missing values, which these algorithms can handle effectively.

5.1.4 Forecast Results

RF: The model projects a decline in GDP per capita for all groups. For instance, the Low-Income group shows a 2.65% decrease for 2023, indicating potential economic contraction.

Chart 5.3: GDP Per Capita Forecast for 2023 (RF)

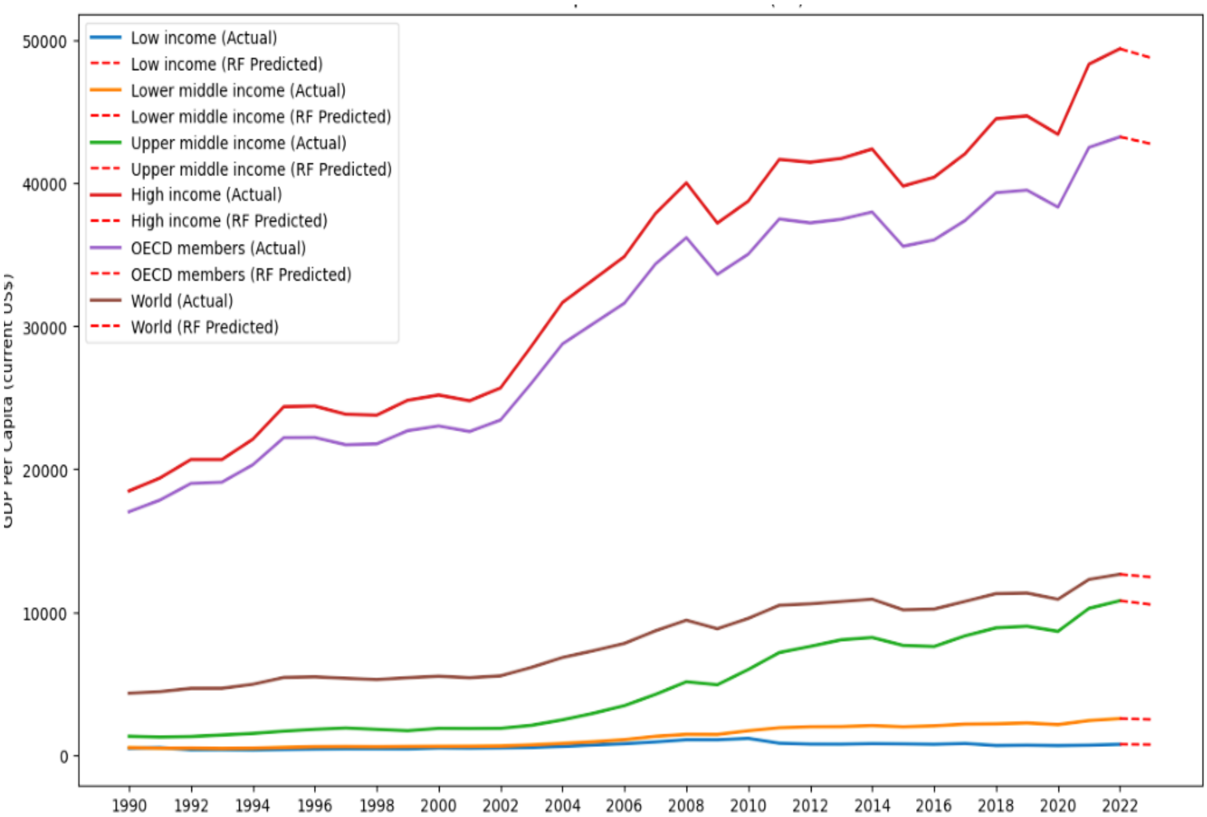


Table 5.1: Predicted GDP Per Capita Value for 2023 (RF)

RF Predicted Value 2023		
	2023 Predicted	% Change
Low-Income	721.62	-2.65
Lower-Middle-Income	2482.95	-2.33
Upper-Middle-Income	10524.60	-2.5
High-Income	48792.64	-1.29
OECD Members	42779.38	-1.11
World	12450.88	-1.55

GBM: This model's projections closely align with those of the RF. The World category, for instance, is also forecasted to experience a marginal 0.07% decrease in GDP per capita for 2023.

Chart 5.4: GDP Per Capita Forecast for 2023 (GBM)

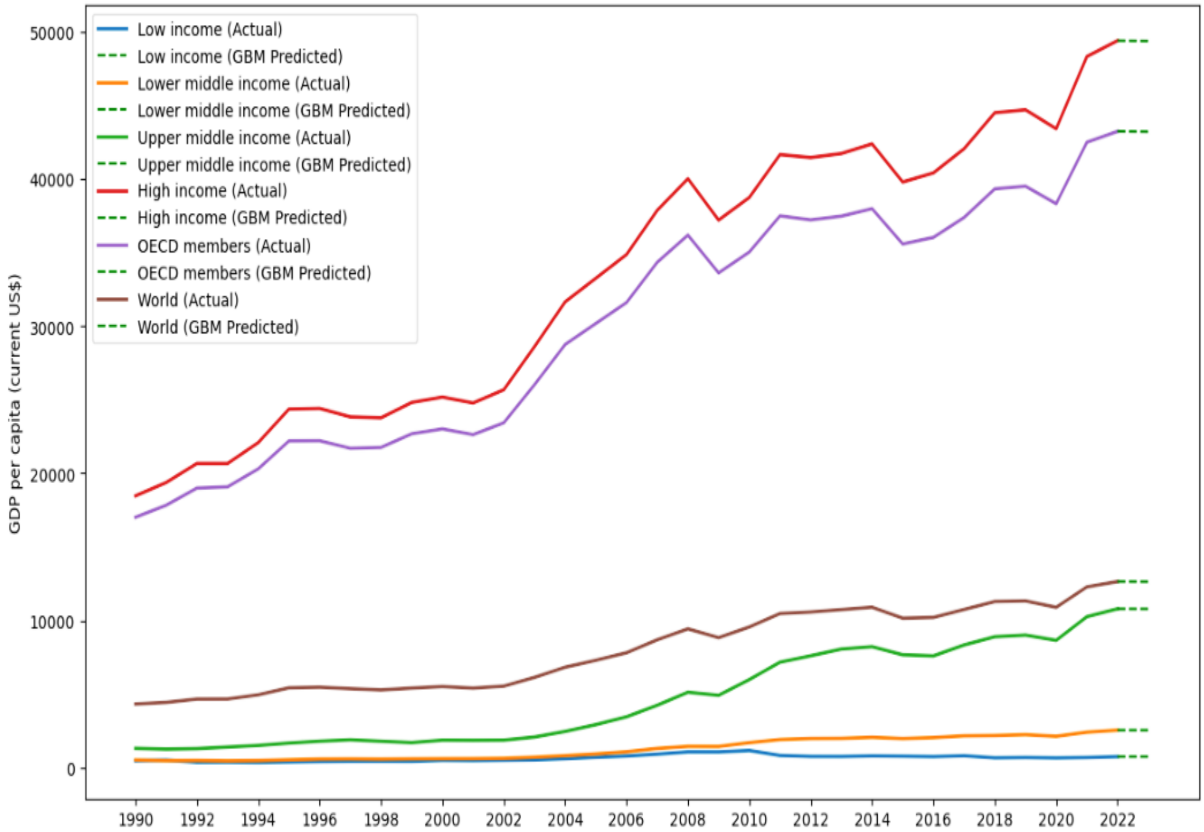


Table 5.2 Predicted GDP Per Capita Value for 2023 (GBM)

GBM Predicted Value 2023		
	2023 Predicted	% Change
Low-Income	739.82	-0.19
Lower-Middle-Income	2541.37	-0.03
Upper-Middle-Income	10789.78	-0.05
High-Income	49406.62	-0.05
OECD Members	43239.26	-0.05
World	12638.46	-0.07

The Python program corresponding to Charts 5.3 and 5.4 and Tables 5.1 and 5.2 are provided in Appendix 3.

5.1.5 Forecast Discussions

The predicted decline in GDP per capita for the year 2023 across various income groups, as projected by both RF and GBM models, could have serious implications for SDG 7. This goal aims to ensure access to affordable, reliable, sustainable, and modern energy for all. A decreasing GDP per capita generally signifies less available financial resources at both the national and individual levels, and this can have ripple effects on investments in sustainable energy solutions.

- **Low-Income Countries:** For low-income countries, the model's projection of a 2.65% decrease in GDP per capita is particularly concerning. These countries already face considerable challenges such as economic instability, infrastructural deficiencies, and policy constraints. A decline in GDP per capita is likely to exacerbate these challenges and could make the attainment of SDG 7 even more elusive. This might lead to reduced investments in green technologies and sustainable energy projects, and potentially even a reversion to cheaper but less environmentally friendly energy sources to meet immediate needs. Consequently, developmental aid strategies and economic reforms targeted at these nations may need to be urgently revisited to ensure that they do not fall further behind in achieving SDG 7.

- **Upper-Middle-Income and High-Income Countries:** For Upper-Middle-Income and High-Income countries, the decline in GDP per capita could slow down the pace of transition to renewable energy sources. These countries usually have the financial capacity and technological infrastructure to invest in more sustainable energy solutions. However, a declining GDP could shift focus towards maintaining economic stability rather than making long-term investments in sustainability. This might also disrupt the trend of economic convergence between Upper-Middle and High-Income countries, as both groups might focus more on short-term economic gains rather than sustainable growth.

- **Global Repercussions:** Globally, a marginal 0.07% decrease in GDP per capita is forecasted for 2023, which, although seemingly small, could signify a critical tipping point. The past decades have seen improvements in global living standards and a transition to cleaner energy sources, but a decline, however marginal, could stall or even reverse this progress.

- **Policy Considerations:** These economic forecasts suggest that policymakers globally may need to re-strategize to ensure that economic setbacks do not derail efforts towards achieving SDG 7. Fiscal policies might need to be adjusted to continue incentivizing investments in renewable energy projects. Additionally, international collaboration and development aid could become even more vital in ensuring that the global community stays on track to meet the ambitious targets set out in SDG 7.

To sum up, the projected decrease in GDP per capita in 2023 poses substantial challenges for achieving SDG 7, necessitating immediate strategy revisions at both national and international levels, particularly within the energy sector.

5.2 SDG Indicator 7.1.1

5.2.1 Results

Indicator 7.1.1, "Access to Electricity," is an essential metric designed to measure the extent to which populations within different regions and income categories have access to electricity services. This indicator underscores the significance of electricity as a fundamental enabler of development, impacting various aspects of human well-being, education, healthcare, and economic productivity. It seeks to capture the percentage of households, communities, and individuals that are connected to the electrical grid or have access to off-grid renewable energy sources. A higher percentage indicates a greater level of progress in achieving universal access to modern energy, in line with the overarching SDG 7.1 target.

The Python program corresponding to section Charts 5.5, 5.6 and 5.7 is provided in Appendix 4.

Chart 5.5: Access to Electricity in Urban Areas Line Chart (2000-2021)

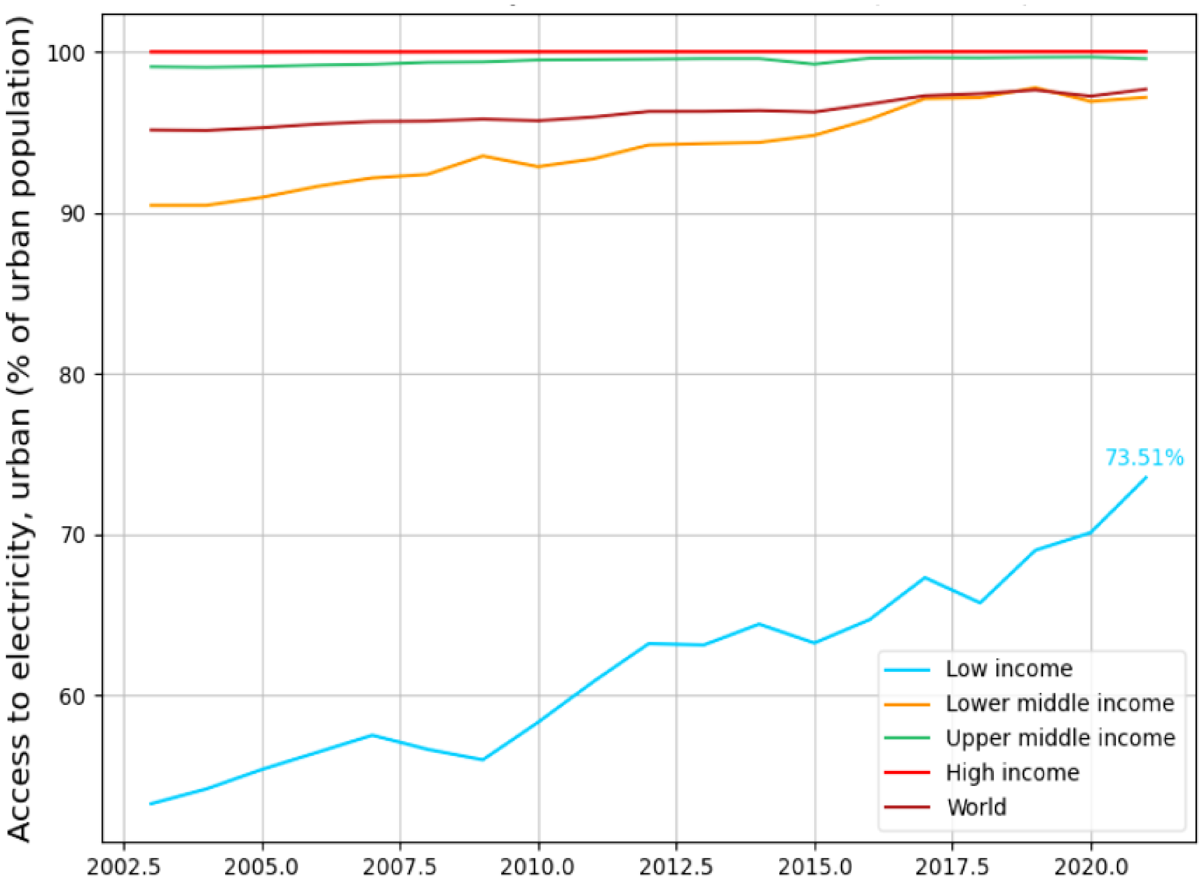


Chart 5.6: Access to Electricity in Rural Area Line Chart (2000-2021)

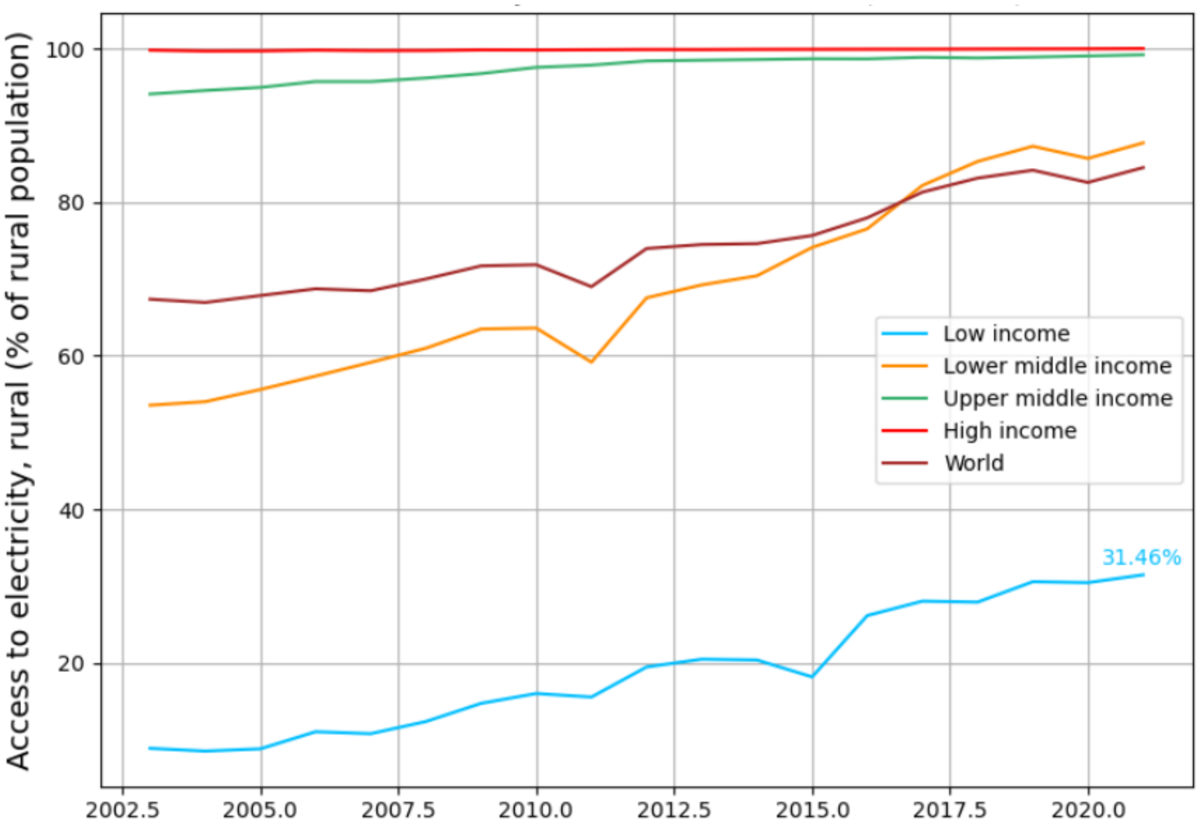
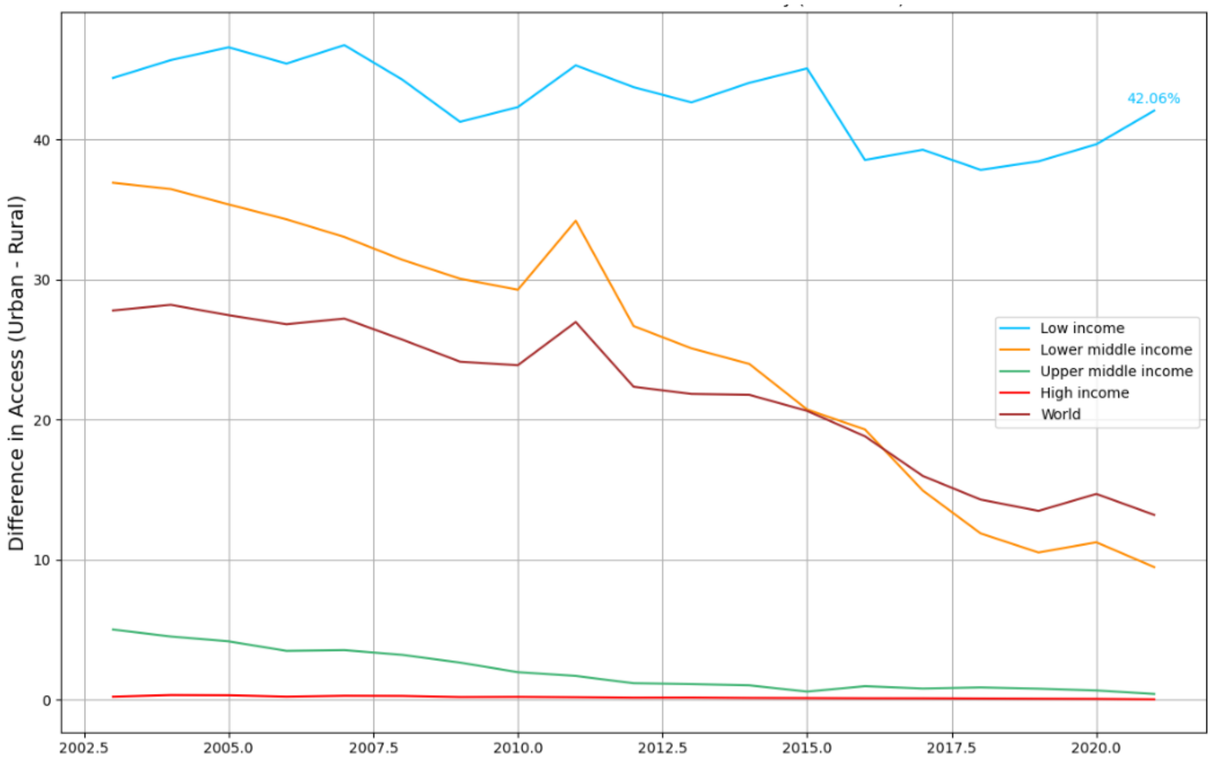


Chart 5.7: Difference in Urban and Rual Access to Electricity (2000-2021)



5.2.2 Discussions

Charts 5.5 and 5.6 present the availability of electricity in urban and rural settings from 2000 to 2021. Chart 5.5 displays the access to electricity for various economic groups in urban areas, while Chart 5.6 does the same for rural populations. The two charts are related in that they highlight the disparities in electricity access between urban and rural areas. Urban regions, due to their dense populations and infrastructure, often have better access to electricity. On the other hand, rural areas, particularly in low-income countries, face challenges due to their remote locations and lack of infrastructure.

Chart 5.7 provides a visual representation of the difference in electricity access between urban and rural areas over time. This was achieved by subtracting the percentage of the rural population with access to electricity from the percentage of the urban population with access to electricity. The purpose of this chart is to emphasize the disparities in electricity access between urban and rural areas, and to provide a direct visual representation of the gap over the years.

5.2.3 Forecast Results

The data available extends only up to the year 2021, and as a result, forecasts for the year 2022 were made using the five ML algorithms outlined in section 5.1.3. Given the dataset's specific characteristics, the LR, RF and GB algorithms have been selected for the prediction of values in the year 2023. The forecast results are summarized in Table 5.3:

Table 5.3: Predicted Access to Electricity in Urban and Rural Areas for 2023

Predicted Value 2022 (% Urban Population)				
	Actual(2021)	LR(2022)	RF(2022)	GBM(2022)
Low-Income	73.51	71.87	72.21	73.51
Lower-Middle-Income	97.16	98.26	97.12	97.16
Upper-Middle-Income	99.57	99.76	99.6	99.57
High-Income	100	100	100	100
World	97.67	97.71	97.55	97.67
Predicted Value 2022 (% Rural Population)				
	Actual(2021)	LR(2022)	RF(2022)	GBM(2022)
Low-Income	31.46	32.92	31.04	31.45
Lower-Middle-Income	87.7	89.83	87.04	87.69
Upper-Middle-Income	99.16	100.23	99.1	99.16
High-Income	99.98	99.98	99.96	99.98
World	84.48	84.92	83.92	84.47

The Python program corresponding to Table 5.3 is provided in Appendix 4.

5.2.4 Forecast Discussion

- For the Low-Income group, predictions across all models indicate a modest rise in electricity accessibility for both urban and rural populations in 2022 when juxtaposed against the 2021 data.

- In the context of the Lower-Middle-Income category, there is a forecasted marginal increment in the percentage of urban dwellers with electricity access in 2022. A similar upward trend is also projected for their rural counterparts.

- For the Upper-Middle-Income group, the models suggest a slight enhancement in electricity accessibility for both urban and rural residents in the year 2022.

- When observing the High-Income category, it's evident that a vast majority of their population already enjoys electricity access. For 2022, the models anticipate this figure to either remain stable or experience a trivial surge.

- Lastly, from the World perspective, the forthcoming year is expected to witness a small increase in electricity access percentages for both urban and rural global populations.

5.3 SDG Indicator 7.1.2

5.3.1 Results

Indicator 7.1.2, "Access to Clean Fuels for Cooking," emphasizes the significance of clean and efficient cooking technologies for both health and environmental sustainability. This indicator measures the proportion of households that have replaced traditional biomass fuels with cleaner alternatives, reducing indoor air pollution and contributing to sustainable energy systems. The scope of this analysis encompasses all countries, rather than the select group of five analyzed in Indicator 7.1.1. Two Heatmaps were generated to showcase the availability of clean cooking fuels for both urban and rural populations.

5.3.2 Discussion

Chart 5.8: Urban Access to Clean Fuels and Technologies for Cooking (2021)

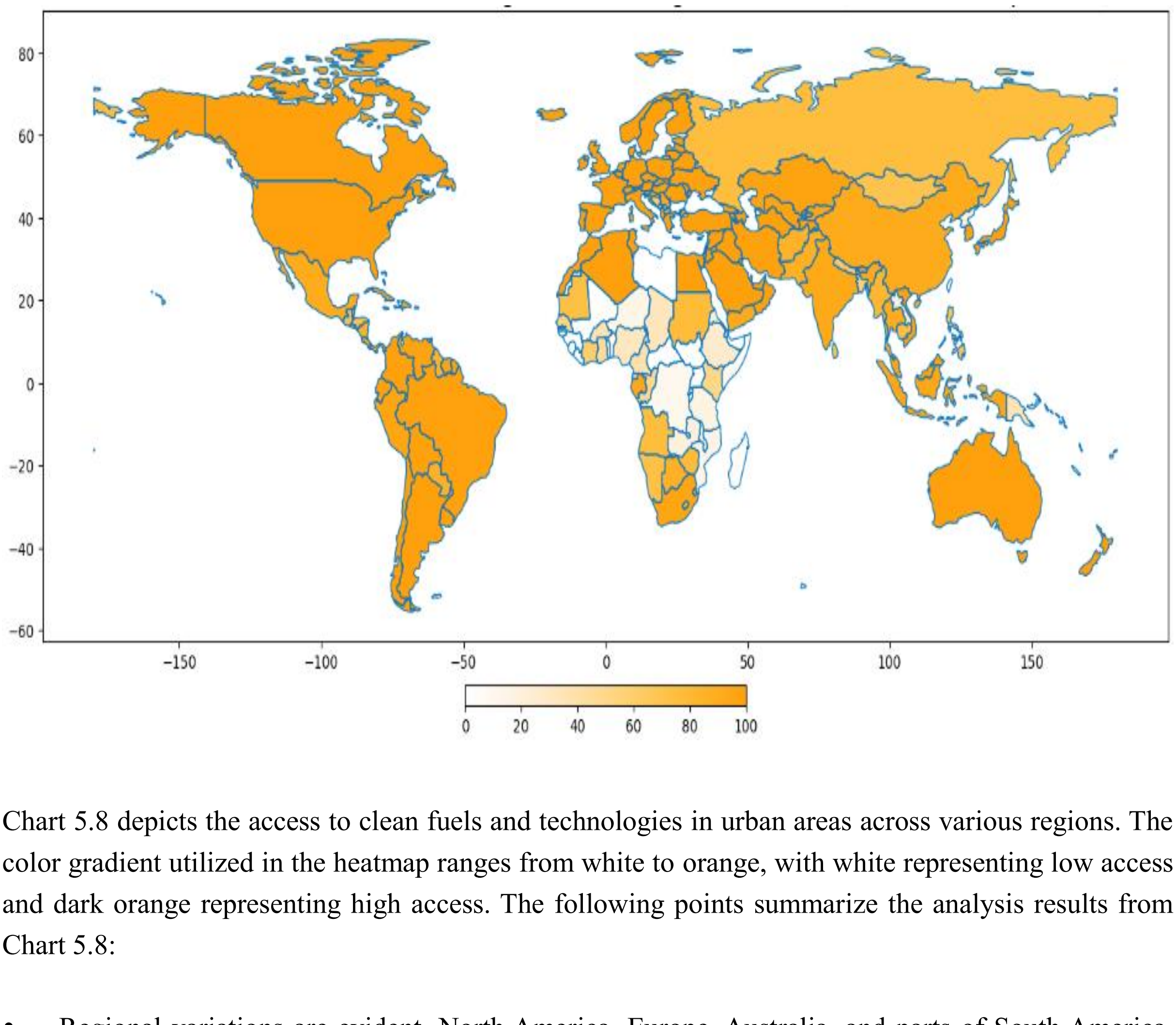


Chart 5.8 depicts the access to clean fuels and technologies in urban areas across various regions. The color gradient utilized in the heatmap ranges from white to orange, with white representing low access and dark orange representing high access. The following points summarize the analysis results from Chart 5.8:

- Regional variations are evident. North America, Europe, Australia, and parts of South America, such as Argentina and Brazil, exhibit a darker shade of orange, signifying high access to clean fuels and technologies in urban areas. In contrast, regions in Asia, like India and China, display a lighter shade of orange, indicating moderate access.

- Furthermore, parts of Africa, especially Central Africa, present a white or very light shade, suggesting low access to clean fuels and technologies in urban areas. Exceptions include South Africa and Egypt, which have higher access compared to their neighboring countries.

Chart 5.9 Rural Access to Clean Fuels and Technologies for Cooking (2021)

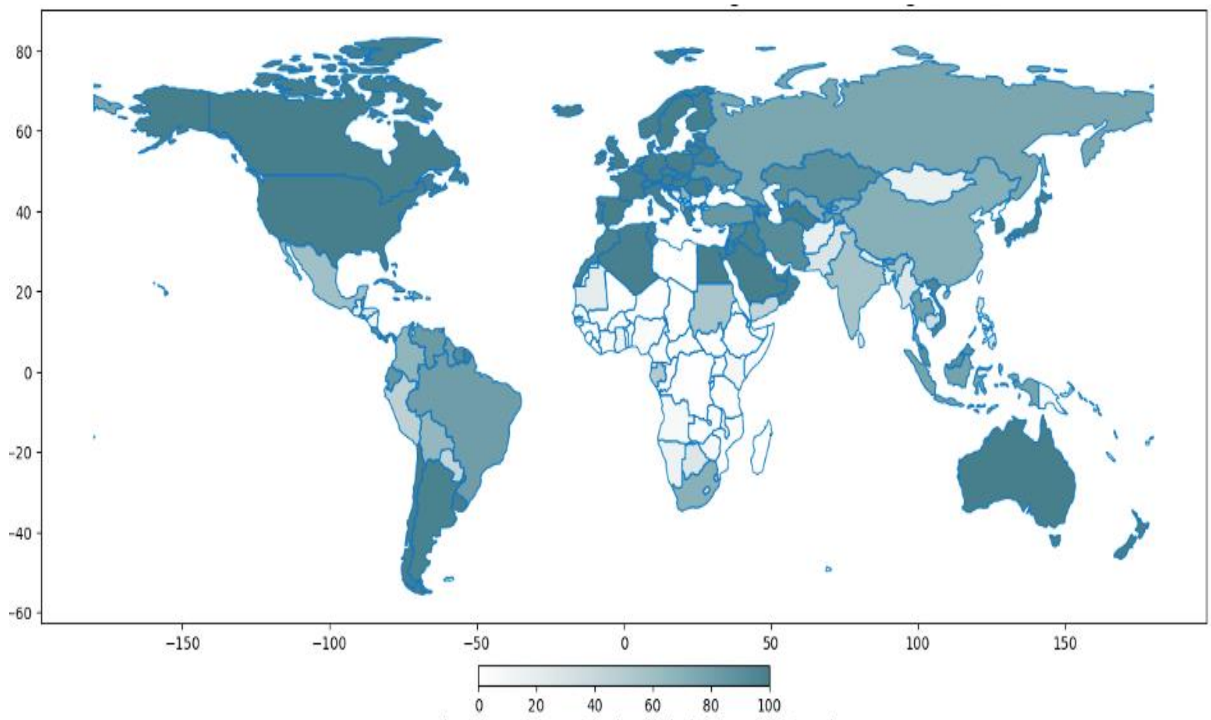


Chart 5.9 depicts the access to clean fuels and technologies in rural areas across various regions. The color gradient utilized in the heatmap ranges from white to blue, with white representing low access and dark blue representing high access. The following points summarize the analysis results from Chart 5.9:

- Countries with access percentages above 99.43% are classified as having High Access. Examples are Andorra, Australia, Belgium, Canada, Germany, Japan, Singapore, the United Kingdom, the United States, and others. Predominantly developed nations, these countries have ensured that a significant portion of their rural populations have access to clean fuels and technologies for cooking.

- Countries with access percentages between 28.11% and 99.43% are deemed to have Moderate Access. This group includes Albania, Argentina, Brazil, China, India, Mexico, Russia, South Africa, Turkey, and more. While they've made substantial progress, portions of their populations still lack full access.

- Countries with access percentages below 28.11% are categorized as having Low Access. This list comprises Afghanistan, Angola, Bangladesh, Burkina Faso, Haiti, Kenya, Madagascar, Nigeria, Uganda, Zambia, and others. Often grappling with challenges like economic constraints, infrastructural issues, or political instability, these countries have a large portion of their rural populations without access.

- Exceptions to these access levels exist. Some developed countries may display higher access levels than their economic status would suggest. In contrast, developing nations may have made significant strides to provide access to rural areas despite lower overall numbers. For instance, countries with vast territories and diverse terrains, such as China and India, could face distribution challenges, positioning them as moderate access nations. Similarly, nations classified as Low Access might be grappling with recent conflicts, natural calamities, or other disruptions that hindered their infrastructure.

The Python program corresponding to Charts 5.8 and 5.9 is provided in Appendix 5.

5.3.3 Forecast

The forecast is not provided for SDG Indicator 7.1.2 as the data deemed appropriate for this purpose is not currently available.

5.4 SDG Indicator 7.2.1

5.4.1 Results

SDG Target 7.2, which aims to increase the share of renewable energy in the global energy mix by 2030, highlights the necessity of transitioning from the current predominant fossil fuels to more sustainable sources such as wind, solar, and hydroelectric power.

SDG Indicator 7.2.1, also known as the "Renewable energy share in the total final energy consumption," serves as a crucial metric in measuring the world's energy consumption from renewable sources.

The data used in this analysis was sourced from The World Bank and covers the percentage of the population with access to electricity from renewable sources across various economic categories of countries, from 2000 to 2021. The countries in this dataset are categorized as 'High-Income', 'Higher-Middle-Income', 'Lower-Middle-Income', 'Low-Income', and overall averages for 'OECD Members' and the 'World'.

The intention behind this dataset is multifaceted:

- Comparative Analysis: Categorizing countries into economic groups allows for a comparative analysis between nations of similar economic stature. This assists in understanding disparities or commonalities in energy transition efforts.

- Trend Identification: Spanning over two decades, the data can be used to identify trends in the adoption of renewable electricity sources. This can highlight progress or stagnation in different economic groups over time.

- Policy Implications: By discerning which groups are lagging in renewable energy adoption, policymakers can tailor strategies to promote green energy in those specific areas.

The Line Chart (Chart 5.10), Heatmap (Chart 5.11) and Area Chart (Chart 5.12) have been selected for Indicator 7.2.1 to visually represent the data.

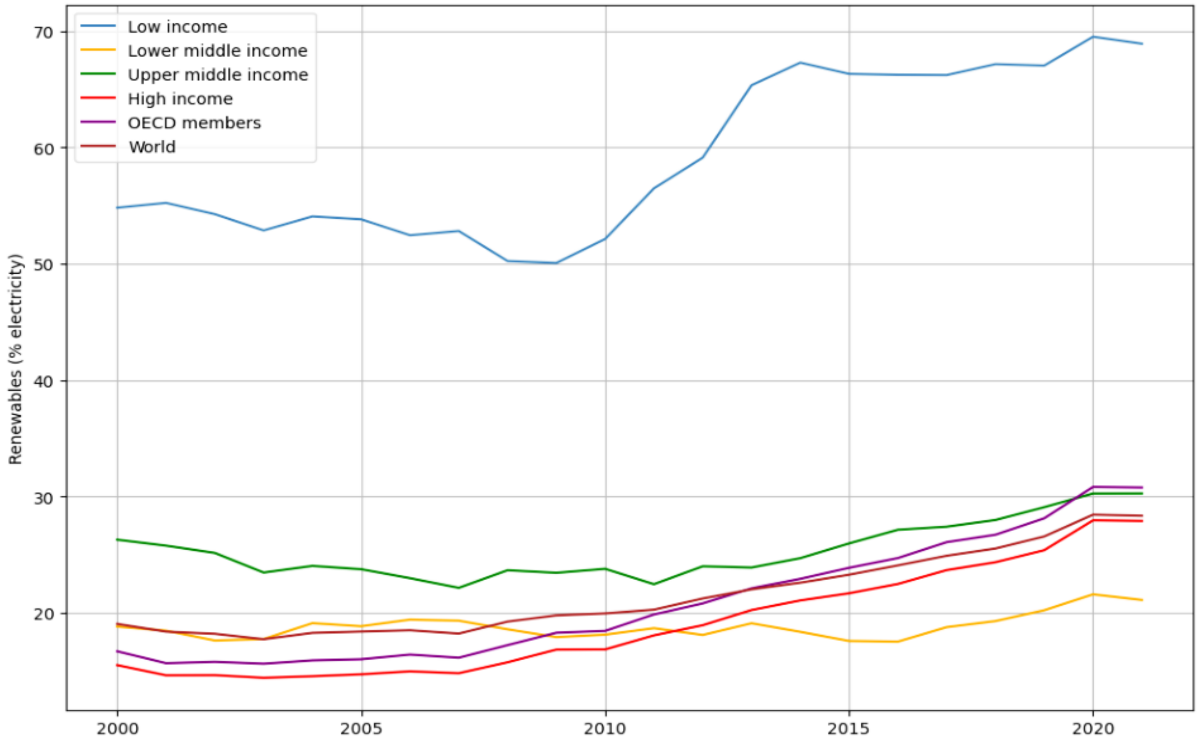
- Line Chart: Line charts are particularly effective for showcasing trends over time. They provide clarity on the trajectory of data points, making it easier to discern patterns, progressions, or regressions over the years.

- Heatmap: Heatmaps allow for a visual representation of data magnitude through color variations. They are ideal for comparing the relative strength of values across two categorical dimensions – in this case, years and economic categories. This aids in quickly spotting years or categories with particularly high or low renewable electricity percentages.

- Area Chart: Area charts emphasize the quantity beneath a line, representing the cumulative effect. In the context of this data, it visually communicates the magnitude of renewable electricity adoption for each economic category over time, while also allowing for comparisons between them.

5.4.2 Discussion

Chart 5.10: Renewable Energy Share in Total Installed Capacity Line Chart (2000-2021)



Based on a thorough examination of Chart 5.10, it is evident that the adoption patterns of renewable energy sources have evolved across various economic strata over the past two decades.

- High-Income Countries' Steady Advance: Nations within the high-income bracket have consistently demonstrated a growing affinity for renewable energy sources, with a sustained upward trajectory that underscores not only their financial capacity but also their societal and policy-driven commitment to a sustainable energy future.

- Low-Income Challenges: The 'Low-Income' segment depicts a more subdued growth curve. Although there are indications of renewable energy adoption, the pace is comparatively slow. This trend suggests inherent challenges, which may stem from infrastructural deficits, limited investments, or the lack of robust policy frameworks promoting green energy.

- Middle-Income Countries' Noteworthy Progress: Both the 'Lower-Middle-Income' and 'Upper-Middle-Income' groups have exhibited notable strides in renewable adoption. Intriguingly, the latter's growth almost parallels that of High-Income nations in recent years, reflecting their evolving priorities and capabilities in the renewable sector.

- OECD Members' Collaborative Excellence: Representing a consortium of 38 nations dedicated to global welfare and equality, the OECD Members showcase a pronounced surge in their renewable energy metrics. This underscores the potency of collaborative efforts and shared visions in expediting green energy adoption.

- Global Perspective: The 'World' aggregate demonstrates a consistent, albeit measured, upswing in renewable energy usage. While commendable, this positive momentum suggests that more aggressive global strategies may be required to achieve ambitious climate benchmarks.

Chart 5.11 is a Heatmap that aids in quickly identifying countries or categories with particularly high or low levels of renewable electricity percentages. The following can be inferred from Chart 5.11:

- A discernible upward shift in renewable energy adoption post-2010 signifies the global impetus towards green energy in the last decade.

- Both the 'High-Income' and 'OECD Members' groups consistently register higher renewable percentages, underscoring the leading role affluent economies play in green energy transitions.
- The more modest metrics from 'Low-Income' and 'Lower-Middle-Income' groups highlight the developmental and infrastructural challenges these economies face in fully embracing renewable energy.

- The 'World' category's gradual ascent in the renewable energy landscape is indicative of global commitment, but simultaneously emphasizes the scope for enhanced efforts.

Chart 5.11: Renewable Energy Share in Total Installed Capacity Heat Map (2000-2021)

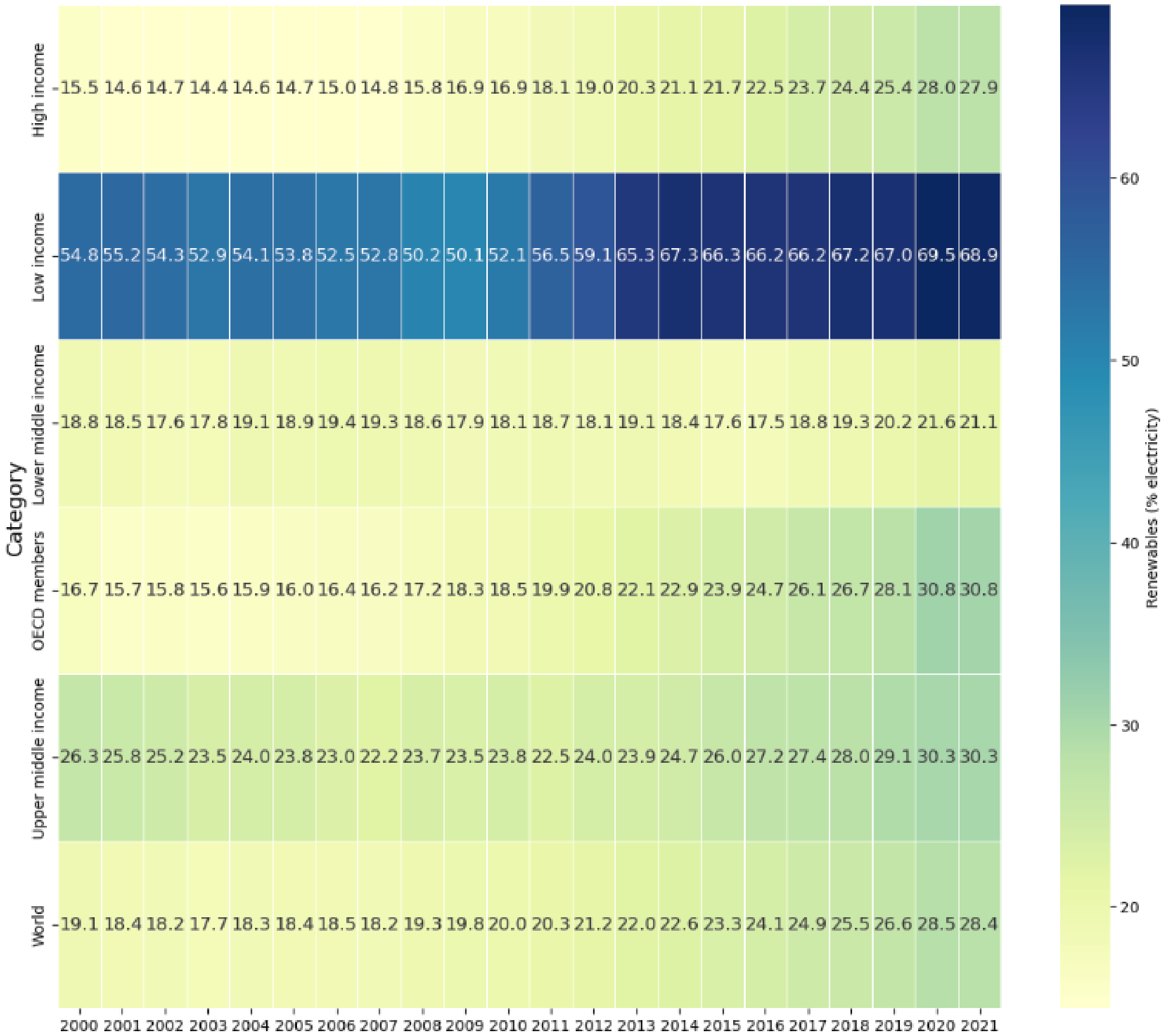


Chart 5.12 is an Area Chart that visually communicates the magnitude of renewable electricity adoption for each economic category over time. The following can be inferred from Chart 4.10:

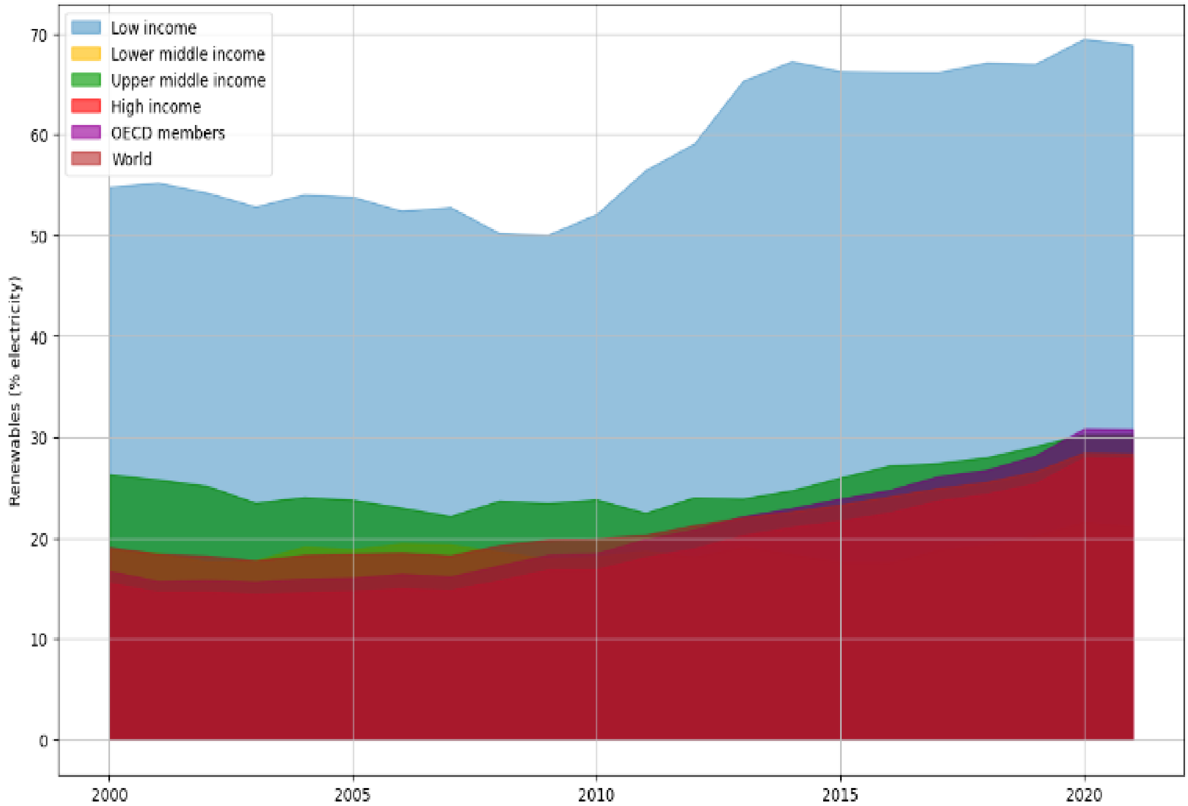
- Low-income countries have surged ahead, boasting a commendable 69% renewable energy fraction as of 2021, bucking conventional wisdom.

- Affluent countries, including High-Income and OECD Members, have a renewable energy fraction hovering around the 28-31% mark. This presents a conundrum given their technological and financial advantages.

- Middle-income countries, including Upper-Middle-Income and Lower-Middle-Income countries, echo High-Income and OECD Members with a 30% renewable share. Conversely, their lower middle income counterparts trail at 21%, indicating diverse challenges within the middle-income bracket.

- The global average, represented by the 'World' category, stands at 28% for renewable energy. This metric is a stark reminder of the disparities between individual economic brackets and the collective global effort.

Chart 5.12: Renewable Energy Share in Total Installed Capacity Area Chart (2000-2021)



The Python program corresponding to Charts 5.10, 5.11 and 5.12 is provided in Appendix 6.

5.4.3 Forecast Results

The data available extends only up to the year 2021, and as a result, forecasts for the year 2022 were made using the five ML algorithms outlined in section 5.1.3. Given the dataset's specific characteristics, the LR, RF, and GB algorithms have been selected for the prediction of values in the year 2022.

The forecast results that shown in Table 5.4 are summarized below:

Table 5.4: Predicted Renewable Energy Share in Total Installed Capacity for 2023

Predicted Value 2022 (%)				
	Actual(2021)	LR(2022)	RF(2022)	GBM(2022)
Low-Income	68.91	69.74	68.57	69.50
Lower-Middle-Income	21.12	19.41	20.96	21.59
Upper-Middle-Income	30.27	27.64	29.63	30.26
High-Income	27.91	26.36	26.83	27.96
OECD Members	30.78	29.11	29.60	30.83
World	28.36	26.92	27.58	28.45

5.4.4 Forecast Discussions

This section outlines the predicted renewable energy adoption percentages for various income groups and regions using three prediction models: LR, RF and GB. The percentages are compared to actual data from 2021 to understand potential trends.

- Low-Income:
  - LR Prediction (69.74%): Reflects a slight increase from the actual 2021 value (68.91%). This implies a continued growth in the use of renewable energy sources in low-income regions.
  - RF Prediction (68.57%): Reflects a minor decline from the 2021 actual value, implying a stabilization in the adoption of renewable energy.
  - GB Prediction (69.50%): Reflects an increase, consistent with the LR prediction, suggesting growth in renewables adoption.

- Lower-Middle-Income:
  - LR Prediction (19.41%): Indicates a significant drop from the 2021 value of 21.12%. This might be a cause of concern, suggesting reduced adoption of renewable energy.
  - RF Prediction (20.96%): Predicts a minor decline from 2021 but is more optimistic than the LR model.
  - GB Prediction (21.59%): Suggests a marginal increase from 2021, indicating stability or slight growth.
- Upper-Middle-Income:
  - LR Prediction (27.64%): Indicates a noticeable decline from 2021's 30.27%. Such a decrease

could be indicative of economic shifts or policy changes.
  - RF Prediction (29.63%): Suggests a moderate decline but is more optimistic than the LR model.
  - GB Prediction (30.26%): Almost matches the 2021 value, suggesting stability in renewable energy adoption.

- High-Income:
  - LR Prediction (26.36%): Indicates a moderate decline from 2021's 27.91%. This could reflect economic factors or evolving energy policies.
  - RF Prediction (26.83%): Suggests a slight decline from 2021 but is slightly more optimistic than the LR model.
  - GB Prediction (27.96%): Predicts a value slightly higher than the actual 2021 value, indicating potential growth.

- OECD Members:
  - LR Prediction (29.11%): Suggests a moderate decline from the 2021 value of 30.78%. This could reflect changes in energy policies among OECD members.
  - RF Prediction (29.60%): Also suggests a decline but is slightly more optimistic than the LR model.
  - GB Prediction (30.83%): Almost matches the 2021 value, indicating stability among OECD members.

- World:
  - LR Prediction (26.92%): Indicates a slight decrease from the actual 2021 value (28.36%).
  - RF Prediction (27.58%): Shows a minor decline from the actual 2021 value.
  - GB Prediction (28.45%): Almost matches the actual 2021 value.

The Python program corresponding to Table 5.4 is provided in Appendix 6.

5.5 SDG Indicator 7.3.1

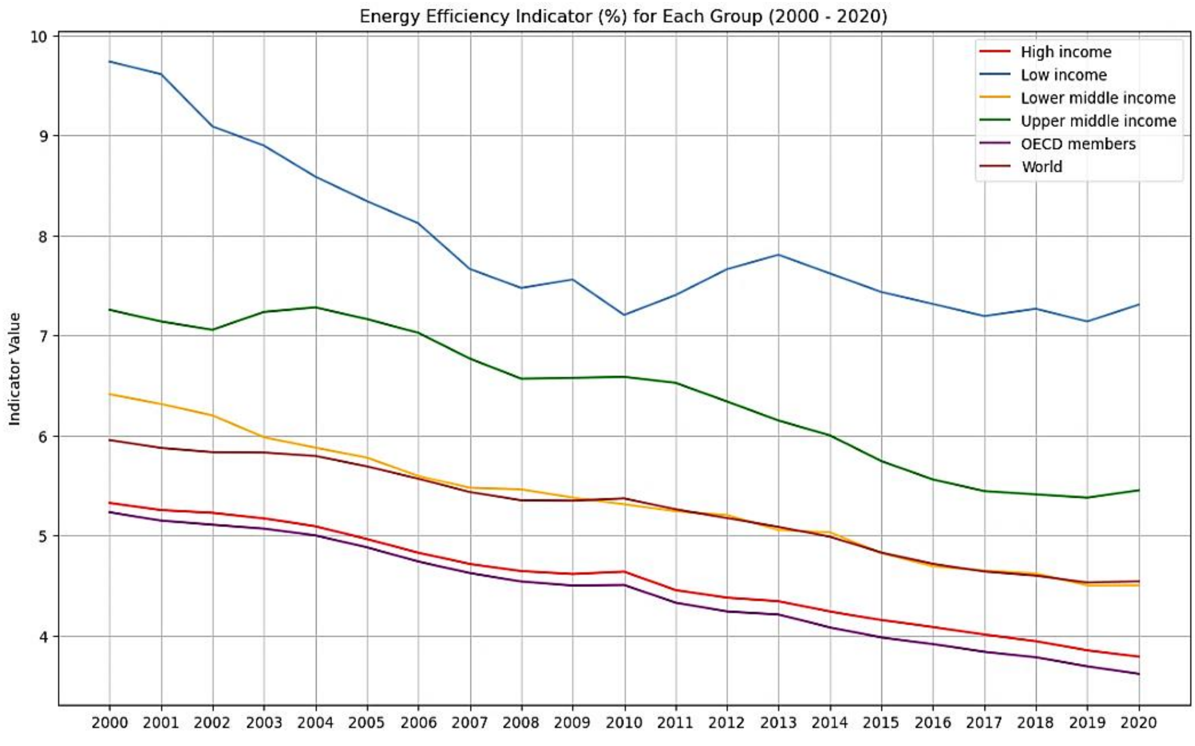
5.5.1 Results

SDG Target 7.3 plays a pivotal role in advancing energy sustainability, with the aim to "By 2030, double the global rate of improvement in energy efficiency." To monitor progress towards this objective, SDG Indicator 7.3.1, defined as the "Percentage of population with access to electricity," is employed. This target and its associated indicator epitomize the global effort to ensure that everyone benefits from the pursuit of an equitable and sustainable energy future.

However, to offer a broader perspective on energy efficiency, the World Bank dataset provides energy intensity indicators across various economic categories of countries from the years 2000 to 2020. Energy intensity denotes the energy required to produce a single unit of economic yield, with a lower value indicating superior energy efficiency. The dataset groups countries into categories such as 'High-Income', 'Upper-Middle-Income', 'Lower-Middle-Income', and 'Low-Income', also offering averages for 'OECD Members' and the 'World'. A Line Chart (Chart 5.13) depicts the trend of energy intensity over time, while an Area Chart (Chart 5.14) showcases the distribution of energy intensity across the different economic groups, offering insights into sustainability practices' progression.

5.5.2 Discussion

Chart 5.13: Energy Intensity Indicator Line Chart (2000-2020)



Analyzing Chart 5.13, the following trends for each entity are observed:

- Low-Income: A gradual decline in energy intensity, defined as the amount of energy needed to produce one unit of economic output, reflects a gradual increase in energy efficiency indicators, suggesting consistent yet cautious adoption of energy-efficient measures.
- Lower-Middle-Income: A more pronounced downward trajectory compared to Low-Income countries, indicating a more aggressive approach towards sustainability.
- Upper-Middle-Income: A steady decline with few fluctuations, highlighting their ongoing commitment to enhancing energy efficiency.
- High-Income: The most notable decline among all categories, reflecting advanced technologies and substantial investments in energy-efficient practices.
- OECD Members: A similar trend to High-Income countries, given that most OECD Members fall within this category.
- World: The global average shows a consistent downward trend, reinforcing the global emphasis on sustainable energy practices.

Chart 5.14: Energy Intensity Indicator Area Chart (2000-2020)

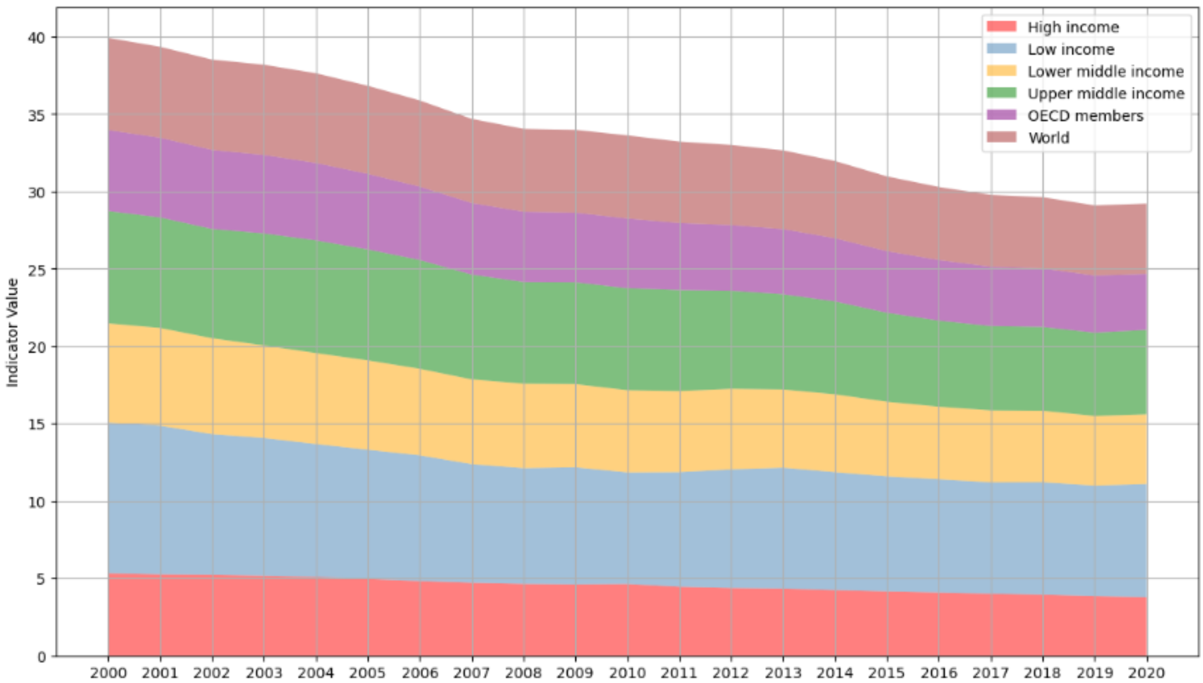


Chart 5.14 provides a comprehensive depiction of the cumulative contributions of each economic group to the global energy efficiency landscape:

- Low-Income: While the stacked area represents a smaller proportion, indicating their limited contribution to the global average, its consistent presence suggests steady efforts towards energy efficiency.

- Lower-Middle-Income: The significant portion reflects their growing emphasis on sustainable practices.

- Upper-Middle-Income: Their contribution has increased over time, in line with their economic growth and focus on sustainability.

- High-Income: Their low energy intensity, reflected in the chart, highlights their exemplary leadership in energy efficiency.

- OECD Members: The layered presence of OECD members signifies the collective efforts of member countries in driving global energy efficiency.

- World: The overall stacked area showcases the global progression and the combined efforts of all economic groups.

From Charts 5.13 and 5.14, the dynamics of energy efficiency across different economic groups provide profound insights into global sustainability efforts:

- Economic Disparities and Energy Efficiency: The disparity between High-Income and Low-Income countries in energy efficiency practices underscores the role of economic resources in adopting sustainable measures. Advanced economies have both the financial muscle and technological prowess to lead in this domain.

- Global Collaboration: The consistent downward trajectory of the global energy intensity average indicates collaborative efforts towards a more sustainable future. International treaties and agreements might be playing a role in steering this collective direction.

- Evolving Priorities in Developing Economies: The decline in energy intensity indicators for Lower- and Upper- Middle-Income countries signifies their evolving priorities. As these nations grow economically, their focus on sustainable and efficient energy practices becomes paramount.

In conclusion, while economic disparities play a role in the adoption of energy-efficient practices, the collective energy intensity downward trend is a testament to global awareness and commitment to a sustainable future.

The Python program corresponding to Charts 5.13 and 5.14 is provided in Appendix 7.

5.5.3 Forecast Results

The data available extends only up to 2020. As a result, forecasts for the years 2021, 2022, and 2023 were made using the five ML algorithms outlined in section 5.13. Given the dataset's specific characteristics, the LR algorithm is selected for the prediction of values in 2021, 2022, and 2023. The Line Chart (Chart 5.15), and a Table (Table 5.5) have been selected to visually represent the data.

Chart 5.15: Energy Intensity Indicator Forecast (2021-2023)

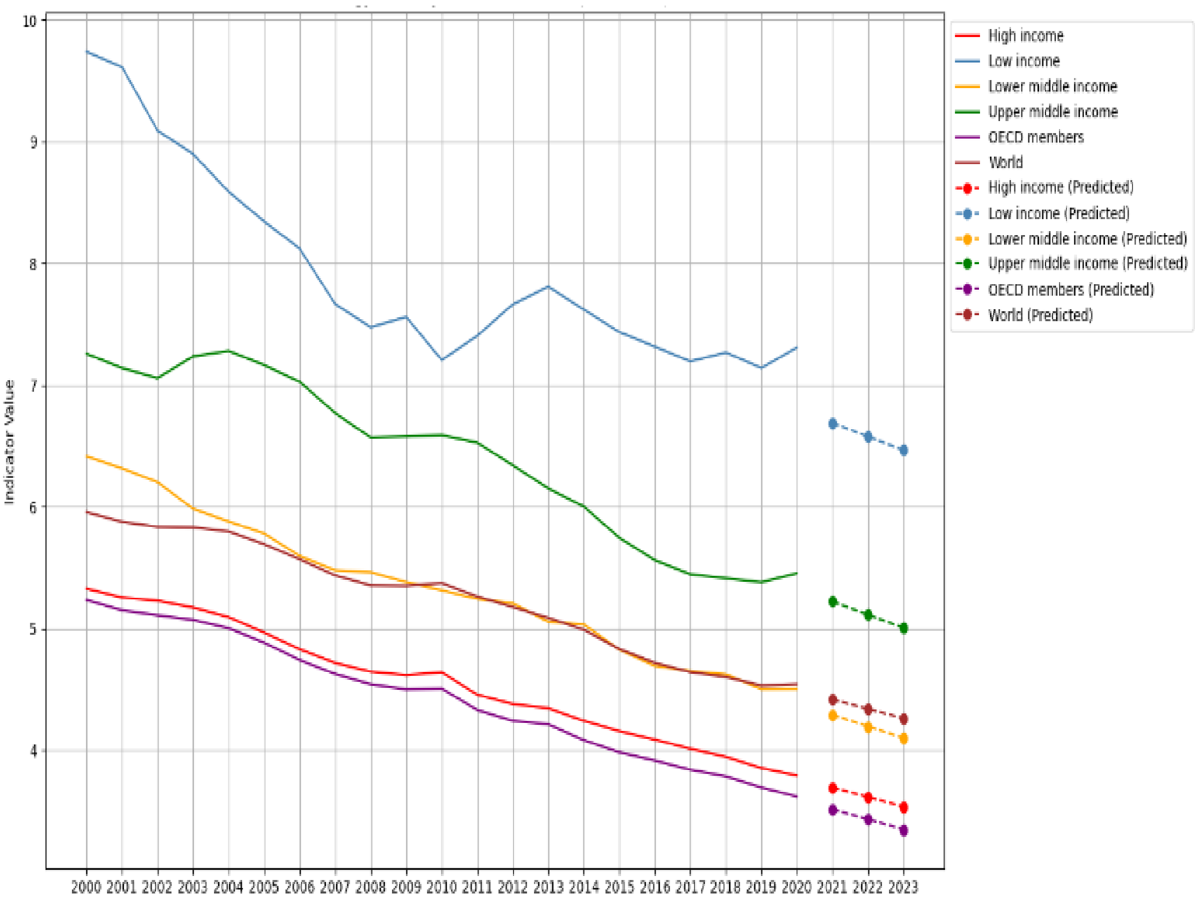


Table 5.5: Energy Intensity Indicator Forecast (2021-2023)

Predicted Value (%)	2021	2022	2023
Low-Income	3.69	3.61	3.54
Lower-Middle-Income	6.69	6.58	6.46
Upper-Middle-Income	4.29	4.20	4.10
High-Income	5.22	5.11	5.00
OECD Members	3.52	3.43	3.35
World	4.42	4.34	4.26

Predicted Value vs. 2020 (%)	2021	2022	2023
Low-Income	-2.56	-4.64	-6.71
Lower-Middle-Income	-8.47	-10.01	-11.55
Upper-Middle-Income	-4.73	-6.85	-8.97
High-Income	-4.26	-6.25	-8.24
OECD Members	-2.84	-5.15	-7.45
World	-2.78	-4.47	-6.16

5.5.4 Forecast Discussion

The following outlines the predicted trends in energy intensity percentages across various income groups and regions. Energy intensity is a crucial metric that provides insights into how effectively a region or country utilizes energy. A decrease in the percentage indicates improved energy efficiency, meaning less energy is wasted for the same output. The data reveals expected changes between 2021 and 2023, highlighting the most significant annual decline and offering potential reasons behind these trends.

- High-Income:
  - Energy efficiency is predicted to improve, with intensity values decreasing from 3.69% in 2021 to 3.54% by 2023.
  - The most substantial efficiency improvement is observed between 2020 and 2021, with a change of -2.56%.
  - Possible drivers behind this improvement include the integration of advanced technologies, potentially stricter energy regulations, and a shift towards renewable energy sources.

- Low-Income:
  - The energy efficiency percentage is set to improve, as intensity values decreasing from 6.69% in 2021 to 6.46% by 2023.
  - Between 2020 and 2021, a significant drop of -8.47% is anticipated.

- This positive trend might be associated with evolving infrastructure, maturation of technologies, and influence from international green initiatives.

- Lower-Middle-Income:
  - Forecasts indicate energy efficiency improvements, with intensity values decreasing from 4.29% in 2021 to 4.10% by 2023.
  - The period from 2020 to 2021 witnesses the most substantial decline at -4.73%.
  - Factors potentially contributing to this trend might include speculated economic shifts and foreign investments that promote energy efficiency.

- Upper-Middle-Income:
  - Energy efficiency trends suggest improvement, with intensity values decreasing from 5.22% in 2021 to 5.00% by 2023.
  - A decline of -4.26% is projected between 2020 and 2021.
  - This improvement might be attributed to industrial modernization and a rising middle-class advocating for more energy-efficient products.

- OECD Members:
  - Predictions highlight an energy efficiency improvement, with intensity values declining from 3.52% in 2021 to 3.35% by 2023.
  - Between 2020 and 2021, a change of -2.84% is expected.
  - Collective policy initiatives and substantial R&D investments, based on general observations, might be driving these improvements.

- World:
  - Globally, energy efficiency is forecasted to improve, with intensity values decreasing from 4.42% in 2021 to 4.26% by 2023.
  - The most notable efficiency gain is expected between 2020 and 2021, with a decline of -2.78%.
  - This global improvement may be a result of heightened awareness about climate change and the influence of international agreements. However, multiple factors likely contribute to this trend.

The Python program corresponding to Chart 5.15 and Table 5.5 is provided in Appendix 7.

5.6 SDG Indicator 7.A.1

SDG Target 7.A explicitly states that international cooperation must be enhanced to facilitate access to clean energy research and technology, including renewable energy, energy efficiency, and advanced and cleaner fossil-fuel technology, and to promote investment in energy infrastructure and clean energy technology by 2030.

The associated SDG Indicator 7.A.1 measures the level of international financial flows to developing countries in support of clean energy research and development and renewable energy production, including in hybrid systems. This indicator is both quantitative and actionable, as it provides a clear picture of the extent to which international cooperation, as outlined in Target 7.A, is being translated into tangible financial support for clean energy projects in developing countries. Tracking this indicator allows for a clear understanding of the progress being made towards achieving Target 7.A and the SDGs.

In this chapter, two prominent datasets sourced from the IEA have been employed to shed light on the progress made towards SDG Indicator 7.A.1. This specific indicator emphasizes the "International financial flows to developing countries in support of clean energy research and development and renewable energy production, including in hybrid systems." Consequently, evaluating datasets that capture the nuances of global investments and funding mechanisms becomes paramount.

5.6.1 Results (Global Investment in Energy Sources)

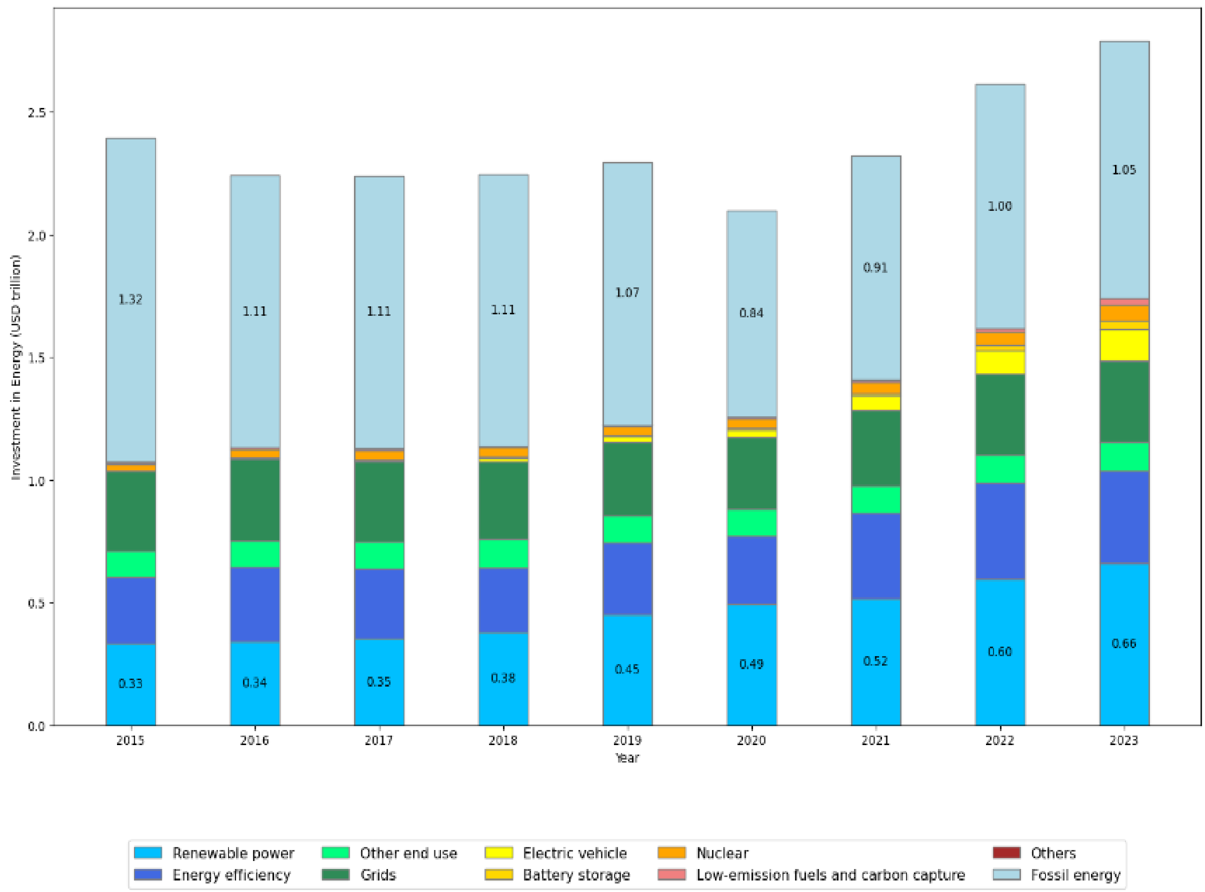
The first dataset, detailing global investments in diverse energy sources from 2015 to 2022, with forecasts extending into 2023, offers a comprehensive overview of the evolving energy landscape. By categorizing investments into sectors such as "Renewable power," "Energy efficiency," "Grids," "Electric vehicles," "Battery storage," "Nuclear," "Low-emission fuels and carbon capture," and "Fossil energy," a multifaceted understanding of the world's energy priorities can be acquired.

Chart 5.16 provides a comprehensive overview of investments in various energy sectors from 2015 to 2022, and offers anticipated figures for 2023, derived from the forecast of the IEA. Below are the key observations from this graphical representation:

- Annual Investments: The energy sectors have exhibited dynamic investment patterns over the past years. For example, while investment in the renewable power sector has increased from USD 331 billion to USD 659 billion between 2015 and 2023, investment in the fossil energy sector has declined from USD 1,320 billion in 2015 to USD 910 billion in 2021 before rebounding to around the USD 1,000 billion level in 2022 and 2023.

- Total Annual Investments: The total yearly investment in the energy sector started at USD 2.394 trillion in 2015, dipped to USD 2.098 trillion in 2020, and rose to USD 2.790 trillion by 2023.

Chart 5.16: Investment in Various Energy Sources (2015-2023)



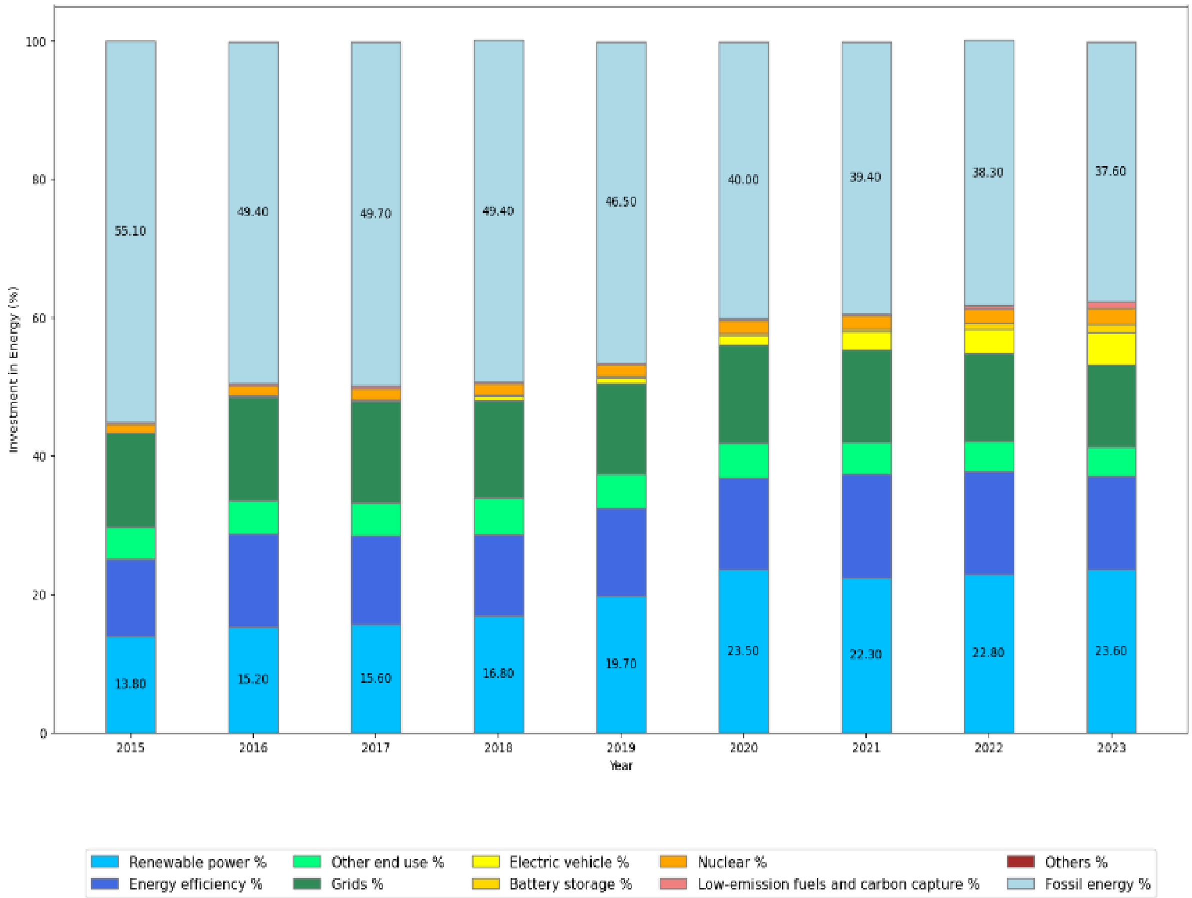
- Growth Patterns: Between 2015 and 2023, renewable power experienced a growth of 99.09%, while the fossil energy sector witnessed a decline of 20.45%. Notably, sectors like electric vehicles and battery storage, which started with negligible investments in 2015, saw substantial increases by 2023, highlighting rapid advancements and market acceptance in these areas.

- Leaders and Laggards in 2023: In the forecasted year of 2023, fossil energy is expected to retain the top spot with an investment of USD 1.05 trillion. Conversely, the "Others" category is projected to have negligible investment, indicating a potential phase-out or reduced significance of this category in the energy landscape.

Chart 5.17 presents a comprehensive overview of the percentage distribution of investments in various energy sources from 2015 to 2022. Additionally, it offers anticipated figures for 2023. A detailed examination of this graphical representation reveals several key observations:

- Distribution of Investments: Over the years, there has been a shift in the proportional investments in different energy sectors, with some sectors gaining prominence while others decline. For example, the investment in renewable power has increased from 13.8% in 2015 to 23.6% in 2023. This growth indicates the global trend towards renewable energy.

Chart 5.17: Investment in Various Energy Sources as a % of Total Investment (2015-2023)



- Growth Dynamics: The investment percentages from 2015 to 2023 reveal certain growth patterns:
  - Renewable power has grown by 9.8 percentage points.
  - Energy efficiency has increased by 2.2 percentage points.
  - Fossil energy has declined by 17.5 percentage points, indicating a reduced dependency on fossil fuels.
  - The electric vehicles and battery storage sectors, which started with negligible percentages, have grown to 4.6% and 1.3% respectively by 2023, highlighting the rapid advancements in these sectors.

- Reprioritization in 2023: In the forecasted year of 2023, despite its decline over the years, the Fossil energy sector is expected to rebound from 22.8% in 2022 to 23.6% in 2023. Meanwhile, the Renewable energy sector, despite its increase over the years, is anticipated to decline from 38.3% in 2022 to 37.6% in 2023.

The Python program corresponding to Charts 5.16 and 5.17 is provided in Appendix 8.

5.6.2 Discussion (Global Investment in Energy Sources)

The shifts in investment percentages across the energy sectors are not merely numerical changes; they mirror the profound evolution in global energy paradigms and policy orientations. Several implications emerge from this data:
Transition to Sustainable Energy: The surge in proportional investments in renewable power signifies an intensified global commitment to sustainable energy. As nations grapple with the twin challenges of energy security and environmental conservation, the move towards renewables suggests a strategic pivot to harness nature's bounty while minimizing ecological impact.

Innovation and Technological Advancements: The notable rise in investments in sectors like electric vehicles and battery storage underscores the role of technological innovation in reshaping the energy landscape. These sectors, once on the peripheries of energy discussions, are now at the forefront, driven by advancements in battery technology, market acceptance, and supportive regulatory frameworks.

Reduced Reliance on Fossil Fuels: The decline in the fossil energy sector's percentage, even though it remains dominant, heralds a paradigm shift. As the world becomes increasingly aware of the environmental repercussions of fossil fuel dependency, there's a deliberate move towards diversifying energy sources. This trend also points to the potential economic risks associated with over-reliance on volatile fossil fuel markets.

Policy Indications: These shifts in investment priorities are invariably linked to policy frameworks. Governments worldwide are crafting policies that incentivize sustainable energy, promote technological innovation, and deter environmentally detrimental practices. The investment patterns are a testament to the efficacy of these policies in guiding market behaviors.

Seasonal Fluctuations: Although the IEA forecast indicates a decline in the percentage of investment in renewable energy in 2023, coupled with a projected rebound in fossil energy investment for the same year, it is important to view this adjustment as a short-term phenomenon. The long-term global trend of increasing investment in renewable energy and declining investment in fossil energy is expected to remain intact.

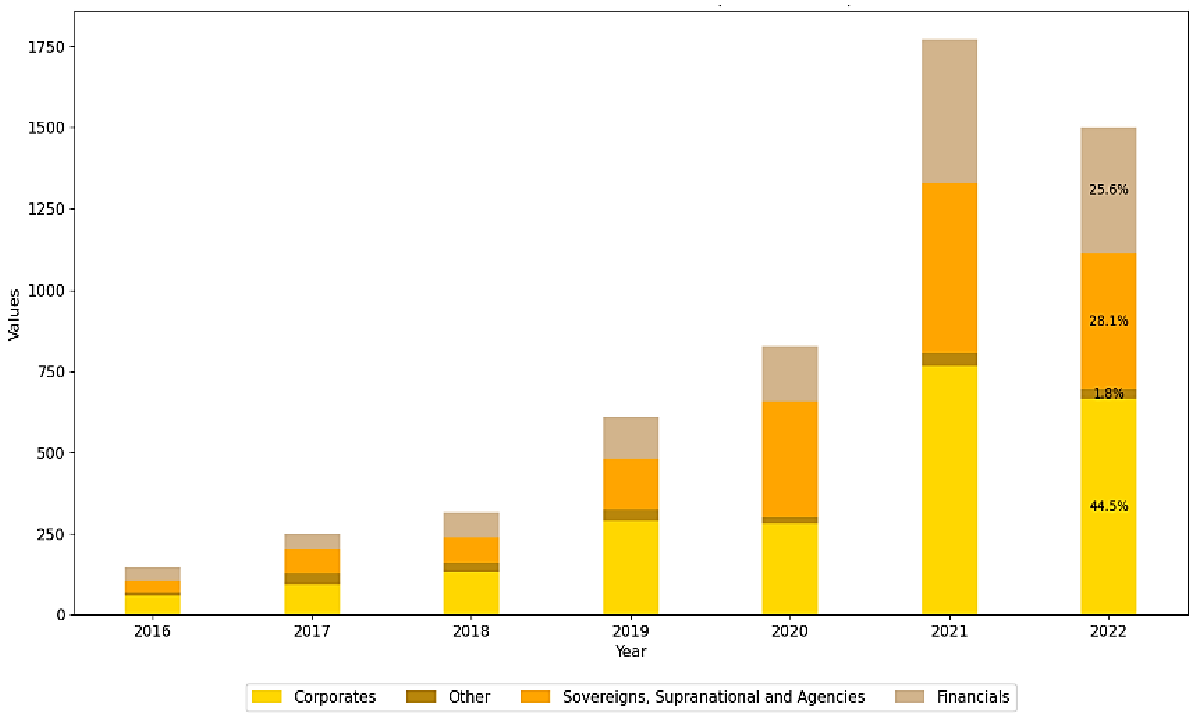
Future Research and Development: The data suggests areas where research and development (R&D) efforts might be intensified in the coming years. With sectors like electric vehicles and battery storage gaining traction, there's an impetus for academia and industry to collaborate, driving innovations that enhance efficiency, reduce costs, and broaden accessibility.

In essence, the evolving investment patterns in the energy sector provide a roadmap for the future. They highlight the areas of growth, flag the sectors that might require revitalization, and underscore the global commitment to a sustainable, technologically advanced, and diversified energy ecosystem.

5.6.3 Results (Sustainable Debt Issuance)

The second dataset explores sustainable debt issuance from 2016 to 2022, providing a comprehensive overview of the funding sources for sustainable energy projects. This includes the involvement of corporates and sovereign entities as sources of funding. To better understand the trends and patterns within this period, a bar chart has been created to show yearly issuances, and a donut chart has been designed to depict the distribution of issuers in 2022.

Chart 5.18: Sustainable Debt Issuance (2016-2022)



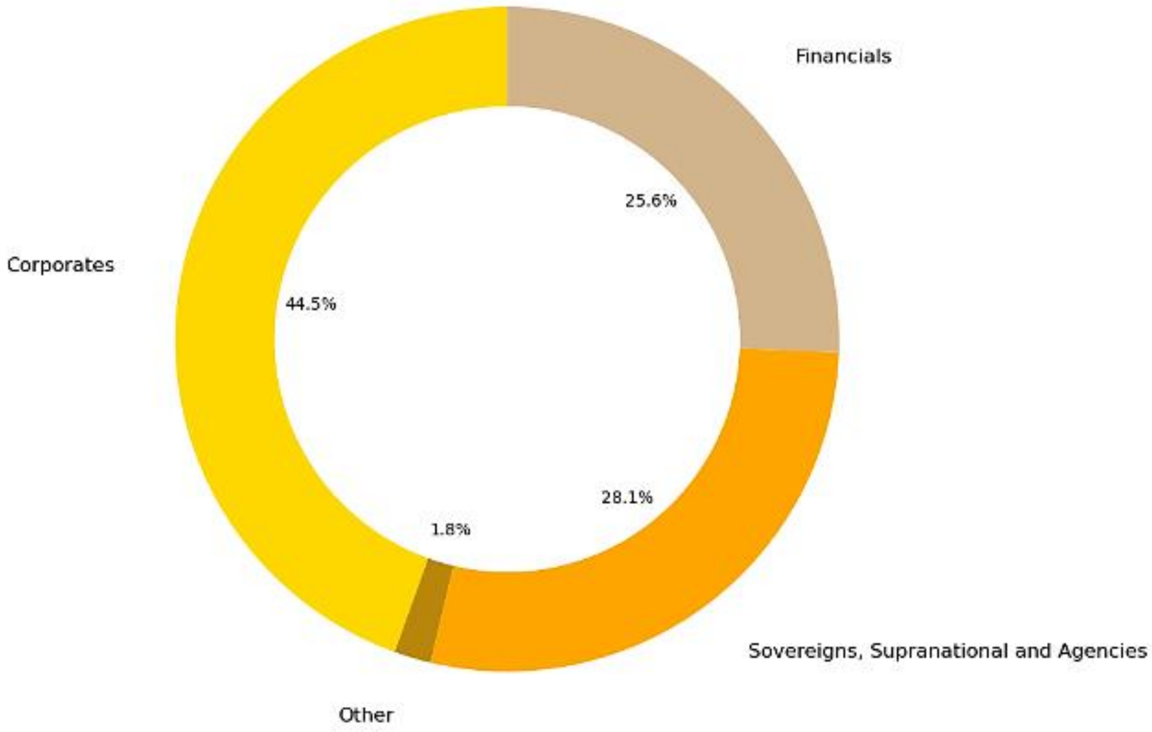
Analyzing Chart 5.18, the following trends are observed:

- Sustainable Debt Issuance Trends (2016-2022): Between 2016 and 2022, sustainable debt saw a consistent rise, reflecting a global move towards eco-friendly initiatives. Corporates led this surge, with Financials also showing notable growth. The Sovereigns, Supranational, and Agencies group peaked in 2020, then stabilized, suggesting possible market adjustments. Meanwhile, the 'Others' category remained relatively steady. Overall, these trends highlight the growing importance of sustainability in financial strategies, particularly in addressing global issues like climate change.

- Analyzing the 2022 Decline in Sustainable Debt Issuance: The 2022 dip in sustainable debt can be attributed to several factors: post-pandemic economic recovery, potential market saturation, evolving regulations, and shifts in investor sentiment. The introduction of diverse sustainable financial tools might also have influenced this decline. Despite the dip, sustainable finance's broader trajectory suggests a continued emphasis in the future financial landscape.

Chart 5.19 offers a detailed visual representation of the sustainable debt issuers for the year 2022. It segments the issuers into distinct categories, portraying their respective contributions to the total issuance. The key observations are:

Chart 5.19: Sustainable Debt Issuers (2022)



- Corporates: Evidently leading the charge, corporates contributed a significant 667 transactions to the total, making up 37.43% of the sustainable debt issuance in 2022.

- Sovereigns, Supranational, and Agencies: These entities, often at the intersection of public and private sectors, manifested a strong commitment to sustainability. They collectively accounted for 23.63% of the year's issuance, contributing 421 transactions.

- Financials: Representing the financial sector's engagement in sustainable ventures, this category contributed 384 transactions, making up 21.55% of the total.

- Other Categories: Despite its modest contribution, the 'Other' segment, comprising 27 transactions (1.52% of the total), is indicative of the broad-based interest in sustainable financing that extends beyond conventional categories.

The Python program corresponding to Charts 5.18 and 5.19 is provided in Appendix 8.

5.6.4 Discussion (Sustainable Debt Issuance)

Strategic Shifts in Corporate and Financial Sectors: The consistent rise in sustainable debt, particularly the dominance of Corporates, showcases a transformative business approach towards integrating sustainability. Concurrently, Financial institutions are evolving, emphasizing not just finance provision but the promotion of sustainable ventures.

Public-Private Synergies: The significant contributions of Sovereigns, Supranational, and Agencies underline the effectiveness of collaborations between public and private entities. This collaboration is crucial for achieving broader sustainable goals and climate initiatives.

2022: A Complex Interplay of Dynamics: The decline in sustainable debt issuance in 2022 indicates the multifaceted nature of sustainable finance. Influenced by global events, regulatory changes, and market saturation, it highlights the need for adaptive strategies in the ever-evolving landscape of sustainable finance.

Broadening Appeal of Sustainable Finance: The detailed 2022 categorization suggests a diversified interest in sustainable finance. Contributions from various sectors, including the 'Other' category, indicate that the realm of sustainable finance is expanding, embracing a wider range of stakeholders and sectors.

In summation, this analysis provides a panoramic view of the sustainable debt issuance landscape over recent years, accentuating the pivotal role of various stakeholders in shaping the future of sustainable finance.

5.6.5 Forecast

The forecast is not provided for SDG Indicator 7.A.1 as the data deemed appropriate for this purpose is not currently available.

5.7 SDG Indicator 7.B.1

5.7.1 Results

SDG Target 7 aims to ensure access to affordable, reliable, sustainable, and modern energy for all. It seeks to expand and upgrade infrastructure for providing clean and sustainable energy in developing countries.

SDG Indicator 7.B.1 focuses on the percentage of renewable energy in the total final energy consumption of a given country. Specifically, it measures the share of renewable energy sources in a nation's overall energy mix.

The evaluation of the indicator is conducted through a comprehensive methodology that involves establishing a benchmark by comparing the installed renewable energy capacity in "Developing Countries" against the averages of countries in the OECD and globally. It should be noted that a universal definition for "Developing Countries" is not provided, so data from "Low-Income countries" and "Low-Middle-Income countries," based on World Bank classification, are aggregated, and utilized as a proxy. To calculate per capita renewable energy access, the installed renewable energy capacity data from the IEA and population data from the World Bank are utilized. Six charts are utilized to understand the progress and achievements of SDG Target 7.

Chart 5.20: World, Developing Country, and OECD Population (2000-2022)

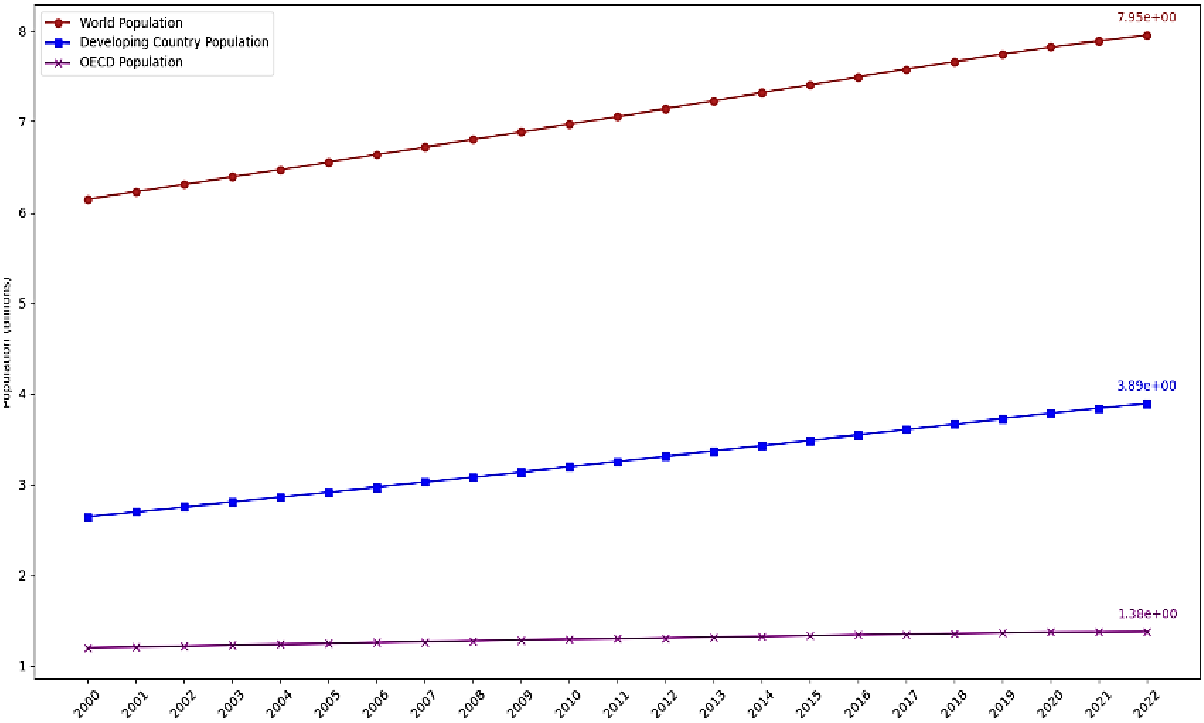


Chart 5.20 displays the population trends from 2000 to 2022 for the World, Developing Countries, and OECD Members. The World population increased from approximately 6.14 billion in 2000 to 7.95

billion in 2022. Developing Countries' populations grew from around 2.64 billion to 3.89 billion, while the OECD Members saw an increase from about 1.2 billion to 1.38 billion over the same period. Numerically, the Developing Countries have seen a more substantial growth (approximately 1.25 billion) compared to OECD Members (approximately 0.18 billion). This divergence signals that most of the global population growth is occurring in Developing Countries.

Chart 5.21: Developing Country and OECD Population as percentage of World Population (2000-2022)

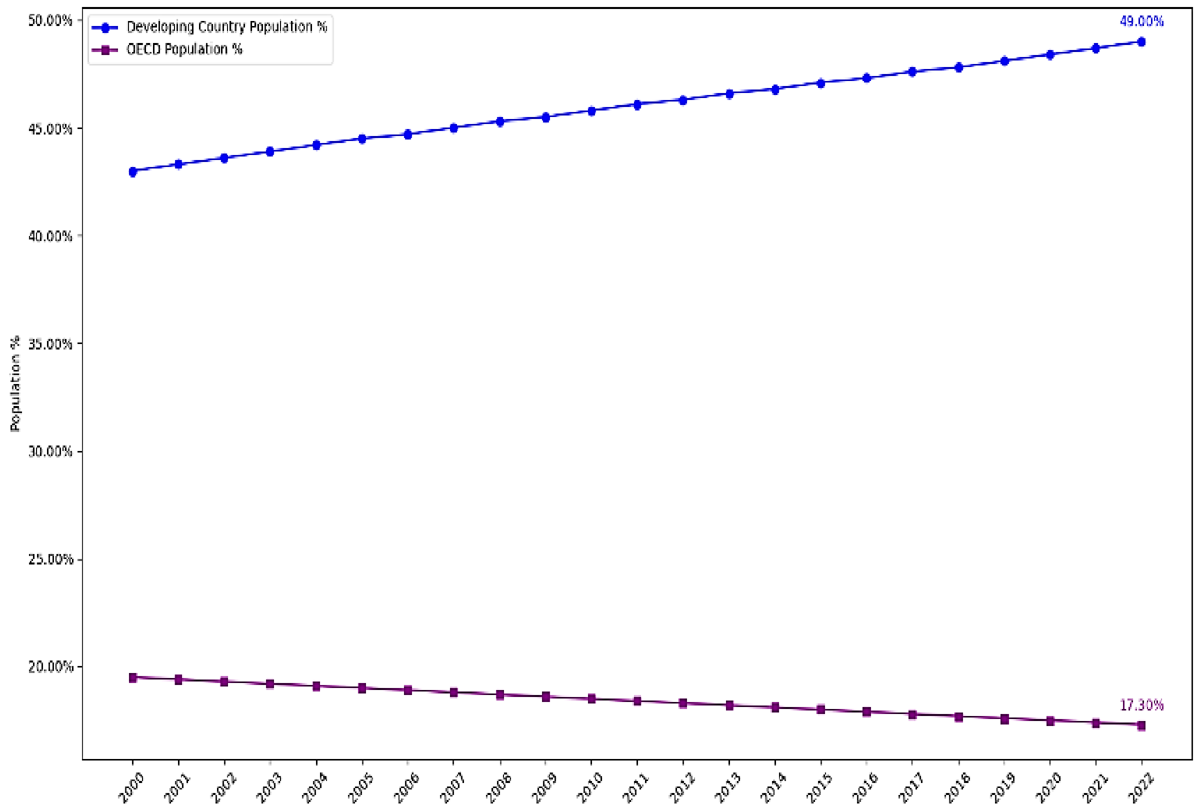


Chart 5.21 complements Chart 5.20 by illustrating the population percentages of Developing Countries and OECD Members relative to the World population. Developing Countries' share increased from 43% in 2000 to 49% in 2022, while the OECD Members' share declined from 19.5% to 17.3%. This reaffirms the inference from Chart 5.20 that Developing Countries are becoming demographically more significant.

Chart 5.22: World, OECD, and Developing Country Renewable MW (2000-2022)

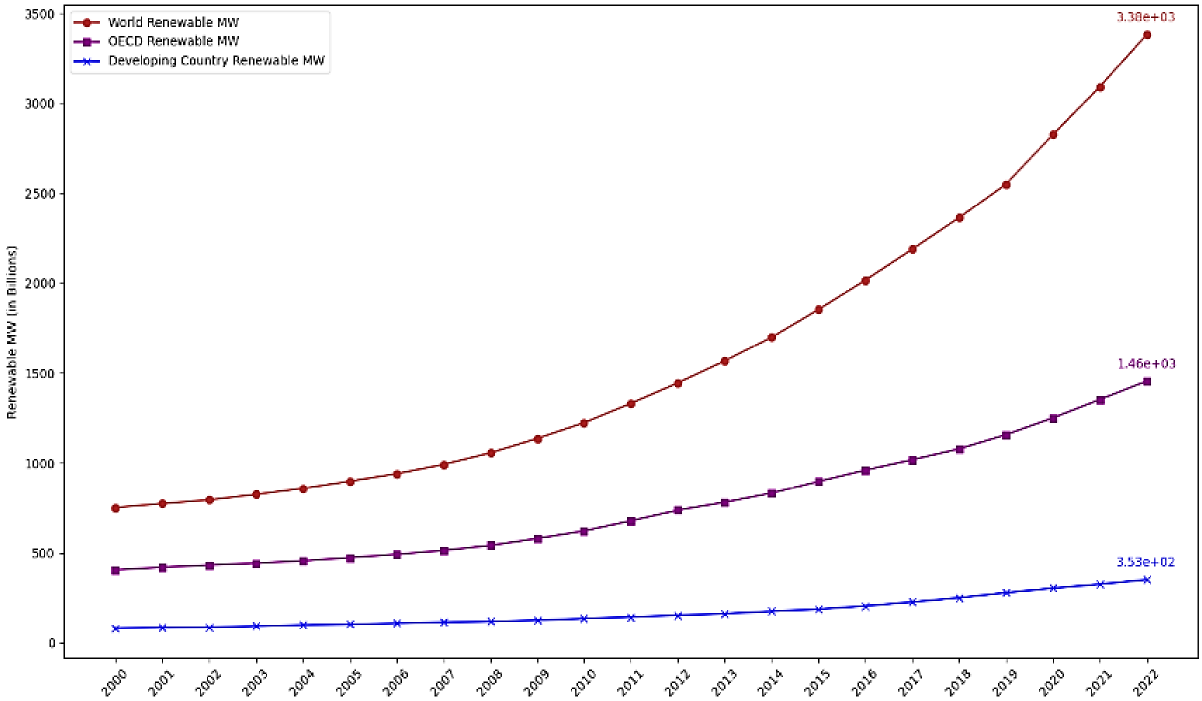


Chart 5.23: World, OECD, and Developing Country kW per Capita (2000-2022)

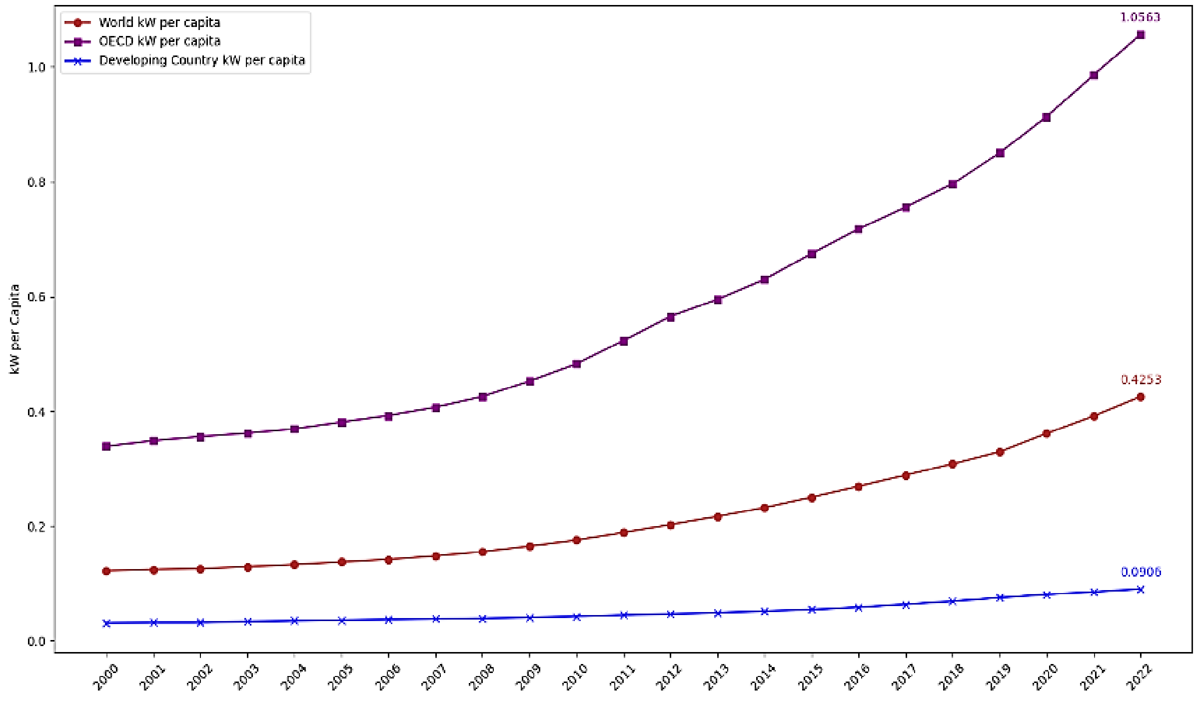


Chart 5.22 shifts the focus to renewable energy capacity measured in Megawatt (MW). While specific figures are not visible, the trends are evident. All three categories—World, OECD Members, and Developing Countries—have seen significant growth in renewable energy capacity. Most notably, Developing Countries have made substantial strides, demonstrating an emerging focus on renewable energy sources.

Chart 5.23 explores the renewable energy capacity per capita in Kilowatt (kW). OECD Members maintain a significantly higher kW per capita compared to Developing Countries. This disparity highlights the inequitable distribution of renewable energy infrastructure, indicating that OECD Members have more extensive access to renewable energy on a per-person basis.

Chart 5.24: OECD & Developing Country Renewable MW as a percentage of World Renewable MW (2000-2022)

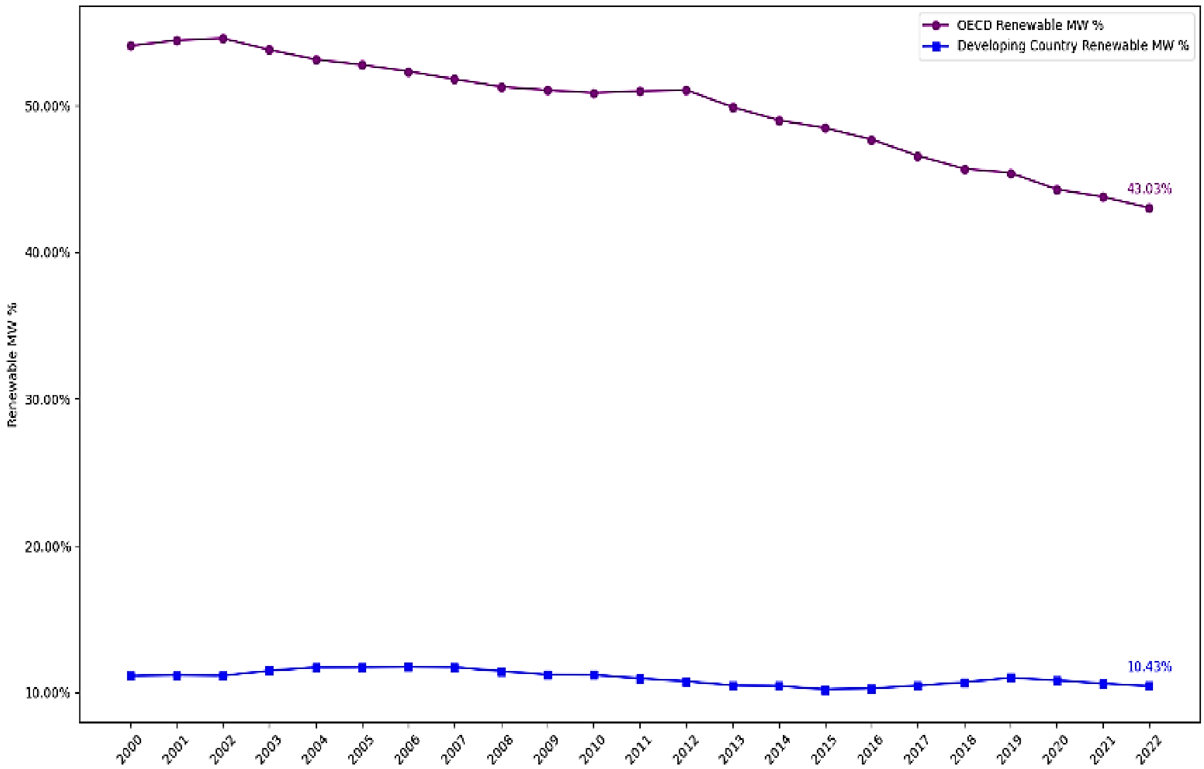


Chart 5.24 continues the narrative on renewable energy but focuses on the share of the world's renewable MW capacity held by OECD Members and Developing Countries. It shows a slight increase in the Developing Countries' share, suggesting they are gradually closing the renewable energy gap, albeit at a slow pace.

Chart 5.25: Developing Country kW per Capita as a percentage of World and OECD kW per Capita (2000-2022)

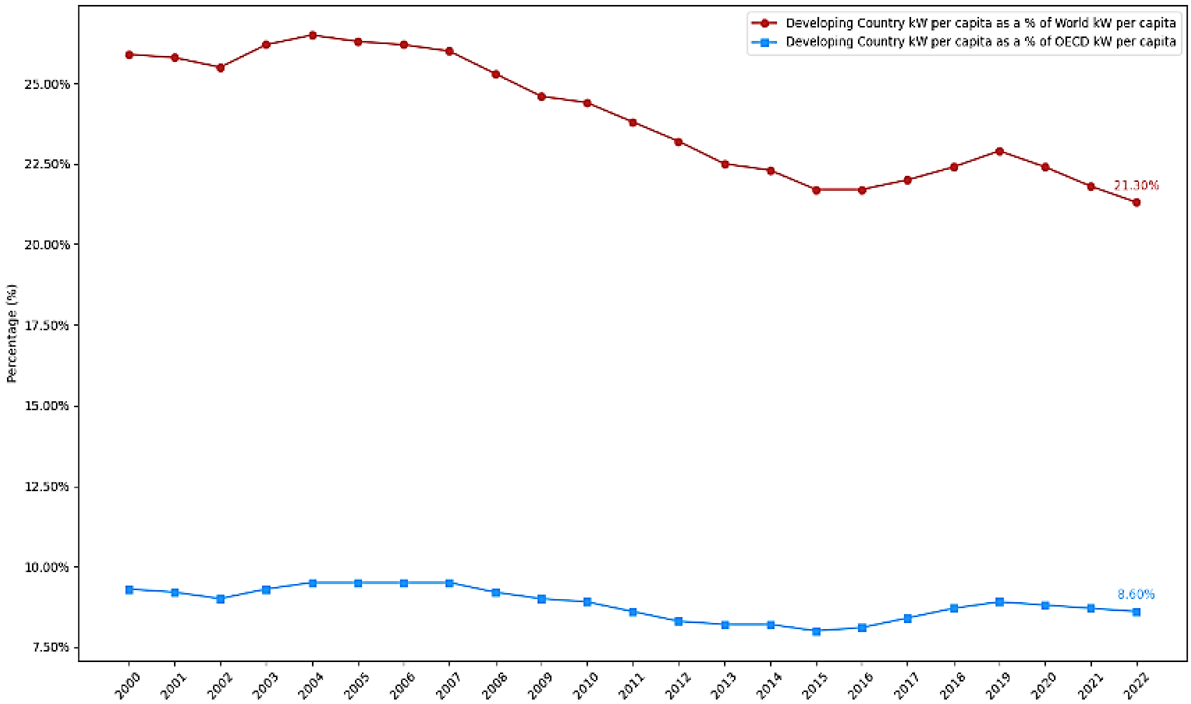


Chart 5.25 provides a comparative measure of the renewable energy capacity per capita in Developing Countries against the OECD Members and the World averages. It shows that Developing Countries have consistently lagged in this metric, reinforcing the point that these countries have a long way to go in reaching the per capita renewable energy capacity of OECD nations or even the World average.

The suite of six charts presents a comprehensive view of the interplay between population growth and renewable energy capacity. Charts 5.20 and 5.21 lay the demographic foundation, showing that Developing Countries are increasingly accounting for a larger share of the world population. Charts 5.22 to 5.25 reveal that despite this demographic significance, Developing Countries still lag in renewable energy capacity, both in absolute terms and per capita. However, there is a silver lining: Developing Countries are gradually increasing their share of global renewable energy capacity, albeit from a lower baseline.

The Python program corresponding to Charts 5.22 to 5.25 is provided in Appendix 9.

5.7.2 Discussion

Social Implications and Relevance: The growing population in Developing Countries, shown in Charts 5.20 and 5.21, has significant social consequences. This population growth increases the demand for energy, especially from renewable sources, to meet the needs of industrialization and urban development. A key challenge is providing everyone with equal access to renewable energy. If this isn't achieved, it could deepen existing social inequalities. However, it's also an ideal time to use this growth to shift towards sustainable energy. This change is crucial as climate change affects vulnerable groups in Developing Countries the most. This situation ties in with the goals of SDG 7, where a growing population could make equal energy access harder to achieve.

Economic Implications and Relevance: Charts 5.22 and 5.23 highlight a noticeable economic gap: the uneven spread of renewable energy resources between OECD Members and Developing Countries. The lower kW per capita in Developing Countries indicates they're not fully part of the global renewable energy network, limiting their economic progress. But there's a positive side: increasing investments in renewable energy in these areas can boost their economies by creating jobs and encouraging technological advances. This trend is vital for achieving SDG 7 since the potential for job creation through renewable energy hasn't been fully explored in Developing Countries compared to OECD Members.

Political Implications and Relevance: The data shows that Developing Countries are gaining more political importance globally. Their growing population suggests they will have more influence in global discussions, especially those about renewable energy and climate change. However, Charts 5.24 and 5.25 show a slower increase in renewable energy use in Developing Countries, indicating possible political challenges in adopting green energy. This gap might lead to internal and international political tensions. Achieving SDG 7 will require navigating these political issues, especially regarding energy security and global cooperation.

Financial Implications and Relevance: Shifting to renewable energy isn't just a technical challenge for Developing Countries; it's also a financial one. They need a lot of investment to build the necessary infrastructure, and the current lower kW per capita suggests they're not investing enough. However, Chart 5.24 shows a positive trend: these countries are increasing their renewable energy use. To speed up this change, they might need more financial support, such as international grants, favorable loans, or collaborations between the public and private sectors. This financial support connects with SDG 7.B, highlighting the need for new financing methods.

Bridging the Gap: The data reveals a clear difference between Developing and OECD Members in renewable energy capacity. OECD Members, with their better renewable energy resources and financial strength, can play a key role in helping Developing Countries reach the aims of SDG 7.B. Actions like sharing knowledge, transferring technology, and providing financial help can close this gap, pushing the world closer to broad sustainability and climate goals.

This section gives a complete view of the challenges and opportunities Developing Countries face, especially regarding SDG 7 Target 7.B. While there's been notable progress, it's still not fast enough, especially when compared to OECD Members. Therefore, a coordinated effort from various groups is essential to speed up the shift to renewable energy in Developing Countries, achieving the goal of sustainable and affordable energy for everyone.

5.7.3 Forecast

The forecast is not provided for SDG Indicator 7.B.1 as the data deemed appropriate for this purpose is not currently available.

CHAPTER 13

CONCLUSION

The United Nations' Sustainable Development Goals underscore the global dedication to confronting multifaceted challenges, including environmental conservation, poverty eradication, gender equality, and the promotion of peace and justice. Notably, the objective of ensuring access to affordable, reliable, sustainable, and modern energy for all, encapsulated in SDG 7—Affordable Clean Energy, is of paramount importance. This research posits that both Data Science and Artificial Intelligence are instrumental in shaping and predicting the trajectories of SDG 7. This chapter consolidates the findings of the research, offers essential insights derived from the investigation, and proposes directions for prospective research endeavors.

13.1 Findings

SDG Indicator 7.1.1 From 2000 to 2021, there were notable disparities in electricity access between urban and rural areas. This has been a significant concern. Chart 5.5 and Chart 5.6 vividly depict this divide. Specifically, they showcase the levels of electricity availability in urban and rural settings. These charts represented different economic groups. Urban areas, characterized by their denser populations and well-established infrastructure, consistently exhibited superior access to electricity. Conversely, rural regions, especially those in low-income countries, grappled with limited access due to their remote locations and inadequate infrastructure. To emphasize this divergence over the years, Chart 5.7 was constructed, representing the difference in electricity access between urban and rural areas over time. This visual representation underscores the persistent gap in access and serves as a stark reminder of the challenges faced by rural communities in gaining equitable access to electricity.

Direct data for the year 2022 is unavailable as the current data only extends up to 2021. To forecast electricity accessibility trends for 2022, predictive models are employed using LR, RF, and GB algorithms. The forecasts presented in Table 5.3 offer several key insights. For the Low-Income group, all models predict a modest increase in electricity access in 2022. This is for both urban and rural populations compared to 2021. For the Lower-Middle-Income category, a slight increase is forecasted for urban dwellers. A similar upward trend is expected for their rural counterparts. The Upper-Middle-Income group is also expected to witness a slight enhancement in electricity accessibility for both urban and rural residents in 2022. Conversely, in the High-Income category, where a significant portion already enjoys electricity access, stability or minimal growth is anticipated. On a global scale, 2022 is poised to witness a small increase in electricity access percentages for both urban and rural populations, underscoring the ongoing efforts to bridge the urban-rural electricity divide worldwide. These forecasts illuminate the potential trajectories of electricity access and inform future policy and infrastructure development strategies.

SDG Indicator 7.1.2 The indicator on clean cooking fuel access provides insights into both achievements and challenges related to SDG 7. Economically, clean fuel access aligns with economic growth, suggesting its broader impact on SDG advancement. Healthwise, better access can mitigate respiratory diseases, leading to reduced healthcare costs. Environmentally, limited access correlates with higher carbon emissions and deforestation, stressing SDG 7's role in environmental protection. The analysis findings based on 2021 data point to the importance of diverse strategies, international cooperation, and addressing the urban-rural disparity in clean cooking fuel access. Overall, the analysis results underscore the need for global collaboration and inclusive policies in promoting sustainable energy, especially in rural settings.

SDG Indicator 7.2.1 The "Renewable energy share in the total final energy consumption" is a pivotal indicator of global renewable energy trends. Between 2000 and 2021, there has been a significant increase in global renewable adoption. High-Income Countries are leading this charge, emphasizing their role in assisting lower-income nations through resources and expertise. Surprisingly, Low-Income Countries have shown a substantial adoption rate, suggesting global strategies need revisiting. Meanwhile, Middle-Income Countries present a distinct divide between the 'Lower-' and 'Upper-' Income brackets, calling for tailored approaches. OECD Nations' success also hints that Developing Countries might benefit from similar cohesive policymaking.

While the past two decades show progress, projections indicate a potential slowdown in renewable energy adoption by 2022, possibly due to economic or policy shifts. Furthermore, regional disparities, especially in Low-Income regions, highlight the need for region-specific energy policies. The overarching narrative remains that international collaboration, adaptable strategies, and proactive policy measures are crucial for a sustainable future.

SDG Indicator 7.3.1 The SDG Indicator 7.3.1 originally denotes the "Percentage of population with access to electricity," shedding light on global energy access. However, energy intensity—a measure of how efficiently energy is used in an economy—is closely linked to this indicator. A decrease in energy intensity often indicates broader, more efficient electricity access. From 2000 to 2020, there have been significant shifts in global energy patterns. A pronounced disparity in energy intensity exists between High-Income and Low-Income countries. This gap underscores the role of economic resources and technology in shaping sustainable energy access.

Yet, a promising global trend has emerged: the consistent reduction in energy intensity. This decline showcases international cooperation's impact, and the increasing emphasis Middle-Income countries place on balancing sustainability with economic growth. Projections for 2022 and 2023 extend this optimistic trend. A falling energy intensity not only brings environmental perks, like fewer emissions, but also economic advantages, including cost savings. Such a trajectory affirms the effectiveness of prevailing energy policies and shows businesses' successful shift towards energy-efficient technologies. In summary, data from 2000 to 2023 indicates a global evolution towards enhanced sustainable energy practices, involving both governments and businesses.

SDG Indicator 7.A.1 The indicator tracks financial flows supporting clean energy research and renewable energy projects in developing nations. Its emphasis aligns with observed global shifts in energy investments and sustainable debt issuance. Between 2015 and 2022, global trends in energy investments and sustainable debt underscore a decisive move towards environmental sustainability. Corporations are leading a shift from traditional fuel sourcing methods to green strategies, powered by technological advancements in areas like electric vehicles and battery storage. While fossil fuels remain significant, there is a growing emphasis on diversifying energy sources to reduce ecological and economic risks. Collaborations, especially between public and private sectors, are crucial in driving this change. Despite short-term market fluctuations, the long-term focus remains on sustainability. The future will see intensified research and innovation in emerging sectors, aiming for broader accessibility and efficiency in a sustainable landscape.

SDG Indicator 7.B.1 The indicator assesses Developing Countries' shift towards renewable energy. Data from 2000 to 2022 indicates a rising demand for renewables, driven by population growth, industrialization, and the need to address social disparities. Yet, Developing Countries lag in global renewable infrastructure, suggesting missed opportunities in job creation and innovation, pivotal for SDG 7. While Developing Countries gain prominence globally, their pace in adopting renewables is slow, indicating political and financial challenges. Collaborative international efforts and innovative funding can address these obstacles. OECD Members, with their expertise and resources, can play a vital role in this transition. Overall, to ensure a sustainable energy future, a unified global approach is crucial to accelerate renewable adoption in Developing Countries.

13.2 Insights

The ensuing passages provide three insights from this study, highlighting global advancements across various SDG metrics:

1. Electrification Disparities and Environmental Impacts

From 2000 to 2022, global efforts towards sustainable energy yielded diverse outcomes across SDG metrics. While urban electrification rates have risen significantly and High-Income countries lead in access, notable disparities persist. Specifically, rural areas in Low-Income and Middle-Income countries continue to face limited electrification. This disparity emphasizes the need for bespoke interventions, channeling increased investments, and strategic focus on these countries. Beyond the clear need for financial investment, there is a call for comprehensive infrastructural evolution and policy reforms to bridge the urban-rural divide.

2. Renewable Energy Adoption and Global Sustainability Initiatives

High-Income and Low-Income countries are consistently expanding their renewable energy capacities. However, Middle-Income countries display varied adoption patterns, underscoring the need for regionally attuned strategies. Forecasts for 2022 point to possible challenges, advocating for adaptive policy interventions. The growing accessibility to renewable energy reflects a global commitment to sustainability, bolstered by economic investments and technological advancements. A commensurate decline in energy intensity resonates with this global shift, reflecting enhanced inter-nation collaboration and the corporate sector's progressive alignment with sustainability.

3. Financial Dynamics and Global Transition

Global financial trends underscore a surge in investments towards innovative renewable sources and products, fueled by technological advancements and supported by both corporate and sovereign/supranational green financing initiatives. OECD government strategies have played a pivotal role in expediting this shift, highlighting the synergy of policy and technology. However, notwithstanding their emerging global significance, Developing Countries still grapple with challenges in securing funds for new renewable initiatives. Herein lies the pivotal role of international consortiums; with OECD nations poised to bridge these financial divides.

In essence, while the progress observed is commendable, a united global approach is indispensable for a seamless renewable transition.

13.3 Guidance for Future Research

The detailed investigation into SDG indicators presented in this dissertation paves the way for further inquiries and examinations in the realm of sustainable energy. The following eight research directions arise from the study's findings:

1. Deepen Urban-Rural Divide Analysis

The observed electrification trends clearly indicate disparities between urban and rural areas, particularly in Low-Income and Middle-Income countries. A closer analysis of socio-economic, cultural, and political factors influencing electrification disparities is crucial.

2. Impact of Renewable Transition

A comprehensive assessment of the tangible environmental, economic, and societal repercussions from a swift shift to renewables, especially in High-Income countries, is essential. Such an assessment would offer insights into the real-world benefits or challenges from shifting rapidly to renewables.

3. Economic Implications of Clean Fuel

The correlation between clean fuel access and economic growth invites a detailed economic study. This could involve assessing job creation potential, industry growth, and the interplay between clean fuel access and broader economic trends.

4. Policy Assessment

This research points to the significant role of policy in steering sustainable energy transitions. Detailed evaluations of policies across nations can pinpoint best practices and gaps.

5. Technological Innovations

As technological advancements play a pivotal role in sustainable energy shifts, a deeper investigation into emerging innovations, their scalability, and accessibility, especially in Low-Income regions is imperative.

6. Examination of Financial Mechanisms

With the spotlight on financial trends and sustainable debt, a deeper dive into innovative funding mechanisms, their efficacy, and their impact on the ground can provide invaluable insights. This might include studying the role of international grants, green bonds, and public-private partnerships.

7. Collaborative Strategies for Renewable Uptake

Considering the emphasized need for international collaboration, a detailed study on how various countries can synergize their resources, knowledge, and expertise to foster faster and more efficient renewable adoption, particularly in Developing Countries, is recommended.

8. Modeling and Predictive Analytics

Disparities in prediction data underscore the importance of enhancing predictive analytics. Prospective studies could focus on enhancing model precision or delving into hybrid models explicitly tailored for energy prognostications.

9. Quantum Computing to Elevate our Understanding of SDG 7

Quantum computing offers the potential to deeply analyze SDG 7's complex indicators. Its advanced capacity can uncover hidden patterns and insights, elevating our understanding of sustainable energy metrics and guiding more informed strategies for a sustainable future.

13.4 Epilogue

The imperative of sustainable energy is unmistakably clear in contemporary global dialogues. This dissertation, through its intricate examination of SDG 7, emphasizes the potency of Data Science and

Artificial Intelligence in shaping these conversations. The journey towards a sustainable future is multi-faceted, with technological advances, policy shifts, and international collaboration at its core. As we venture further into this realm, a commitment to continued research, knowledge sharing, and policy evolution remains paramount to realizing the ambitions set forth by the United Nations' Sustainable Development Goals.

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Appendix 1: OECD Members List

Australia	Denmark	Israel	Netherlands	Sweden
Austria	Estonia	Italy	New Zealand	Switzerland
Belgium	Finland	Japan	Norway	Turkiye
Canada	France	Korea	Poland	United Kingdom
Chile	Germany	Latvia	Portugal	United States
Colombia	Greece	Lithuania	Slovak Republic	
Costa Rica	Hungary	Luxembourg	Slovenia	
Czech Republic	Iceland	Mexico	Spain	

Source: OECD

Appendix 2: Developing Countries List

Data from "Low-Income countries" and "Low-Middle-Income countries", based on the World Bank classification, are aggregated, and utilized as a proxy for "Developing Countries" in this dissertation.

Low-Income Economies (GNIPC: USD 1,135 or lower)

Afghanistan	Korea, Dem. People's Rep	South Sudan
Burkina Faso	Liberia	Sudan
Burundi	Madagascar	Syrian Arab Republic
Central African Republic	Malawi	Togo
Chad	Mali	Uganda
Congo, Dem. Rep	Mozambique	Yemen, Rep.
Eritrea	Niger	
Ethiopia	Rwanda	
Gambia, The	Sierra Leone	
Guinea-Bissau	Somalia	

Lower-Middle Income Economies (GNIPC: USD 1,136 to USD 4,465)

Angola	Jordan	Philippines
Algeria	India	Samoa
Bangladesh	Iran, Islamic Rep	Sao Tome and Principe
Benin	Kenya	Senegal
Bhutan	Kiribati	Solomon Islands
Bolivia	Kyrgyz Republic	Sri Lanka
Cabo Verde	Lao PDR	Tanzania
Cambodia	Lebanon	Tajikistan
Cameroon	Lesotho	Timor-Leste
Comoros	Mauritania	Tunisia
Congo, Rep.	Micronesia, Fed. Sts.	Ukraine
C?te d'Ivoire	Mongolia	Uzbekistan
Djibouti	Morocco	Vanuatu
Egypt, Arab Rep.	Myanmar	Vietnam
Eswatini	Nepal	Zambia
Ghana	Nicaragua	Zimbabwe
Guinea	Nigeria	
Haiti	Pakistan	
Honduras	Papua New Guinea	

Source: World Bank

Appendix 3: Python Program for GDP Per Capita

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
import numpy as np

# Load the data
data = pd.read_csv('CSV_GDPPC.csv', skiprows=4)

# Define the groups of interest
groups = ["Low income", "Lower middle income", "Upper middle income", "High income", "OECD members",
"World"]

# Filter the data for these groups
data_filtered = data[data['Country Name'].isin(groups)]

# Define the years of interest
years = list(map(str, range(1990, 2023)))

# Function to calculate percentage change
def calc_percentage_change(new_val, old_val):
    return ((new_val - old_val) / old_val) * 100

# 1. Line Chart with actual value from 1990 to 2022 (Chart 5.1)
plt.figure(figsize=(14, 8))
for i, group in enumerate(groups):
    plt.plot(years, data_filtered[data_filtered['Country Name'] == group][years].values[0], label=group)
plt.xticks(years[::2])
plt.title('GDP Per Capita Line Chart (1990-2022)')
plt.xlabel('Year')
plt.ylabel('GDP Per Capita (current US$)')
plt.legend()
plt.show()

# 2. Heat Map actual value from 1990 to 2022 (Chart 5.2)
plt.figure(figsize=(12, 8))
sns.heatmap(data_filtered.set_index('Country Name').loc[groups, years], annot=False, cmap="coolwarm")
plt.title('GDP Per Capita Heat Map (1990-2022)')
plt.xlabel('Year')
plt.ylabel('Income Group')
```

```
plt.show()

# 3. RF Prediction Table and Line Chart for 2023
#(Chart 5.3 & 5.4 and Table 5.1 & 5.2)
rf_predictions_2023 = {}
rf_percent_changes_2023 = {}
plt.figure(figsize=(14, 8))
for i, group in enumerate(groups):
    gdp_data = data_filtered[data_filtered['Country Name'] == group][years].values[0]
    last_known_value = gdp_data[-1] if not np.isnan(gdp_data[-1]) else gdp_data[-2]
    gdp_data = pd.Series(gdp_data, index=pd.to_numeric(years)).dropna()
    X = gdp_data.index.values.reshape(-1, 1)
    y = gdp_data.values
    rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
    rf_model.fit(X, y)
    prediction_2023 = rf_model.predict([[2023]])[0]
    rf_predictions_2023[group] = prediction_2023
    percent_change = calc_percentage_change(prediction_2023, last_known_value)
    rf_percent_changes_2023[group] = percent_change
    plt.plot(years, gdp_data.values, label=f"{group} (Actual)", linewidth=2)
    plt.plot(['2022', '2023'], [last_known_value, prediction_2023], 'r--', label=f"{group} (RF Predicted)")

plt.xticks(years[::2])
plt.title('GDP Per Capita Forecast for 2023 (RF)')
plt.xlabel('Year')
plt.ylabel('GDP Per Capita (current US$)')
plt.legend()
plt.show()

# Display RF Prediction table for 2023
rf_predictions_2023_df = pd.DataFrame({
    '2023 Predicted': list(rf_predictions_2023.values()),
    '% Change': list(rf_percent_changes_2023.values())
}, index=list(rf_predictions_2023.keys()))
print("RF Predicted Value 2023")
print(rf_predictions_2023_df)

# 5. GBM Prediction Table and Line Chart for 2023
gbm_predictions_2023 = {}
gbm_percent_changes_2023 = {}
plt.figure(figsize=(14, 8))
for i, group in enumerate(groups):
```

```python
    gdp_data = data_filtered[data_filtered['Country Name'] == group][years].values[0]
    last_known_value = gdp_data[-1] if not np.isnan(gdp_data[-1]) else gdp_data[-2]
    gdp_data = pd.Series(gdp_data, index=pd.to_numeric(years)).dropna()
    X = gdp_data.index.values.reshape(-1, 1)
    y = gdp_data.values
    gbm_model = GradientBoostingRegressor(n_estimators=100, random_state=42)
    gbm_model.fit(X, y)
    prediction_2023 = gbm_model.predict([[2023]])[0]
    gbm_predictions_2023[group] = prediction_2023
    percent_change = calc_percentage_change(prediction_2023, last_known_value)
    gbm_percent_changes_2023[group] = percent_change
    plt.plot(years, gdp_data.values, label=f"{group} (Actual)", linewidth=2)
    plt.plot(['2022', '2023'], [last_known_value, prediction_2023], 'g--', label=f"{group} (GBM Predicted)")

plt.xticks(years[::2])
plt.title('GDP Per Capita Forecast for 2023 (GBM)')
plt.xlabel('Year')
plt.ylabel('GDP per capita (current US$)')
plt.legend()
plt.show()

# Display GBM Prediction table for 2023
gbm_predictions_2023_df = pd.DataFrame({
    '2023 Predicted': list(gbm_predictions_2023.values()),
    '% Change': list(gbm_percent_changes_2023.values())
}, index=list(gbm_predictions_2023.keys()))
print("GBM Predicted Value 2023")
print(gbm_predictions_2023_df)

# Python codes are available on GitHub at: https://github.com/BlockQuant18/SU-PHD-TM
```

Appendix 4: Python Program for SDG Indicator 7.1.1

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from IPython.display import display

#Remove warning
import warnings
warnings.filterwarnings('ignore')

# Load the CSV data into a DataFrame
df = pd.read_csv('CSV_7.1.1.csv')

# Modify the entities dictionary
entities = {
    'Low income': 'deepskyblue',
    'Lower middle income': 'darkorange',
    'Upper middle income': 'mediumseagreen',
    'High income': 'red',
    'World': 'brown'
}
# Filter the data for years 2003 to 2021 and make a copy to prevent warnings
df_filtered = df[(df['Year'] >= 2003) & (df['Year'] <= 2021)].copy()

# Get the 2021 value for Low income for annotations
low_income_2021_check = df[(df['Entity'] == 'Low income') & (df['Year'] == 2021)]

# Chart 5.5 Access to Electricity in Urban Areas (2000-2021)
plt.figure(figsize=(8, 6))
for entity, color in entities.items():
    entity_data = df_filtered[df_filtered['Entity'] == entity]
    plt.plot(entity_data['Year'], entity_data['Access to electricity, urban (% of urban population)'], label=entity,
color=color)
    if entity == 'Low income':
        plt.annotate(f"{low_income_2021_check['Access to electricity, urban (% of urban
population)'].values[0]:.2f}%",
                     (2021, low_income_2021_check['Access to electricity, urban (% of urban population)'].values[0]),
                     textcoords="offset points", xytext=(0,5), ha='center', color=color)
plt.xlabel('Year', fontsize=14)
```

```
plt.ylabel('Access to electricity, urban (% of urban population)', fontsize=14)
plt.title('Access to Electricity in Urban Areas Line Chart (2000-2021)')
plt.legend(loc='best')
plt.grid(True)
plt.tight_layout()
plt.show()

# Chart 5.6 Access to Electricity in Rural Areas (2000-2021)
plt.figure(figsize=(8, 6))
for entity, color in entities.items():
    entity_data = df_filtered[df_filtered['Entity'] == entity]
    plt.plot(entity_data['Year'], entity_data['Access to electricity, rural (% of rural population)'], label=entity,
color=color)
    if entity == 'Low income':
        plt.annotate(f"{low_income_2021_check['Access to electricity, rural (% of rural population)'].values[0]:.2f}%",
                     (2021, low_income_2021_check['Access to electricity, rural (% of rural population)'].values[0]),
                     textcoords="offset points", xytext=(0,5), ha='center', color=color)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Access to electricity, rural (% of rural population)', fontsize=14)
plt.title('Access to Electricity in Rural Areas Line Chart (2000-2021)')
plt.legend(loc='best')
plt.grid(True)
plt.tight_layout()
plt.show()

# Chart 5.7 Difference in Urban and Rural Access Over Time
df_filtered['Difference'] = df_filtered['Access to electricity, urban (% of urban population)'] - df_filtered['Access to
electricity, rural (% of rural population)']
plt.figure(figsize=(12, 8))
for entity, color in entities.items():
    entity_data = df_filtered[df_filtered['Entity'] == entity]
    plt.plot(entity_data['Year'], entity_data['Difference'], label=entity, color=color)
    if entity == 'Low income':
        diff_value = low_income_2021_check['Access to electricity, urban (% of urban population)'].values[0] - \
                     low_income_2021_check['Access to electricity, rural (% of rural population)'].values[0]
        plt.annotate(f"{diff_value:.2f}%",
                     (2021, diff_value),
                     textcoords="offset points", xytext=(0,5), ha='center', color=color)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Difference in Access (Urban - Rural)', fontsize=14)
plt.title('Difference in Urban and Rural Access to Electricity (2000-2021)')
```

```
plt.legend(loc='best')
plt.grid(True)
plt.tight_layout()
plt.show()

# Table 5.3 2022 forecast function for both urban and rural
def forecast_2022(entity, feature_col):
    entity_data = df_filtered[df_filtered['Entity'] == entity][['Year', feature_col]]
    X = entity_data[['Year']]
    y = entity_data[feature_col]
    lr = LinearRegression().fit(X, y)
    rf = RandomForestRegressor(n_estimators=100, random_state=42).fit(X, y)
    gb = GradientBoostingRegressor(n_estimators=100, random_state=42).fit(X, y)
    year_2022 = pd.DataFrame([2022], columns=['Year'])
    return lr.predict(year_2022)[0], rf.predict(year_2022)[0], gb.predict(year_2022)[0]

# Forecasting values for urban and rural populations for 2022
forecasted_values_urban = {entity: forecast_2022(entity, 'Access to electricity, urban (% of urban population)') for
entity in entities}
forecasted_values_rural = {entity: forecast_2022(entity, 'Access to electricity, rural (% of rural population)') for
entity in entities}

# Get 2021 values for urban and rural populations
values_2021_urban = df_filtered[df_filtered['Year'] == 2021].set_index('Entity')['Access to electricity, urban (% of
urban population)'].to_dict()
values_2021_rural = df_filtered[df_filtered['Year'] == 2021].set_index('Entity')['Access to electricity, rural (% of
rural population)'].to_dict()

# Create DataFrames for urban and rural forecasted values
df_combined_urban = pd.DataFrame.from_dict(forecasted_values_urban, orient='index', columns=['LR(2022)',
'RF(2022)', 'GBM(2022)'])
df_combined_rural = pd.DataFrame.from_dict(forecasted_values_rural, orient='index', columns=['LR(2022)',
'RF(2022)', 'GBM(2022)'])

# Insert 2021 values for urban and rural populations
df_combined_urban.insert(0, 'Actual(2021)', df_combined_urban.index.map(values_2021_urban))
df_combined_rural.insert(0, 'Actual(2021)', df_combined_rural.index.map(values_2021_rural))

# Style the DataFrames for better visualization (for both urban and rural populations)
styled_table_urban = df_combined_urban.style.set_table_attributes("border=1; font-size: 12pt") \
                                     .set_caption("<span style='font-size: 12pt;'>Predicted Value 2022 (% Urban
```

```
Population)</span>") \
                                .format("{:.2f}")
styled_table_rural = df_combined_rural.style.set_table_attributes("border=1; font-size: 12pt") \
                                .set_caption("<span style='font-size: 12pt;'>Predicted Value 2022 (% Rural
Population)</span>") \
                                .format("{:.2f}")

# Display the styled tables
display(styled_table_urban)
display(styled_table_rural)

# Python codes are available on GitHub at: https://github.com/BlockQuant18/SU-PHD-TM


i
```

Appendix 5: Python Program for SDG Indicator 7.1.2

```
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt
import matplotlib.colors as mcolors

#Remove warning
import warnings
warnings.filterwarnings('ignore')

# Chart 5.8 Load and preprocess data (Urban)
data = pd.read_csv('CSV_7.1.2_Urban.csv')
data_cleaned = data.iloc[4:].reset_index(drop=True)
data_cleaned.columns = data.iloc[3]
data_cleaned = data_cleaned.rename(columns={'Country Name': 'Country', 'Country Code': 'Code', 'Indicator
Name': 'Indicator', 'Indicator Code': 'Indicator_Code'})
data_cleaned = data_cleaned.drop(0)
data_2021 = data_cleaned[["Country", "Code", 2021.0]]
data_2021[2021.0] = data_2021[2021.0].astype(float)

# Load geospatial data and merge
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

# Remove Greenland and Antarctica
world = world[(world.name != "Greenland") & (world.name != "Antarctica")]
world_merged = world.merge(data_2021, left_on='iso_a3', right_on='Code')

# Create a custom color map with a single HEX color
cmap_custom = mcolors.LinearSegmentedColormap.from_list("custom", ["#ffffff", "#FF9912"], N=256)
#537f8a
#e28743
#EEB422
#CD981D

# Visualization with adjustments and custom colormap
title_font_size = 18
fig, ax = plt.subplots(1, 1, figsize=(16, 9))
world.boundary.plot(ax=ax, linewidth=1)
world_merged.plot(column=2021.0, ax=ax, legend=True,
                 cmap=cmap_custom,
                 legend_kwds={'label': "Urban Access to Clean Fuels and Technologies for Cooking (2021)",
                              'orientation': "horizontal",
                              'shrink': 0.25,
                              'pad': 0.05,
                              'location': 'bottom'})
ax.set_title('Urban Access to Clean Fuels and Technologies for Cooking (2021)', fontsize=title_font_size)
plt.show()

# Chart 5.9 Load and preprocess data (Rural)
data = pd.read_csv('CSV_7.1.2_Rural.csv')
data_cleaned = data.iloc[4:].reset_index(drop=True)
data_cleaned.columns = data.iloc[3]
data_cleaned = data_cleaned.rename(columns={'Country Name': 'Country', 'Country Code': 'Code', 'Indicator
```

```
Name': 'Indicator', 'Indicator Code': 'Indicator_Code'})
data_cleaned = data_cleaned.drop(0)
data_2021 = data_cleaned[["Country", "Code", 2021.0]]
data_2021[2021.0] = data_2021[2021.0].astype(float)

# Load geospatial data and merge
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

# Remove Greenland and Antarctica
world = world[(world.name != "Greenland") & (world.name != "Antarctica")]

world_merged = world.merge(data_2021, left_on='iso_a3', right_on='Code')

# Create a custom color map with a single HEX color
cmap_custom = mcolors.LinearSegmentedColormap.from_list("custom", ["#ffffff", "#537f8a"], N=256)
#e28743
#537f8a

# Visualization with adjustments and custom colormap
title_font_size = 18
fig, ax = plt.subplots(1, 1, figsize=(16, 9))
world.boundary.plot(ax=ax, linewidth=1)
world_merged.plot(column=2021.0, ax=ax, legend=True,
            cmap=cmap_custom,
            legend_kwds={'label': "Rural Access to Clean Fuels and Technologies for Cooking (2021)",
                    'orientation': "horizontal",
                    'shrink': 0.25,
                    'pad': 0.05,
                    'location': 'bottom'})
ax.set_title('Rural Access to Clean Fuels and Technologies for Cooking (2021)', fontsize=title_font_size)
plt.show()

# Python codes are available on GitHub at: https://github.com/BlockQuant18/SU-PHD-TM
```

Appendix 6: Python Program for SDG Indicator 7.2.1

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset from the CSV file
data = pd.read_csv('CSV_7.2.1.csv')

# Define the groups of interest and filter the data
groups = ["Low income", "Lower middle income", "Upper middle income", "High income", "OECD members",
"World"]
data_filtered = data[data['Entity'].isin(groups)]

# Define the years of interest
years = list(map(int, range(2000, 2022)))

# Filter the data for the years and groups of interest
data_filtered_years = data_filtered[data_filtered['Year'].isin(years)]

# Define the colors as per user's request
colors_dict = {
    "Low income": 'steelblue',
    "Lower middle income": 'orange',
    "Upper middle income": 'green',
    "High income": 'red',
    "OECD members": 'purple',
    "World": 'brown'
}

# Create the line chart (Chart 5.10)
plt.figure(figsize=(12, 8))
for entity in groups:
    entity_data = data_filtered_years[data_filtered_years['Entity'] == entity]
    plt.plot(entity_data['Year'], entity_data['Renewables (% electricity)'], label=entity, color=colors_dict[entity])
plt.title('Renewable Energy Share in Total Installed Capacity Line Chart (2000-2021)')
plt.xlabel('Year')
plt.ylabel('Renewables (% electricity)')
plt.legend()
plt.grid(True)
plt.show()
```

```
# Prepare data for heatmap (Chart 5.11)
heatmap_data = data_filtered_years.pivot(index='Entity', columns='Year', values='Renewables (% electricity)')

# Create the refined heatmap with Y-Axis label as "Category"
plt.figure(figsize=(14, 12))
sns.heatmap(heatmap_data, annot=True, fmt=".1f", cmap='YlGnBu', cbar_kws={'label': 'Renewables (%
electricity)'},
            annot_kws={"size": 12}, linewidths=.5)
plt.title('Renewable Energy Share in Total Installed Capacity Heat Map (2000-2021)', fontsize=16)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Category', fontsize=14)
plt.show()

# Prepare data for area chart (Chart 5.12)
area_chart_data = data_filtered_years.pivot(index='Year', columns='Entity', values='Renewables (% electricity)')

# Create the unstacked area chart
plt.figure(figsize=(14, 8))
for entity in groups:
    entity_data = area_chart_data[entity]
    plt.fill_between(area_chart_data.index, entity_data, label=entity, color=colors_dict[entity], alpha=0.6)
plt.title('Renewable Energy Share in Total Installed Capacity Area Chart (2000-2021)')
plt.xlabel('Year')
plt.ylabel('Renewables (% electricity)')
plt.legend(loc='upper left')
plt.grid(True)
plt.show()

# Predicted Renewable Energy Share in Total Installed Capacity for 2023 (Table 5.4)
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.model_selection import train_test_split

#Remove warning
import warnings
warnings.filterwarnings('ignore')

# Load the dataset
#data = pd.read_csv('/mnt/data/share-electricity-renewables-r.csv')
data = pd.read_csv('CSV_7.2.1.csv')
```

```
# Filter data
groups = ["Low income", "Lower middle income", "Upper middle income", "High income", "OECD members",
"World"]
data_filtered = data[data['Entity'].isin(groups)]
years = list(map(int, range(2000, 2022)))
data_filtered_years = data_filtered[data_filtered['Year'].isin(years)]

# Initialize regression models
lin_reg = LinearRegression()
rf_reg = RandomForestRegressor(n_estimators=100, random_state=42)
gb_reg = GradientBoostingRegressor(n_estimators=100, random_state=42)

# Dataframe to store the predictions
predictions = pd.DataFrame(columns=['Entity', 'Actual(2021)', 'LR(2022)', 'RF(2022)', 'GB(2022)'])

# Forecasting
for entity in groups:
    entity_data = data_filtered_years[data_filtered_years['Entity'] == entity]
    X = entity_data[['Year']]
    y = entity_data['Renewables (% electricity)']
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=1, shuffle=False)

    # Train models
    lin_reg.fit(X_train, y_train)
    rf_reg.fit(X_train, y_train)
    gb_reg.fit(X_train, y_train)

    # Predict values for 2022
    lin_pred = lin_reg.predict([[2022]])[0]
    rf_pred = rf_reg.predict([[2022]])[0]
    gb_pred = gb_reg.predict([[2022]])[0]

    # Store results
    predictions = predictions.append({
        'Entity': entity,
        'Actual(2021)': y_test.values[0],
        'LR(2022)': lin_pred,
        'RF(2022)': rf_pred,
        'GB(2022)': gb_pred
    }, ignore_index=True)

# Display the improved table without the index and the "Entity" label
```

```
styled_table = predictions.style.set_table_styles({
    '': [{'selector': 'th',
         'props': [('font-size', '14pt'),
                   ('text-align', 'center'),
                   ('background-color', 'lightgrey')]},
        {'selector': 'td',
         'props': [('font-size', '13pt'),
                   ('text-align', 'center')]}]
}).hide_index().set_properties(**{'background-color': 'white', 'color': 'black'}).set_caption("Predicted Value 2022
(%)")

# Remove the "Entity" label from the header
styled_table.columns.name = None

styled_table

# Python codes are available on GitHub at: https://github.com/BlockQuant18/SU-PHD-TM
```

Appendix 7: Python Program for SDG Indicator 7.3.1

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
import numpy as np

# Remove warning
import warnings
warnings.filterwarnings('ignore')

# Load the CSV file into a DataFrame
file_path = 'CSV_7.3.1.csv'
df = pd.read_csv(file_path, skiprows=4)

# Define the groups of interest and filter the DataFrame
groups = ["Low income", "Lower middle income", "Upper middle income", "High income", "OECD members",
"World"]
filtered_df = df[df['Country Name'].isin(groups)]

# Define the colors as per user's request
colors_dict = {
    "Low income": 'steelblue',
    "Lower middle income": 'orange',
    "Upper middle income": 'green',
    "High income": 'red',
    "OECD members": 'purple',
    "World": 'brown'
}

# Filter the columns to only include years from 2000 to 2020
years_columns = [str(year) for year in range(2000, 2021)]
filtered_years_df = filtered_df[['Country Name'] + years_columns]

# Plot the existing Line Chart (Chart 5.13)
plt.figure(figsize=(14, 8))
for index, row in filtered_years_df.iterrows():
    plt.plot(years_columns, row[years_columns], label=row['Country Name'], color=colors_dict[row['Country
Name']])
plt.title('Energy Intensity Indicator Line Chart (2000-2020)')
plt.xlabel('Year')
plt.ylabel('Indicator Value')
```

```
plt.legend()
plt.grid(True)
plt.show()

# Prepare data for stacked area chart(Chart 5.14)
stacked_data = filtered_years_df.set_index('Country Name')[years_columns].T

# Plot the existing Stacked Area Chart
plt.figure(figsize=(14, 8))
plt.stackplot(stacked_data.index, stacked_data.values.T, labels=stacked_data.columns,
colors=[colors_dict[group] for group in stacked_data.columns], alpha=0.5)
plt.title('Energy Intensity Indicator Area Chart (2000-2020)')
plt.xlabel('Year')
plt.ylabel('Indicator Value')
plt.legend()
plt.grid(True)
plt.show()

# Initialize an empty DataFrame to store predictions
predicted_df = pd.DataFrame()

# Initialize the model
model = LinearRegression()

for index, row in filtered_years_df.iterrows():
    # Prepare the data
    X = np.array(range(len(years_columns))).reshape(-1, 1)  # Years as numerical values
    y = row[years_columns].values  # Indicator values

    # Train the model
    model.fit(X, y)

    # Predict for 2021, 2022, and 2023 (years 21, 22, and 23 from 2000)
    predictions = model.predict(np.array([[21], [22], [23]]))

    # Append to the predicted_df DataFrame
    predicted_df = predicted_df.append(pd.Series([row['Country Name'], predictions[0], predictions[1],
predictions[2]], index=['Country Name', '2021_pred', '2022_pred', '2023_pred']), ignore_index=True)

# Add the actual values for 2020 to the predicted_df
predicted_df['2020_actual'] = filtered_years_df['2020'].values
```

```
# Calculate the percentage changes for 2021, 2022, and 2023 compared to 2020
predicted_df['2021_change'] = ((predicted_df['2021_pred'] - predicted_df['2020_actual']) /
predicted_df['2020_actual']) * 100
predicted_df['2022_change'] = ((predicted_df['2022_pred'] - predicted_df['2020_actual']) /
predicted_df['2020_actual']) * 100
predicted_df['2023_change'] = ((predicted_df['2023_pred'] - predicted_df['2020_actual']) /
predicted_df['2020_actual']) * 100

# Remove the index column to delete the first column on the left-hand side
predicted_df.set_index('Country Name', inplace=True)

# Plot the Line Chart with both actual and predicted values (Chart 5.15)
plt.figure(figsize=(14, 8))

# Plot actual values for 2000-2020 in solid lines
for index, row in filtered_years_df.iterrows():
    plt.plot(years_columns, row[years_columns], label=row['Country Name'], color=colors_dict[row['Country
Name']])

# Plot predicted values for 2021-2023 in dotted lines
predicted_years = ['2021', '2022', '2023']
for index, row in predicted_df.iterrows():
    plt.plot(predicted_years, [row['2021_pred'], row['2022_pred'], row['2023_pred']], 'o--', color=colors_dict[index],
label=f"{index} (Predicted)")

plt.title('Energy Intensity Indicator Forecast (2021-2023)')
plt.xlabel('Year')
plt.ylabel('Indicator Value')
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))
plt.grid(True)
plt.tight_layout()
plt.show()


# Use linear regression to generate predictions (Table 5.3)

# Initialize the model
lr = LinearRegression()

# Create columns for predicted values and changes
predicted_values = []
changes = []
```

```
# Loop through each group and generate predictions
for index, row in filtered_years_df.iterrows():
    X = np.array(list(range(2000, 2021))).reshape(-1, 1)
    y = row[years_columns].values
    lr.fit(X, y)

    # Predict for 2021, 2022, and 2023
    predictions = lr.predict(np.array([[2021], [2022], [2023]]))

    predicted_values.append(predictions)
    changes.append((predictions - y[-1]) / y[-1] * 100)  # % change relative to 2020

# Convert lists to DataFrame
predicted_df = pd.DataFrame(predicted_values, columns=['2021_pred', '2022_pred', '2023_pred'])
predicted_df['Country Name'] = filtered_years_df['Country Name'].values
predicted_df = predicted_df.set_index('Country Name')

changes_df = pd.DataFrame(changes, columns=['2021_change', '2022_change', '2023_change'])
changes_df['Country Name'] = filtered_years_df['Country Name'].values
changes_df = changes_df.set_index('Country Name')

# Merge the two dataframes
predicted_df = pd.concat([predicted_df, changes_df], axis=1)

# Display the two tables

print("Predicted Value (%)")
print("-------------------")
print(predicted_df[['2021_pred', '2022_pred', '2023_pred']].rename(columns={
    '2021_pred': '2021',
    '2022_pred': '2022',
    '2023_pred': '2023'
}))

print("\nPredicted Value vs. 2020 (%)")
print("----------------------------")
print(predicted_df[['2021_change', '2022_change', '2023_change']].round(2).rename(columns={
    '2021_change': '2021',
    '2022_change': '2022',
    '2023_change': '2023'
}))
# Python codes are available on GitHub at: https://github.com/BlockQuant18/SU-PHD-TM
```

Appendix 8: Python Program for SDG Indicator 7.A.1

```
# Chart 5.16 and 5.17

import pandas as pd
import matplotlib.pyplot as plt

# Load the data from the CSV file
#df = pd.read_csv('/mnt/data/Global_Energy_Investment_Dataset_7A1.csv')
df = pd.read_csv('CSV_7.A.1_EnInv.csv')

# Remove the percentage sign (%) from the percentage columns and convert the data type to float
percentage_columns = ['Renewable power %', 'Energy efficiency %', 'Other end use %', 'Grids %', 'Electric vehicle %', 'Battery storage %', 'Nuclear %', 'Low-emission fuels and carbon capture %', 'Others %', 'Clean eneregy %', 'Fossil energy %']
for column in percentage_columns:
    df[column] = df[column].str.rstrip('%').astype('float')

# Define the column names
columns = ['Renewable power', 'Energy efficiency', 'Other end use', 'Grids', 'Electric vehicle', 'Battery storage', 'Nuclear', 'Low-emission fuels and carbon capture', 'Others', 'Fossil energy']
columns_percentage = [column + ' %' for column in columns]
barWidth = 0.4

# Define color for each column
color_dict = {
    'Renewable power': 'deepskyblue',
    'Energy efficiency': 'royalblue',
    'Other end use': 'springgreen',
    'Grids': 'seagreen',
    'Electric vehicle': 'yellow',
    'Battery storage': 'gold',
    'Nuclear': 'orange',
    'Low-emission fuels and carbon capture': 'lightcoral',
    'Others': 'brown',
    'Fossil energy': 'lightblue',
    'Renewable power %': 'deepskyblue',
    'Energy efficiency %': 'royalblue',
    'Other end use %': 'springgreen',
    'Grids %': 'seagreen',
    'Electric vehicle %': 'yellow',
    'Battery storage %': 'gold',
```

```
    'Nuclear %': 'orange',
    'Low-emission fuels and carbon capture %': 'lightcoral',
    'Others %': 'brown',
    'Fossil energy %': 'lightblue'
}


# Create first combined bar chart with larger legend at the bottom
plt.figure(figsize=(18, 10))
for i, column in enumerate(columns):
    bottoms = df[columns[:i]].sum(axis=1) / 1e12 if i > 0 else 0
    plt.bar(df['Year'], df[column] / 1e12, bottom=bottoms, color=color_dict[column], edgecolor ='grey', width =
barWidth)
    if column == 'Fossil energy' or column == 'Renewable power':
        for x,y in zip(df['Year'], df[column] / 1e12):
            bottom_val = bottoms.loc[x - df['Year'].min()] if isinstance(bottoms, pd.Series) else bottoms
            plt.text(x, y/2 + bottom_val, '{:.2f}'.format(y), ha = 'center', va = 'center')
plt.legend(columns, bbox_to_anchor=(0.5, -0.15), loc='upper center', ncol=5, prop={'size': 12})
plt.xlabel('Year')
plt.xticks(df['Year'])
plt.ylabel('Investment in Energy (USD trillion)')
plt.title('Investment in Various Energy Sources (2015-2023)', fontsize=20)
plt.show()

# Create second combined bar chart with larger legend at the bottom
plt.figure(figsize=(18, 10))
for i, column in enumerate(columns_percentage):
    bottoms = df[columns_percentage[:i]].sum(axis=1) if i > 0 else 0
    plt.bar(df['Year'], df[column], bottom=bottoms, color=color_dict[column], edgecolor ='grey', width = barWidth)
    if column == 'Fossil energy %' or column == 'Renewable power %':
        for x,y in zip(df['Year'], df[column]):
            bottom_val = bottoms.loc[x - df['Year'].min()] if isinstance(bottoms, pd.Series) else bottoms
            plt.text(x, y/2 + bottom_val, '{:.2f}'.format(y), ha = 'center', va = 'center')
plt.legend(columns_percentage, bbox_to_anchor=(0.5, -0.15), loc='upper center', ncol=5, prop={'size': 12})
plt.xlabel('Year')
plt.xticks(df['Year'])
plt.ylabel('Investment in Energy (%)')
plt.title('Investment in Various Energy Sources as a Percentage of Total Investment (2015-2023)', fontsize=20)
plt.show()

# Chart 5.18 and 5.19
```

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Load the data
#data = pd.read_csv('/mnt/data/Sustainable_Debt_Issuance_7A1.csv')
data = pd.read_csv('CSV_7.A.1_SusDebt.csv')

# Drop the extraneous column
data = data.drop(columns=['Unnamed: 8'])

# Process the data
data = data[data['Unnamed: 0'] != 'Total']
data = data.rename(columns={'Unnamed: 0': 'Category'})
colors = ['gold', 'darkgoldenrod', 'orange', 'tan']
data_reordered = data.set_index('Category').reindex(['Corporates', 'Other', 'Sovereigns, Supranational and
Agencies', 'Financials']).reset_index()
wide_data = data_reordered.set_index("Category").T
wide_data.index = wide_data.index.astype(int)

# Function to compute percentage values for 2022
def compute_percentage(row):
    total = row.sum()
    return [(val/total)*100 for val in row]

percentages_2022 = compute_percentage(wide_data.loc[2022])

# Adjust label function for doughnut chart
def adjust_labels(patches, labels, ax):
    for patch, label in zip(patches, labels):
        angle = (patch.theta2 - patch.theta1)/2. + patch.theta1
        y = np.sin(np.deg2rad(angle))
        x = np.cos(np.deg2rad(angle))
        horizontalalignment = {-1: "right", 1: "left"}[int(np.sign(x))]
        if label == "Sovereigns, Supranational and agencies":
            ax.text(x*1.2, y-0.1, label, horizontalalignment=horizontalalignment, fontsize=12)
        else:
            ax.text(x*1.2, y*1.2, label, horizontalalignment=horizontalalignment, fontsize=12)

# Plotting function with updated bar chart with percentages for 2022
def plot_charts():
    fig, ax = plt.subplots(2, 1, figsize=(16, 20))
```

```
    fig.subplots_adjust(hspace=0.5)
    positions = np.arange(len(wide_data.index))
    ax[0].set_title("Sustainable Debt Issuance (2016-2022)", fontsize=18)
    ax[0].set_ylabel('Values', fontsize=12)
    ax[0].set_xlabel('Year', fontsize=12)
    ax[0].tick_params(axis='both', which='major', labelsize=12)
    bar_width = 0.35
    for i, category in enumerate(wide_data.columns):
        bars = ax[0].bar(positions, wide_data[category],
              bottom=(wide_data.iloc[:, :i].sum(axis=1) if i > 0 else 0),
              color=colors[i], label=category, width=bar_width)
        # Add percentage labels for 2022
        if wide_data.columns[i] in data_reordered['Category'].values:
            height = bars.patches[-1].get_height()
            ax[0].text(positions[-1], bars.patches[-1].get_y() + height/2, f"{percentages_2022[i]:.1f}%", ha='center',
va='center', color='black', fontsize=10)
    ax[0].set_xticks(positions)
    ax[0].set_xticklabels(wide_data.index)
    ax[0].legend(loc='upper center', bbox_to_anchor=(0.5, -0.1), ncol=4, fontsize=12)
    ax[0].tick_params(axis='x', rotation=0)
    ax[1].set_title("Sustainable Debt Issuers (2022)", fontsize=18)
    patches, texts, autotexts = ax[1].pie(data_reordered['2022'], labels=data_reordered['Category'],
autopct='%1.1f%%', startangle=90, colors=colors, wedgeprops=dict(width=0.3))
    for text in texts:
        text.set_visible(False)
    adjust_labels(patches, data_reordered['Category'], ax[1])
    centre_circle = plt.Circle((0,0),0.70,fc='white')
    fig.gca().add_artist(centre_circle)
    ax[1].axis('equal')
    plt.show()

plot_charts()

# Python codes are available on GitHub at: https://github.com/BlockQuant18/SU-PHD-TM
```

Appendix 9: Python Program for SDG Indicator 7.B.1

```
import pandas as pd
import matplotlib.pyplot as plt

# Load the dataset
file_path = 'CSV_7.B.1.csv'
df = pd.read_csv(file_path, index_col=0)
df_transposed = df.transpose()
years = df.columns

# Modify the annotate_last_point function to support different formats
def annotate_last_point(ax, years, data, color, format_str="{:.2e}"):
    last_year = years[-1]
    last_value = data[last_year]
    ax.annotate(format_str.format(last_value), (last_year, last_value), textcoords="offset points", xytext=(0, 10),
ha='center', color=color)

# Extract the data for plotting
world_population = df_transposed['World Population'].astype('float') / 1e9
developing_country_population = df_transposed['Developing Country Population'].astype('float') / 1e9
oecd_population = df_transposed['OECD Population'].astype('float') / 1e9
developing_country_population_percent = df_transposed['Developing Country
Population%'].str.rstrip('%').astype('float')
oecd_population_percent = df_transposed['OECD Population%'].str.rstrip('%').astype('float')
world_renewable_mw = df_transposed['World Renewable MW'].astype('float') / 1e3
oecd_renewable_mw = df_transposed['OECD Renewable MW'].astype('float') / 1e3
developing_country_renewable_mw = df_transposed['Developing Country Renewable MW'].astype('float') / 1e3
oecd_renewable_mw_percent = df_transposed['OECD Renewable MW%'].str.rstrip('%').astype('float')
developing_country_renewable_mw_percent = df_transposed['Developing Country Renewable
MW%'].str.rstrip('%').astype('float')
world_kw_per_capita = df_transposed['World kW per capita'].astype('float')
oecd_kw_per_capita = df_transposed['OECD kW per capita'].astype('float')
developing_country_kw_per_capita = df_transposed['Developing Country kW per capita'].astype('float')

# Extract the last two rows for the sixth chart
last_two_rows = df.loc[['Developing Country kW per capita as a % of World kW per capita', 'Developing Country
kW per capita as a % of OECD kW per capita']]
last_two_rows_percentage = last_two_rows.astype('float')

# Chart 5.20
plt.figure(figsize=(14, 8))
```

```
ax1 = plt.gca()
plt.plot(years, world_population, color='brown', marker='o', label='World Population')
plt.plot(years, developing_country_population, color='blue', marker='s', label='Developing Country Population')
plt.plot(years, oecd_population, color='purple', marker='x', label='OECD Population')
annotate_last_point(ax1, years, world_population, 'brown')
annotate_last_point(ax1, years, developing_country_population, 'blue')
annotate_last_point(ax1, years, oecd_population, 'purple')
plt.title('World, Developing Country, and OECD Population (2000-2022)')
plt.xlabel('Year')
plt.ylabel('Population (Billions)')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Chart 5.21 with Y-axis in % to two decimal points
plt.figure(figsize=(14, 8))
ax2 = plt.gca()
plt.plot(years, developing_country_population_percent, color='blue', marker='o', label='Developing Country
Population %')
plt.plot(years, oecd_population_percent, color='purple', marker='s', label='OECD Population %')
annotate_last_point(ax2, years, developing_country_population_percent, 'blue', "{:.2f}%")
annotate_last_point(ax2, years, oecd_population_percent, 'purple', "{:.2f}%")
ax2.yaxis.set_major_formatter(lambda x, _: '{:.2f}%'.format(x))
plt.title('Developing Country and OECD Population as % of World Population (2000-2022)')
plt.xlabel('Year')
plt.ylabel('Population %')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Chart 5.22
plt.figure(figsize=(14, 8))
ax3 = plt.gca()
plt.plot(years, world_renewable_mw, color='brown', marker='o', label='World Renewable MW')
plt.plot(years, oecd_renewable_mw, color='purple', marker='s', label='OECD Renewable MW')
plt.plot(years, developing_country_renewable_mw, color='blue', marker='x', label='Developing Country
Renewable MW')
annotate_last_point(ax3, years, world_renewable_mw, 'brown')
annotate_last_point(ax3, years, oecd_renewable_mw, 'purple')
annotate_last_point(ax3, years, developing_country_renewable_mw, 'blue')
```

```
plt.title('World, OECD, and Developing Country Renewable MW (2000-2022)')
plt.xlabel('Year')
plt.ylabel('Renewable MW (in Billions)')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Chart 5.23
plt.figure(figsize=(14, 8))
ax4 = plt.gca()
plt.plot(years, world_kw_per_capita, color='brown', marker='o', label='World kW per capita')
plt.plot(years, oecd_kw_per_capita, color='purple', marker='s', label='OECD kW per capita')
plt.plot(years, developing_country_kw_per_capita, color='blue', marker='x', label='Developing Country kW per
capita')
annotate_last_point(ax4, years, world_kw_per_capita, 'brown', "{:.4f}")
annotate_last_point(ax4, years, oecd_kw_per_capita, 'purple', "{:.4f}")
annotate_last_point(ax4, years, developing_country_kw_per_capita, 'blue', "{:.4f}")
plt.title('World, OECD, and Developing Country kW per Capita (2000-2022)')
plt.xlabel('Year')
plt.ylabel('kW per Capita')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Chart 5.24
plt.figure(figsize=(14, 8))
ax5 = plt.gca()
plt.plot(years, oecd_renewable_mw_percent * 100, color='purple', marker='o', label='OECD Renewable MW %')
plt.plot(years, developing_country_renewable_mw_percent * 100, color='blue', marker='s', label='Developing
Country Renewable MW %')
annotate_last_point(ax5, years, oecd_renewable_mw_percent * 100, 'purple', "{:.2f}%")
annotate_last_point(ax5, years, developing_country_renewable_mw_percent * 100, 'blue', "{:.2f}%")
ax5.yaxis.set_major_formatter(lambda x, _: '{:.2f}%'.format(x))
plt.title('OECD and Developing Country Renewable MW as % of World Renewable MW (2000-2022)')
plt.xlabel('Year')
plt.ylabel('Renewable MW %')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
# Chart 5.25
plt.figure(figsize=(14, 8))
ax6 = plt.gca()
plt.plot(years, last_two_rows_percentage.loc['Developing Country kW per capita as a % of World kW per capita'] * 100, color='firebrick', marker='o', label='Developing Country kW per capita as a % of World kW per capita')
plt.plot(years, last_two_rows_percentage.loc['Developing Country kW per capita as a % of OECD kW per capita'] * 100, color='dodgerblue', marker='s', label='Developing Country kW per capita as a % of OECD kW per capita')
annotate_last_point(ax6, years, last_two_rows_percentage.loc['Developing Country kW per capita as a % of World kW per capita'] * 100, 'firebrick', "{:.2f}%")
annotate_last_point(ax6, years, last_two_rows_percentage.loc['Developing Country kW per capita as a % of OECD kW per capita'] * 100, 'dodgerblue', "{:.2f}%")
ax6.yaxis.set_major_formatter(lambda x, _: '{:.2f}%'.format(x))
plt.title('Developing Country kW per Capita as a Percentage of World and OECD kW per Capita (2000-2022)')
plt.xlabel('Year')
plt.ylabel('Percentage (%)')
plt.legend()
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Note:The CSV files and Python Code are available on GitHub at this link: https://github.com/BlockQuant18/SU-PHD-TM
```

DEDICATION

To Timeless Pursuits of Knowledge: For Pandora, Claire, and Veronica

In our ever-evolving world, I dedicate this work to my wife, Pandora, and our daughters, Claire, and Veronica. Your unwavering support has highlighted the value of continuous learning and kindled our shared curiosity. This dissertation reflects our joint commitment to embracing change, overcoming obstacles, and the perpetual quest for understanding. Together, we symbolize the boundless potential within us all.

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