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Chapter 1

Introduction

1.1 Global effects of global warming

Increasing levels of emissions of carbon dioxide (CO_2) and other greenhouse gases (GHGs) have caused irreversible changes to Earth's climate through. This has been a subject of research for decades. The 2021 IPCC report on widespread and rapid changes in the climate estimates the chances of the following decades observing an increase in the global warming level. According to this report, anthropogenic activities have contributed to approximately 1.1°C of the measured level of warming over the last one and a half centuries. The increase in global temperature is expected to reach 1.5°C in the next two decades (IPCC (2021)) (IPCC, 2021).

IPCCC reports with high confidence that beyond natural climate variability, human-induced climate change. This includes more frequent and intense extreme events. Consequently, it has resulted in widespread negative impacts and related losses and damages to nature and people. The most vulnerable people and systems are disproportionately affected across sectors and regions.

Climate change, including increases in the frequency and severity of extreme weather events, has hindered initiatives to reach the Sustainable Development Goals. Widespread deterioration of ecosystem structure and function, resilience, natural adaptive capacity and shifts in seasonal timing has occurred due to climate change, with adverse socioeconomic consequences.

Due to climatic and non-climatic drivers, roughly half of the world's population currently faces severe water shortages for at least some of the year.

Even though as a whole, crop yield has increased - climate change has decelerated this growth in the last 50 years globally. The associated adverse effects were primarily in mid and low-latitude regions, with some positive impacts in high-latitude regions. This has long-lasting effects on global food security (Ray et al. (2019)) illustrated in Figure 1.1[1].

[1]Brown colors : reduction in yield due to mean climate change;
Green colors : gains in yield due to mean climate change;
(a) barley; (b) cassava; (c) maize; (d) oil palm; (e) rapeseed;
(f) rice; (g) sorghum; (h) soybean; (i) sugarcane; and (j) wheat;
The study was not conducted in the white areas.

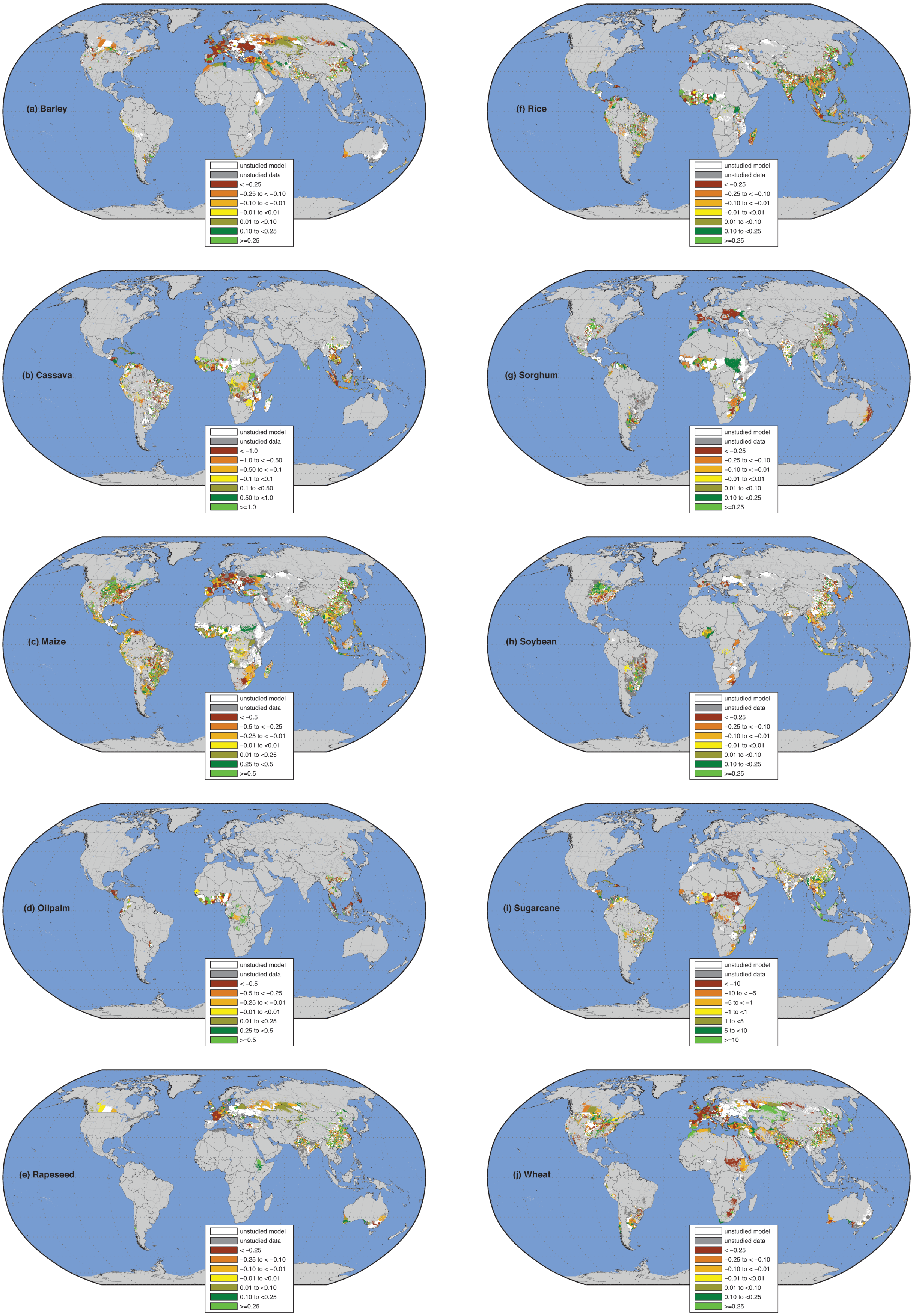

Figure 1.1: Impact of mean climate change on crop yield ($tons/ha/year$)[1] (Ray et al. (2019))

The statistical association between weather and agricultural yields was substantial in 54% to 88% of harvested regions globally across all crops, despite recent changes in mean climate occurring throughout all croplands. The link was significant in 88% (125 million hectares (Mha)) of the world's rice-harvesting croplands, but only in 54% (22 Mha) of the world's sorghum-harvesting croplands. In North and Central America, recent climate change has had a substantial influence on 89% of maize production areas but just 71% of wheat harvesting areas (Ray et al. (2019)).

It has been observed in some states of India to have a consistent pattern of yield losses for all major crops, such as the core Green Revolution states of Haryana and western Uttar Pradesh, as well as for rice in southern India (Tamil Nadu and Kerala), with overall production losses in India in wheat (-0.7% or -0.5 MT) and rice (-2.1% or -2.2 MT). On average, consumable food calories in India decreased by 1.2% for each of these ten crops and by 0.8% annually (Ray et al. (2019)).

1.1.1 The cost of pollution

Most environmental resources can be categorised as pure public goods - fulfilling both the "non-rivalry" and "non-excludability" criteria (Matthew Kotchen (2012)). *Non-excludable goods*, as the name suggests, do not exclude individuals or group of individuals from being able to use them. The supply of *non-rival goods* are typically not affected by other people's consumption of the same. Quality of air available is the same for all people in any given region and no person or group is excluded from being able to use the available air. One person breathing too much air in one space does not affect the supply of air for the next person either. However, external factors like pollution can not only expose minority and low-income populations to environmental stressors but also deprive them from a healthy life as a consequence (Institute of Medicine (US) Committee on Environmental Justice (1999)). Thereby, both excluding as well as depriving people from a quality life. This is one of those factors of global warming that needs to be mitigated instead of adapted to as the damage to human health. The environmental damage is catastrophically higher than what was previously understood. This is not only a future threat but also one with clear evidence of present and ongoing damage to society, as seen in the new Global Air Quality Guidelines (AQGs) published by WHO. The damaging effects of lowering air quality and increasing levels of air pollution and the growing disparity of its exposure worldwide are explicitly observed in low and middle-income countries. These countries primarily rely on burning fossil fuels to support their large-scale urbanisation and economic development goals (World Health Organization (2021)).

The impact of climate change interaction on ecosystems and human health are reflected through changes in exposure and susceptibility. Increased radiation could boost the development of ground-level ozone, worsening health and vegetation damage. An extended growing season, as well as altered water availability, might alter vegetation's sensitivity to ozone damage. Increased nitrogen deposition from air pollution combined with a decrease in plant development as a result of pollution may alter plants' capacity to store carbon (Swart et al. (2004)).

In a market economy - a perfectly competitive market contributes to the maximised social welfare (Feldman (2012)). However, as seen with all other practical aspects of life, markets rarely are perfectly competitive due to information asymmetry, monopolistic behaviour of firms, vague assignment of property rights and externalities. When left on their own, these imperfect markets fail to allocate resources efficiently, eventually leading to market failure (N. Gregory Mankiw (2018)). One of the key concepts that influence market failures is externalities, where positive externalities will improve the quality of life for people and negative externalities will decrease society's welfare (Theory of Pollution Control, n.d.). Negative environmental externalities are observed when society bears the costs of damage done by polluters instead of the polluters themselves. The impact of such negative environmental externality is seen through a reduction in economic welfare. Market failures caused by such negative environmental externalities generally arise when environmental endowments possess the characteristics of "public good".

The Social Cost of Carbon (SCC) is another method of estimating the economic cost of emitting an additional ton of CO_2 into the atmosphere. This estimate not only gives the monetary benefit of reducing emissions, but also serves as the basis for policy and investment decisions worth billions of dollars worldwide (Rennert et al. (2021)). India's country-level SCC is the highest at US\$86 per tCO_2 accounting for 21% of the global SCC), followed closely by the United States at US\$48 per tCO_2 (Ricke et al. (2018)).

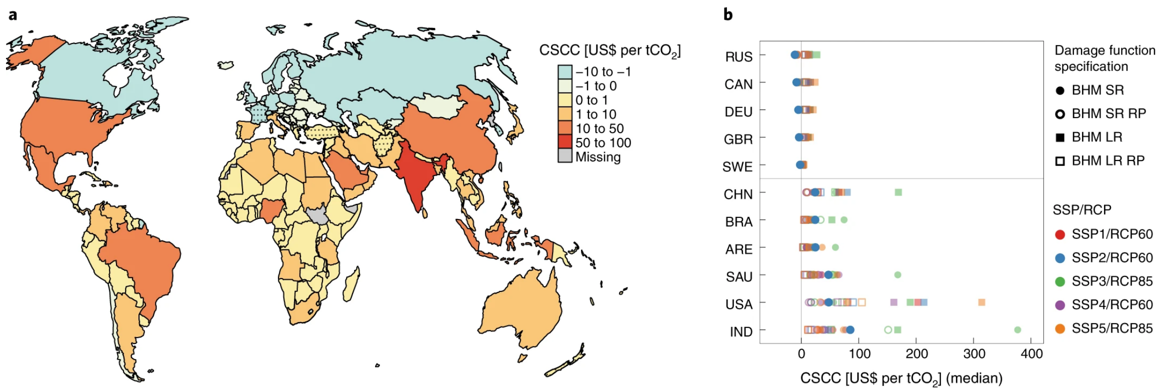

Figure 1.2: Country-level social cost of carbon (Ricke et al. (2018))

Market solutions like tradable pollution permits as seen in the EU Emissions Trading market (noa (b) EU Emissions Trading System (EU ETS), n.d.)) and Carbon-offsetting as seen through Clean Development Mechanism (CDM) (noa (a)The Clean Development Mechanism, n.d.) force consumers and producers to consider pollution as a private cost. This can be, in theory, an effective tool to keep pollution levels low - it does not guarantee the alteration of behaviour to lower pollution to sufficient levels. Other tools like pollution taxes designed to internalise such negative externalities again suffer from the lack of consideration of consumers' inelastic behaviour resulting from a relative insensitivity to fuel prices due to a lack of economically viable alternatives. Given the propensity of market failures for such solutions - a closer examination of the sources of pollutants is instrumental in formulating effective strategies and policies.

1.1.2 Impacts of Carbon dioxide emissions

Carbon dioxide (CO_2) is one of the gases in our atmosphere that traps heat and makes the planet habitable. It is one of the most long-lived greenhouse gases on the planet. While it absorbs less heat than other greenhouse gases, it is more abundant. This contributes the most to the heating imbalance that causes the Earth's temperature to rise. Atmospheric

CO2 has been on a constant rise over the past couple of decades, with the global average atmospheric carbon dioxide at 412.5 parts per million in 2020 - which has been a record high. In the past 800,000 years, carbon dioxide levels have not been observed as high as they are today (Rebecca Lindsey (2021) Lindsey, 2020).

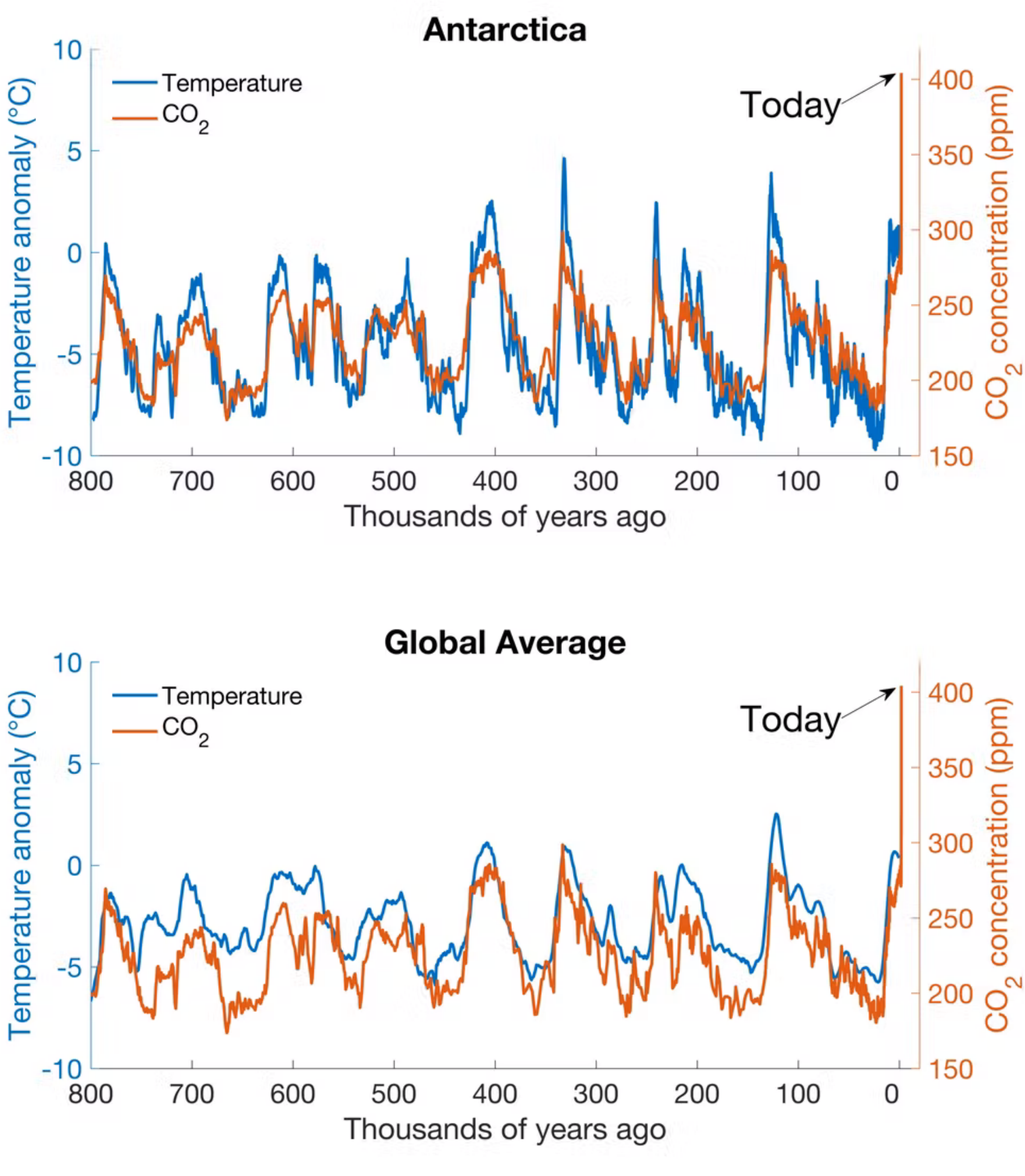

Figure 1.3: Historical Temperature and CO2 trends (Henley and Abram (2017)Henley & Abram, 2017)

Global climate change driven by carbon dioxide (CO_2) plays a direct role in deteriorating human health and negatively impacting local economies. Extreme weather events and climate disasters in the U. S. alone have caused estimated damages of up to 2.085 trillion USD (including CPI adjustment to 2021) between 1980 and 2021 (Smith (2020)). Effects of climate change is predicted with a 51% probability to drive down global GDP by more than 20% (Burke et al. (2015)). Approximately 22.5 million people were displaced between 2008 and 2017 due to climate change events. (?UNHCR, 2005) It is, therefore, essential that we focus on the contributing factors of climate change. CO_2 is the leading contributor to rising global temperatures.

Discussions on carbon emissions in 2021 require a cross-sectoral and regional analysis. In addition, how these components have responded to the COVID-19 pandemic should also be studied. The largest-ever decline in global CO_2 emissions was observed in 2020, with a dip of 5.8%. This decline is five times the figures from 2009 following the global financial crisis. Global energy-related CO_2 emissions was a key contributor to the annual average concentration of CO_2 reaching unprecedented levels despite its decline in 2020. (IEA, 2021) More than two-thirds of the global CO_2 emissions are attributed to emerging markets and developing economies, while the emissions from advanced economies have shown a structural decline over the years. The economic recovery of India in 2020 has been predicted to cause emissions 200 Mt higher than that of 2020. This prediction implies that the emission levels will be 1.4% higher than before the pandemic in 2019. Despite low per capita emissions, India happens to be the third-largest global emitter of CO_2 – indicating a higher than global average carbon intensity of its power sector. Over a million premature deaths in 2019 have been attributed to ambient and household air pollution, as particulate matter emissions play a significant role in air pollution in India. As the country aimed to provide electricity to all households by 2019, energy consumption has doubled since 2000. Lack of reliable electricity supply complicated by the pandemic has driven almost 660 million consumers to continue using solid biomass as a primary source of fuel for cooking: consequently, making Indian cities are few of the most polluted in the world (IEA, 2021).

1.2 Situation for India

The latest UN IPCC report paints a bleak picture for India, warning that the country may face a slew of climate-related disasters over the next two decades. It stated that unless greenhouse gas emissions are reduced dramatically by 2030, it will be impossible for India to avert an impending climate disaster. According to the report, upwards of 40% of India's population will experience water shortages by 2050, while rising sea levels will affect the country's coastlines, including major cities like Mumbai. Flooding will worsen in the Ganges and Brahmaputra River basins, while crop production will be hampered by droughts and scarcity of water (IPCC, 2021).

CO_2 emissions in India rose sharply above 2019 levels, due to increasing coal use in power generation again in 2021. Coal-fired power generation in India reached an all-time high and was 13% above 2020 levels, in part due to renewable energy growth slowing to one-third of the five years average rate (Global CO2 Emissions Rebounded to Their Highest Level in History in 2021 - News, 2022).

The frequency of thermal extremes over India has increased since 1951, with the warming trend accelerating over the past 30 years. Since 1986, temperatures have risen significantly for the warmest day, warmest night, and coldest night. The frequency, duration, intensity, and areal extent of pre-monsoon heat waves over India are projected to increase significantly this century (Krishnan et al., 2020). More recently, as the Indian subcontinent was gripped by one of the harshest heatwaves – the governments of India and Pakistan rolled out health action plans to save lives from extreme heat. While it is premature to conclude that climate change is the causal agent for the heatwave – it is consistent with the changes predicted as a consequence of climate change (India and Pakistan Act to Save Lives from Extreme Heat, 2022).

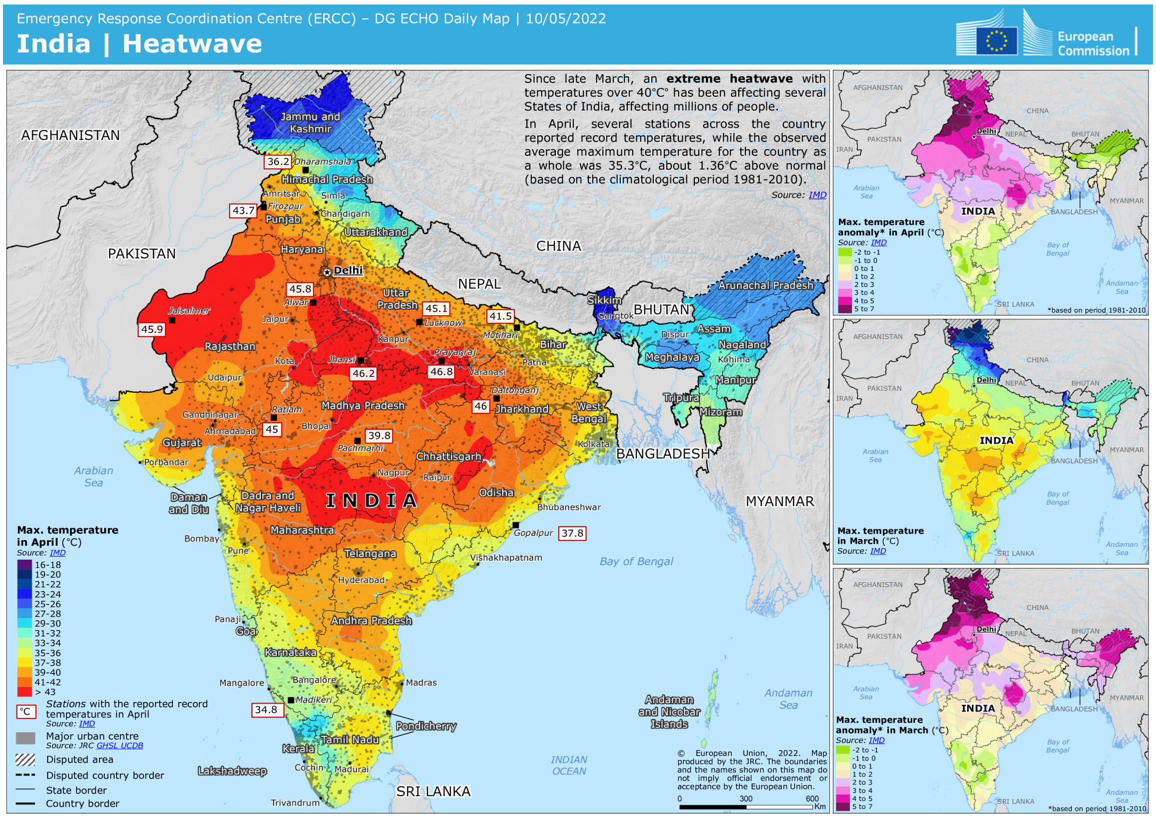

Figure 1.4: Heatwave in India (India — Heatwave - DG ECHO Daily Map— ReliefWeb, 2022)

1.2.1 India NDCs

In November 2021, at the Glasgow climate summit, India pledged through its Nationally Determined Contributions (NDCs) to reduce cumulative emissions by 1 billion tonnes by 2030, achieve net-zero emissions by 2070, and reduce the emissions intensity of the economy to 45% below the 2005 level. Further, the country aims to increase its power generation capacity without the usage of fossil fuels by 500 gigawatts and rely on renewable energy for 50% of its energy requirements (COP26, 2021).

This study explores and analyses the current state and link between India's energy demand and consumption, carbon emissions drivers across various sectors, and its economic growth through tools like *Environmental Kuznets Curve* and *Kaya Decomposition*. Following the analysis of the carbon emissions, this paper further touches upon how India fares against its goals set in the Nationally Determined Contribution (NDC) under the Paris Agreement. This also helps analyse policies targeted to maintain sustained economic growth while meeting the energy needs of its growing population, urbanisation, and industrialisation. This thesis aims to extrapolate the Indian emission figures and their underlying drivers towards 2030 to examine how realistic India's NDCs and its commitment to achieving total carbon neutrality, especially in comparison to other regions like the United States, European Union, and China.

Chapter 2

Literature Review

2.1 The Indian Economy

It is no surprise that a country populated with about 1.4 billion people heavily relies on fossil fuels to drive its economy. Last-minute changes in the agreement at the COP26 U.N. climate talks held in Glasgow in November 2021 attracted much criticism from the rest of the world. India, backed by China and other developing countries that find fossil fuels at the driving seat of their economies- switched the wording from "phase out" to "phase down" in the final text of the agreement (Volcovici et al. (2021)). (Volcovici et al., 2021)

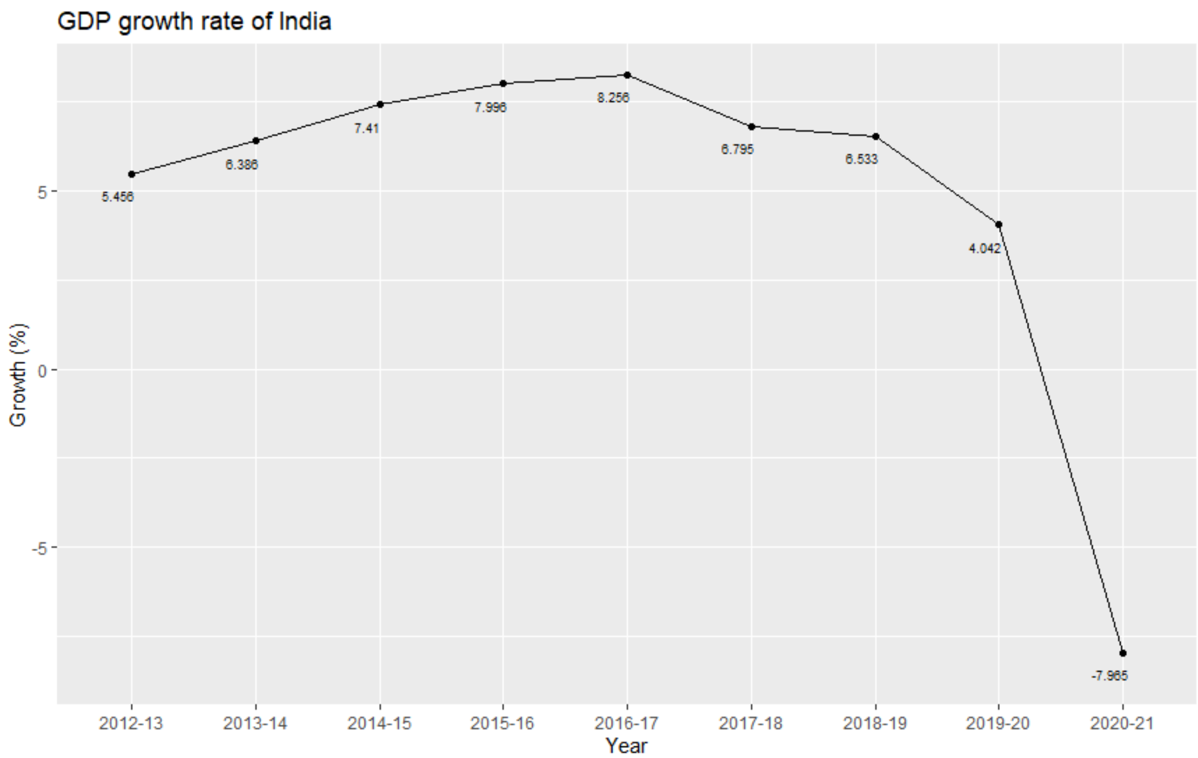

Figure 2.1: Growth rate of GDP (Ministry of Statistics and Programme Implementation, 2021)

For the last five years of the previous decade - the GDP growth rate has been a source of increasing concern. Although the RBI does not mention it, the government's move to demonetize 86% of India's currency overnight on November 8, 2016, is thought to be a key factor that triggered India's growth into a downward spiral (Singh (2019)) (Singh, 2019).

The GDP growth rate fell steadily from over 8% in FY17 to around 4% in FY20 (NATIONAL STATISTICAL OFFICE (2021)), just before COVID-19 hit the country, as possible consequences of demonetization and a poorly designed and hastily implemented goods and services tax (GST) (Udai et al. (2019) (Udai et al., 2019) spread through an economy that was already struggling with sizeable bad loans in its banking system.

In 2015, India switched to measuring its output in Gross Value Added (GVA) instead of Gross Domestic Product (GDP). GVA is an economic productivity metric to measure the contributions of various stakeholders to an economy, a sector, or a region. The domestic product is a measure of the GVA and net taxes combined (Seshadri, 2020). We, therefore, see that most figures reported by various Indian institutions are expressed in terms of GVA instead of GDP. GDP is derived as the sum of the gross value added (GVA) at basic prices, plus all taxes on products, less all subsidies on products. The total tax revenue used for GDP compilation includes Non-GST Revenue and GST Revenue.

2.1.1 Economic activities and their emissions

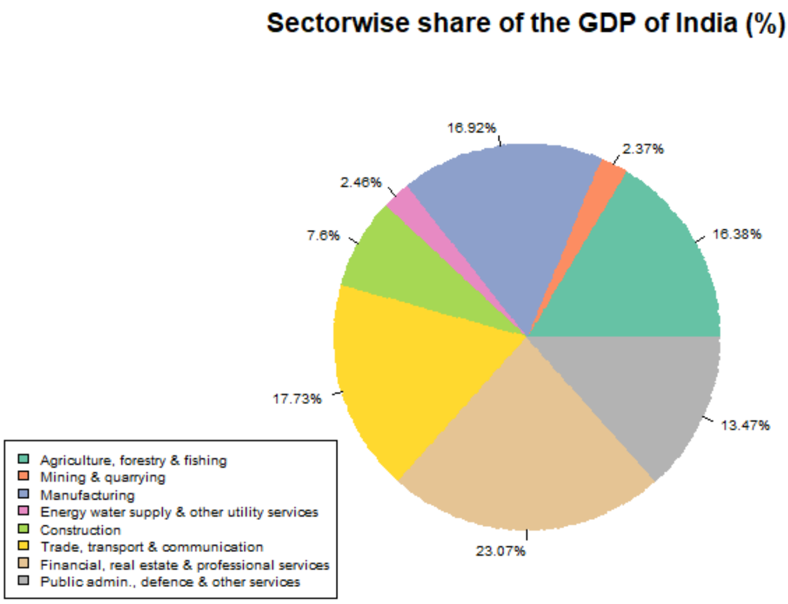

Figure 2.2: Sectorwise shares of India's GDP drivers (Ministry of Statistics and Programme Implementation, 2021)

The services sector accounts for 54.27% of the total GVA of India at 2011-12 prices is India's largest sector [1]. While the industry sector [2] - accounts for 29.34%. The agriculture sector accounts for 16.38% (Ministry of Statistics and Programme Implementation, 2021). The average GVA growth rates are observed at the 2011-12 prices at 3.49%, 3.82% and 6.23%, respectively, for agriculture, industry and services sectors for the period between 2012 and 2021.

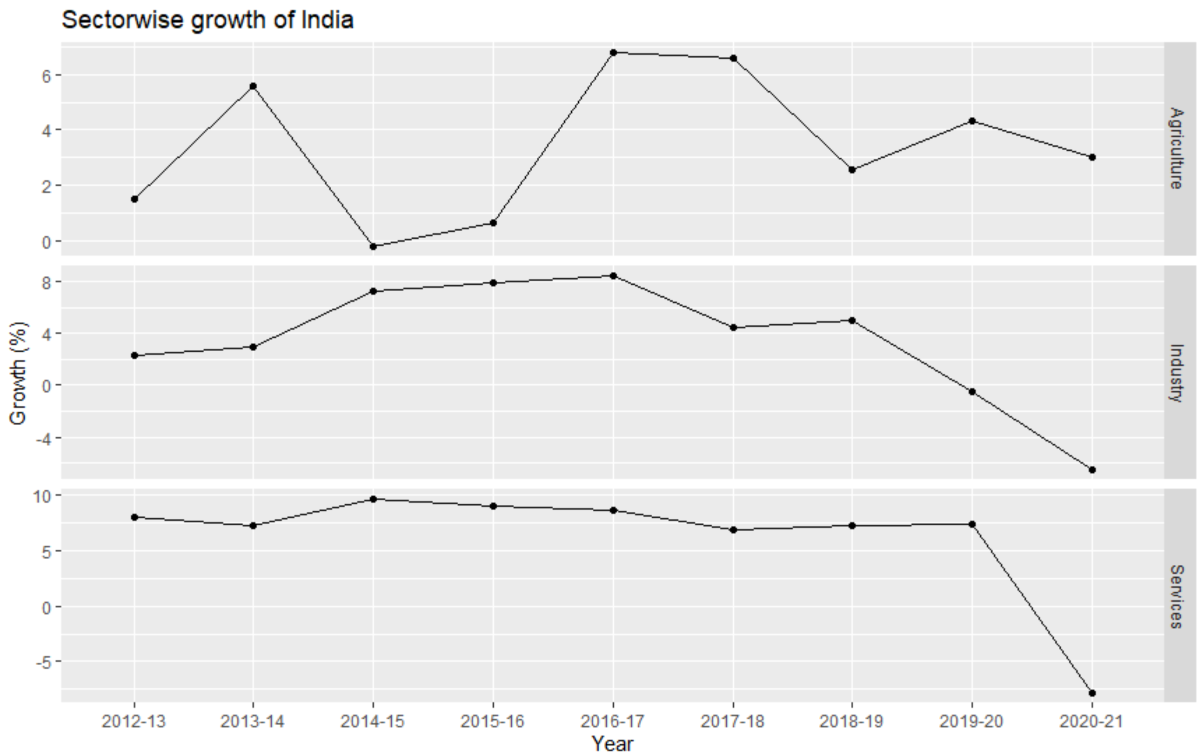

Figure 2.3: Growth trends in sectors of GDP drivers (Ministry of Statistics and Programme Implementation, 2021)

In Figure 2.3 the growth rates of agriculture, industry and services sectors are depicted[3]. While the industry and services sectors have seen steep declines in growth - partly owing to the Covid-19 pandemic, the agricultural sector has been resilient to the pandemic-induced disarray (Singh, 2021).

16% of India's greenhouse gas (GHG) emissions come from agriculture. Methane emissions from livestock, primarily cows and buffalo, and rice farming account for 74% of this. N_2O emissions from fertilizers account for the remaining 26% (Ganesan et al. (2017)). With two-thirds of the country's population relying on farming as a primary source of their livelihood, India houses about 15% of the world's cattle population. Electricity generation is the most significant emissions contributor in the energy sector, contributing

[1] The "Services" sector comprises of the "Trade, hotels, transport, communication and services related to broadcasting", "Financial, real estate and professional services" and "Public Administration, defence and other services" sectors.

[2] The "Industry" sector comprises of "Mining and quarrying", "Manufacturing", "Construction" and "Electricity, gas, water supply and other utility services" sectors.

[3] The growth rates for the "Industry" and "Services" sectors are obtained by averaging the growth rates of their respective sub-sectors.

68.3% of the total energy-based emissions with an estimated 958.37 MtCO$_2$-e in 2015. (Mohan et al., 2019) The transport sector (including maritime transport), through fuel combustion alone, has contributed an estimate of 300 Mt of CO_2 in 2020. (International Transport Forum, 2021) As of 2018, industrial processes have contributed approximately 125.30 million tonnes CO_2 equivalent (MtCO$_2$e) of GHGs. The emissions of gases by this sector have observed a steady rise over the past two decades. (Friedrich, 2020)

2.1.2 Emissions embodied in international trade

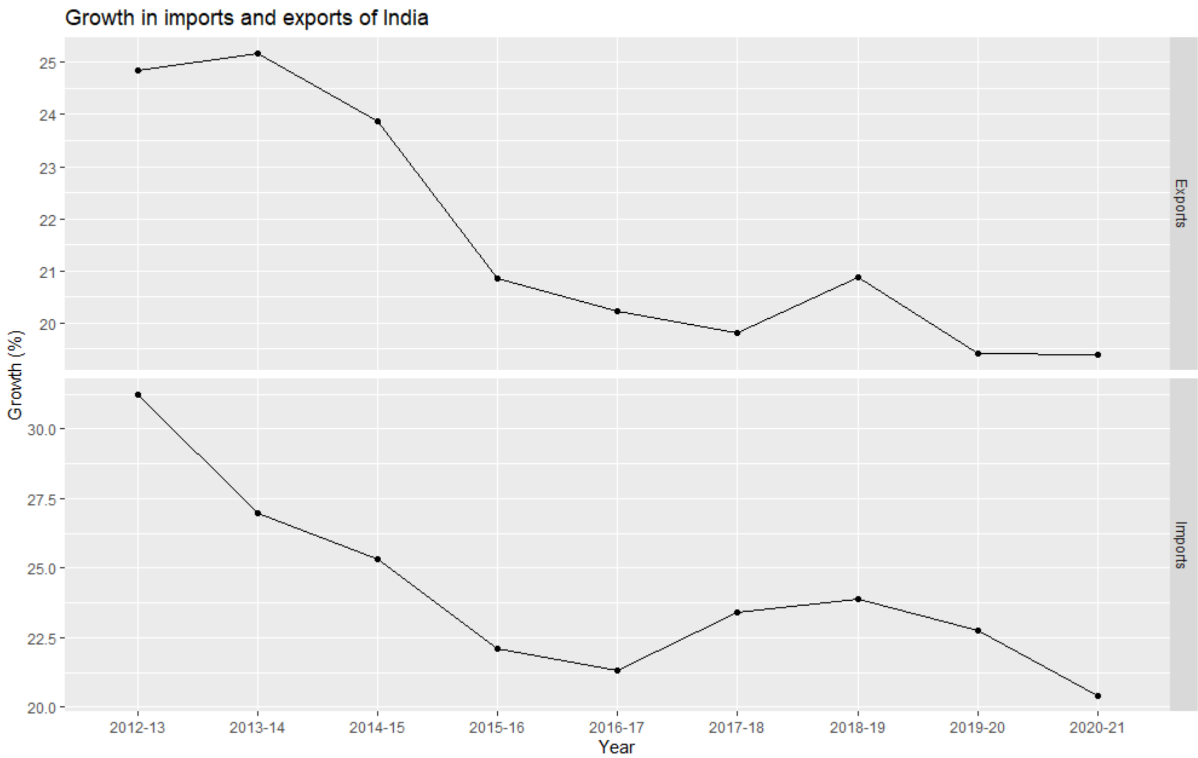

Figure 2.4: Growth trends in imports and exports (Ministry of Statistics and Programme Implementation, 2021)

As observed in Figure 2.4 there has been a downward trend in the growth rates of imports and exports Since 2012-13 with slight increases in 2018-2019. Despite this downward trend in growth of imports and exports, we see a steep rise in annual CO_2 emissions in Figure 2.5 shown below.

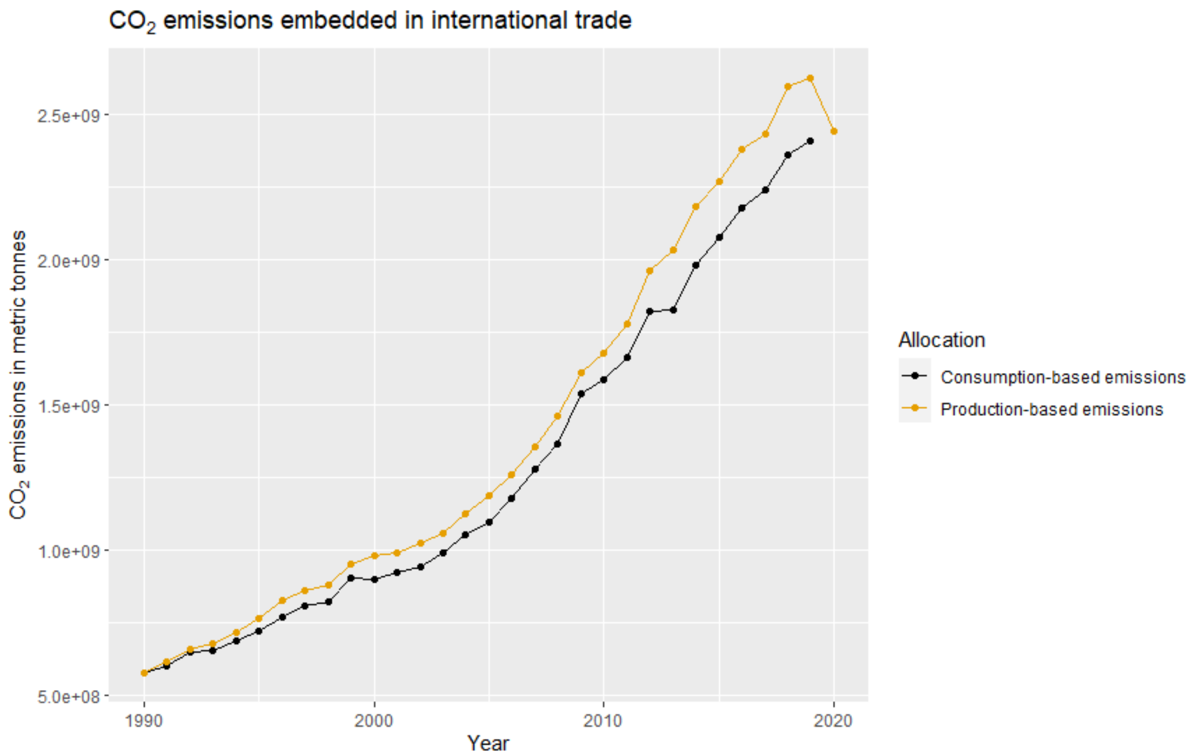

Figure 2.5: Annual consumption based CO_2 emissions (Our World in Data (2022b))

Trends in annual consumption-based CO_2 emissions as observed in Figure 2.5 - consumption-based emissions have been consistently lower than production-based CO_2 emissions. This indicates that India is a net-exporter of CO_2 emissions. Emissions from India need to therefore be adjusted for trade as parts of it may be reduced by offshoring the emissions.

Emissions embodied in domestic consumption and exports have increased steadily over the past three decades. The differences in the two emissions is mainly caused by intermediate products, especially products manufactured in India. The electricity, gas, and water sectors were also significant contributors to India's exported emissions, with many of these emissions going to end users in the European Union and the United States, though their percentage has decreased over time (Wang et al., 2018).

Since 1990, emissions have dramatically increased in both China and India. Despite the enormous growth in exports, especially from China, the majority of their emissions still result from domestic use. China's consumption emissions have climbed by 400%, compared to a somewhat lower 430% increase in output emissions. Similar to China, India has seen a 349% increase in production emissions and a 319% increase in consumption emissions. China's CO_2 exports have actually dropped by about 25% from their 2007 peak, while India is still seeing an increase. This is partially brought on by rising middle-class-related imports of commodities into China and India, which counteract rising CO_2 exports (Zeke Hausfather (2017)).

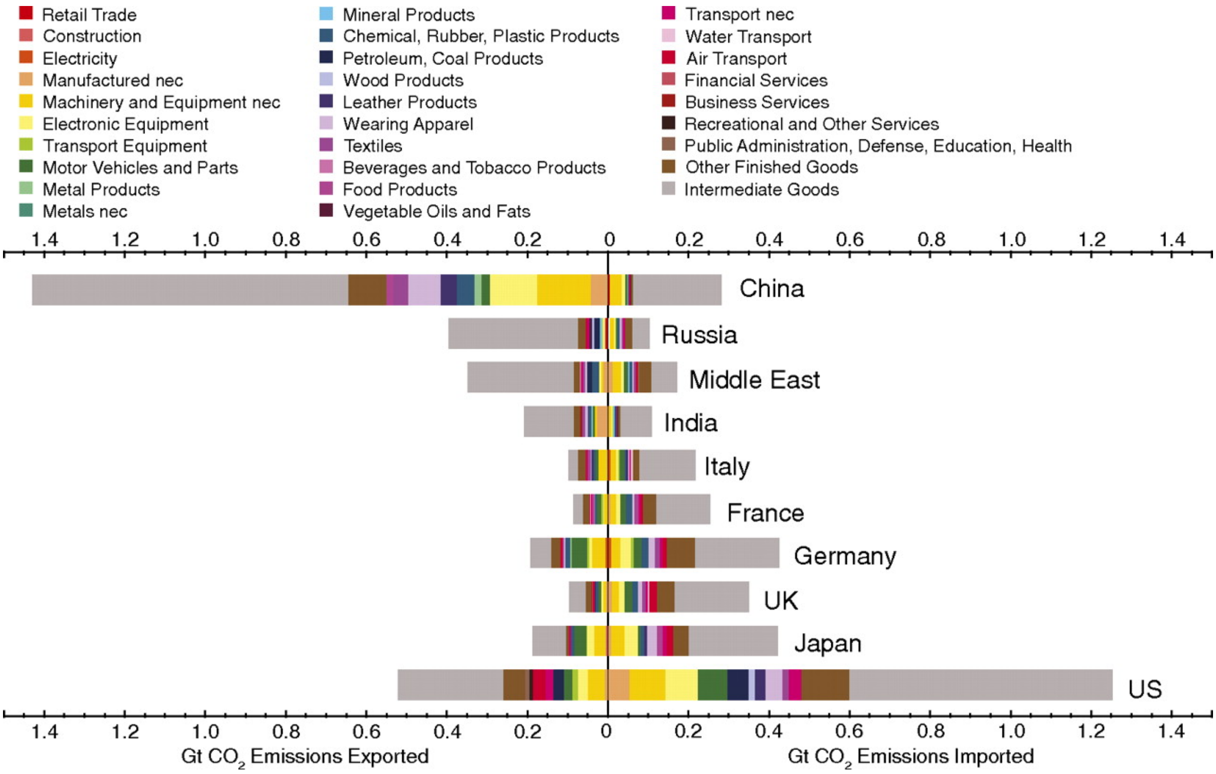

Figure 2.6: CO_2 emissions attributable to the largest net importing/exporting countries (Davis and Caldeira (2010))

Developed nations with lower per-capita emissions will often derive a larger part of their CO_2 emissions from imports and a smaller amount from exports to balance this as seen in Figure 2.6.

2.1.3 Energy mix

Access to clean fuels and technologies for cooking has almost doubled - from 22.15% of the population having access in 2000 to 41.04% in 2016 (World Development Indicators — DataBank, 2022). Kerosene is excluded from clean cooking fuels as per WHO guidelines.

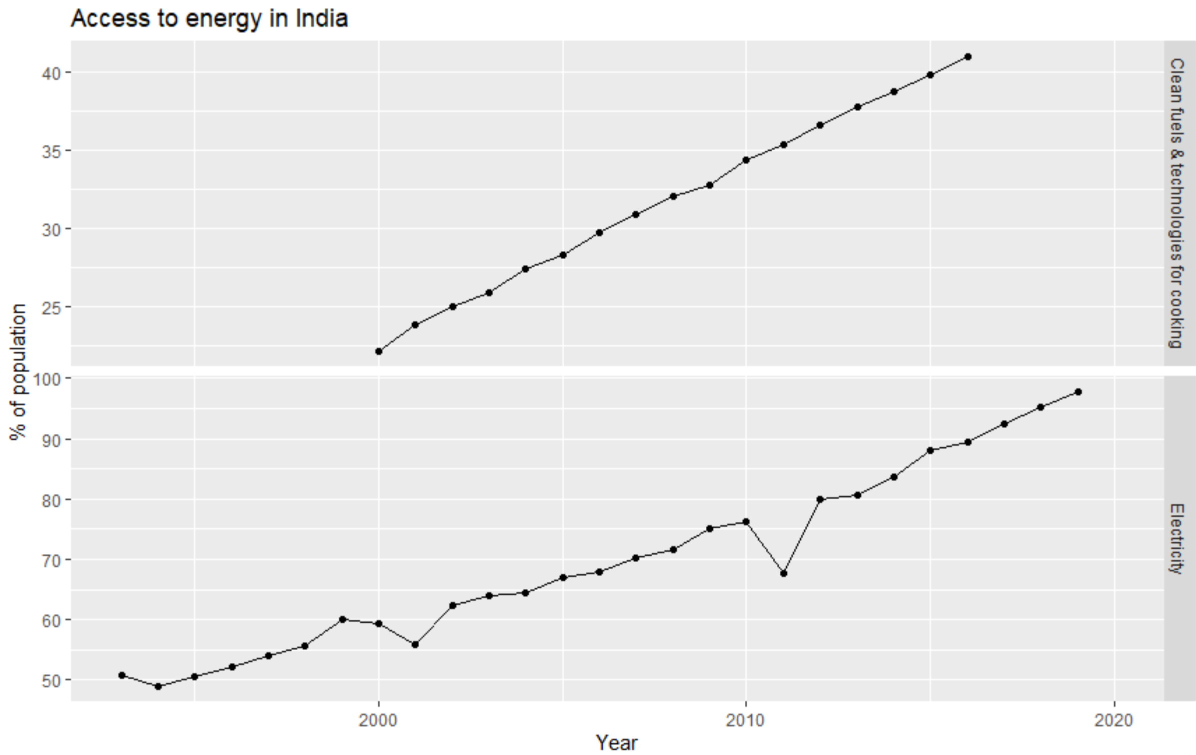

Figure 2.7: Access to energy (World Development Indicators — DataBank, 2022)

Energy access has grown from 50.90% of the population of India in 1993 to 97.82% in 2019 (World Development Indicators — DataBank, 2022). However, the threshold used in international statistics assumes a very low definition for what it means to 'have access to electricity'. Here it is defined as being able to provide very basic lighting, and charge an electrical appliance for 4 hours per day.

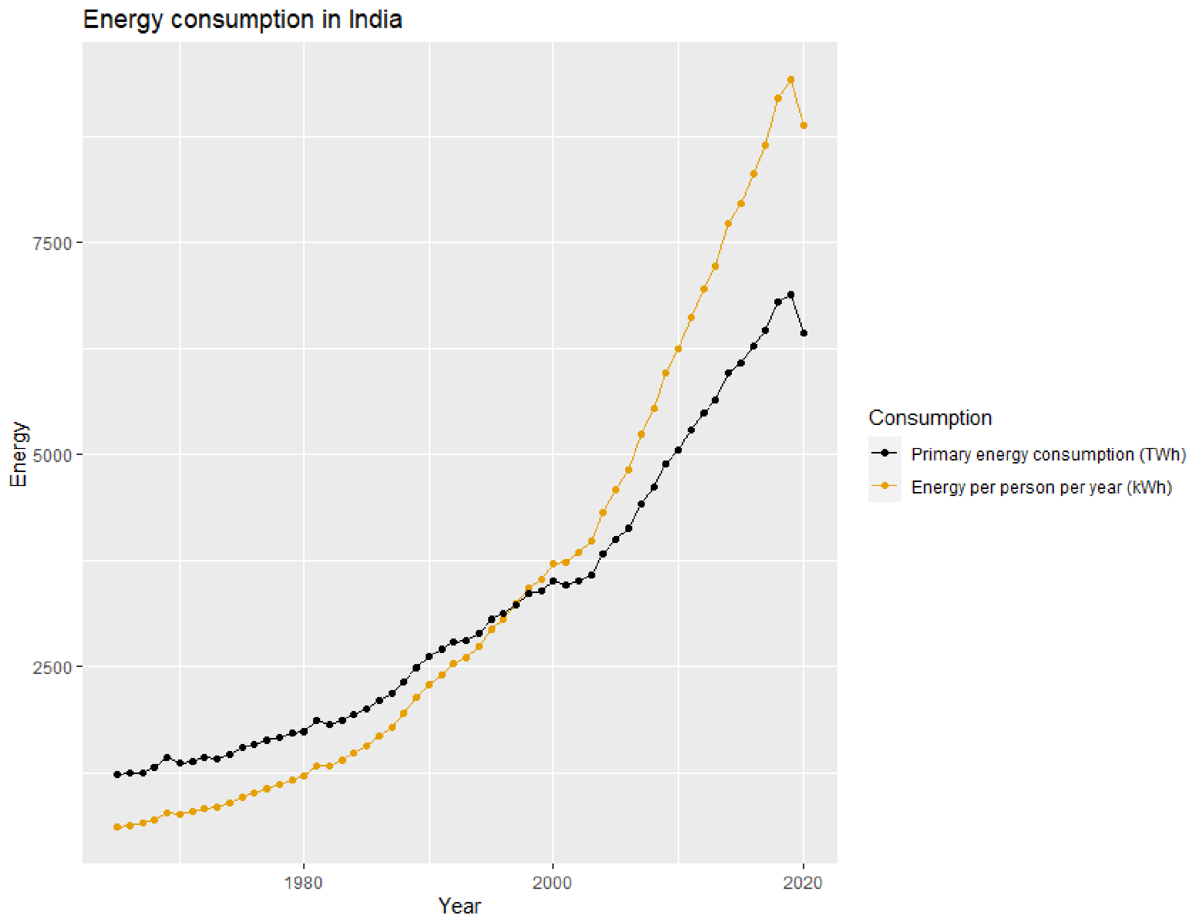

Figure 2.8: Energy consumption (Our World in Data (2022a))

The annual energy use per person shows a consistent increase over the last three decades (Figure 2.8) - peaking at 6890 kilowatt-hours (kWh) in 2019 and then dropping to 6438 kWh in 2020 possibly as ripple effects of the COVID-19 pandemic. A similar trend is observed in the total energy consumption every year in India (Figure 2.8) - peaking at 9414 terrawatt-hours (TWh) in 2019 and dropping to 8884 TWh in 2020.

In the past ten years, India's imports of coal have more than tripled. According to Ministry of Coal figures, the similar amount for 2010–2011 was only 68.92 million tonnes. India is the second-largest importer of coal in the world. The main main sources being the US, Australia, South Africa, and Indonesia (Bureau (2022)).

One of the most dominant energy sources that meet nearly 44% of the country's primary energy demand – coal has played a vital role in India's economic development-contributes significantly to air pollution and greenhouse gases (GHG) emissions. Coal remains the fuel of choice for heavy industries like iron and steel. As the second-largest coal market globally, India mines over 700Mt of coal per year.

In the past six years, India has seen an annual average GDP growth rate of 6.7% while introducing several economic reforms. Included in these reforms was a uniform tax code called Goods and Services Tax (GST) for most economic activities in India - excluding petroleum products, natural gas and electricity. (IEA, 2021, p. 22)

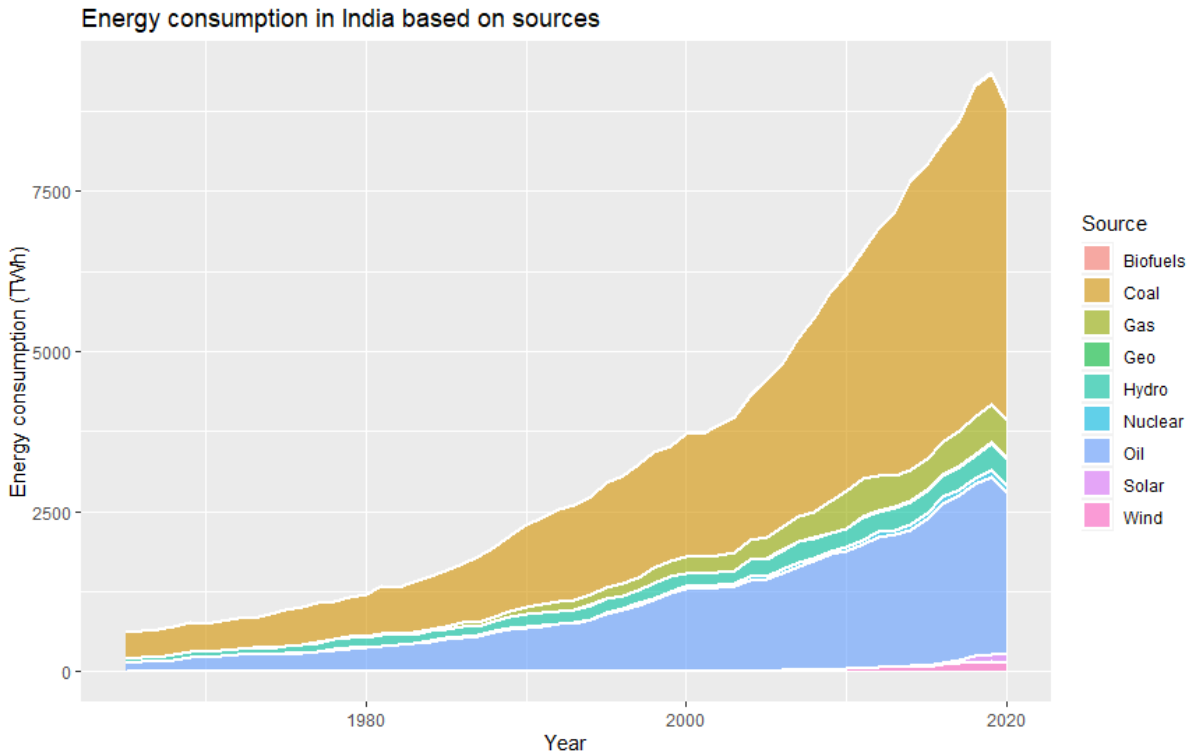

Figure 2.9: Energy consumption by source (Statistical Review of World Energy — Energy Economics — Home, 2021)

As a consequence of the decline in costs of solar photovoltaics, India increased its solar capacity in 2019 by about five times compared to what it had in 2015. (IEA, 2021, p. 22) India has a majority of the world's top polluted cities in terms of air pollution despite its increasing deployment of renewables. (IQAir, 2020) A shift to renewable sources of energy from conventional sources in India's energy mix can be inferred from the fact that the installed capacity thermal sources of electricity generation grew by 1.91% between 2019 and 2020, whereas the capacity for electricity generation from renewable resources excluding hydroelectricity grew by 12% for the same period.

Despite growing demand, domestic production of natural gas has been lower than the figures projected in 2015. (IEA, 2021, p. 23) India focussed its subsidies on liquified petroleum gas (LPG) to meet its objectives for clean cooking access. While the growth in renewable energy has negatively affected the growth in coal capacity, it has not prevented the same. Oil consumption has proportionately increased with urbanization and growth in GDP. (IEA, 2021, p. 23) Coal, oil and biomass have largely and consistently met over 80% of the country's energy demand since 1990.

2.2 Environmental Kuznets Curve

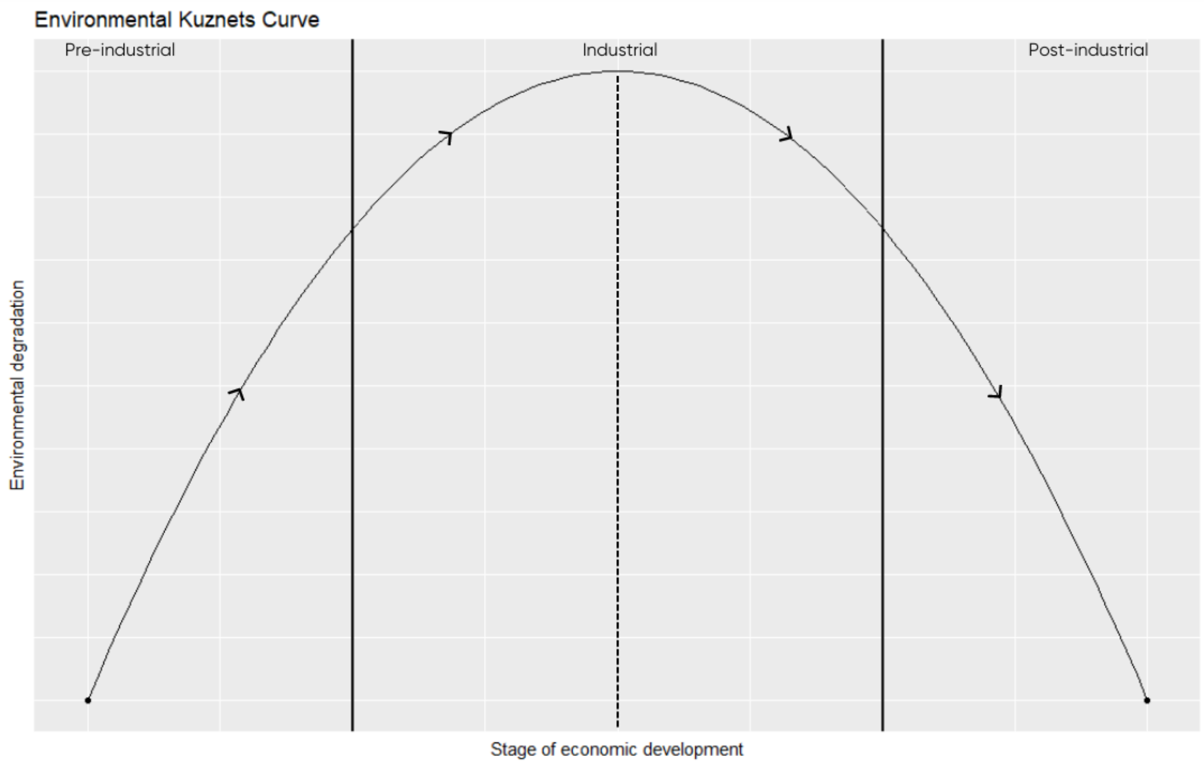

Figure 2.10: Environmental Kuznets Curve (Panayotou, 1993)

A widely applied concept in environmental economics that attempts to examine causality between CO_2 emissions and economic growth is the Environmental Kuznets Curve hypothesis. (Kuznets, 1984) The EKC, empirically identified by Grossman and Krueger in 1995, is a relationship between income per capita and indicators of environmental degradation. This hypothesis claims that economic growth past a certain threshold shows a change in environmental degradation trend from upwards to downwards. We see a decline in the environmental quality as pollution increases during the early stages of the economic growth of a region. This trend is reversed at high levels of economic growth where environmental improvements are also observed.

For the analysis proposed in this thesis, we need to begin with an examination of the stage of economic development that India is in. EKC is used for this examination where CO_2 emissions are used as an indicator for environmental degradation and GDP measured in U.S. dollars represents the economic output of the country. While such analysis gives some indications towards the rise or decline of the concentrations of pollutants, it does not provide any clarity on the source of such emissions. Further exploration of the different drivers of emission can be done by the use of Kaya decomposition. This decomposition method allows us to analyse the carbon content of energy, the energy intensity of the economy and production per person.

The Environmental Kuznets Curve with an indicator of environmental degradation plotted along the Y-axis and the economic performance of the country along the X-axis forms an inverted U-shaped curve as seen in the figure. Economies in their early stages that primarily rely on agriculture, mining and domestic services see a slow rise in environmental deterioration. Industrial economies that are reliant on manufacturing, intensive mining, mechanised industrial processes see a steeper rise in degradation of environmental conditions until it reaches the maxima of the curve where the pollution is at its peak. Following the peak of the curve, the trend is observed to go downwards as environmental degradation slows down for post-industrial economies that have a relatively higher per capita income.

2.3 The Kaya identity

The Kaya identity (Kaya, 1990) is another functional equation to analyse CO_2 emissions and changes in its underlying drivers. It helps quantify the total anthropogenic CO_2 emissions as a function of economic growth, energy intensity and carbon intensity. This identity is instrumental in understanding how the related factors need to change relative to the other factors to attain the target CO_2 emission level.

The Kaya identity states the total emission level of CO_2 as the product of four fundamental factors:

$$C = P \times \frac{G}{P} \times \frac{E}{G} \times \frac{C}{E} \tag{2.1}$$

where:
C = CO_2 emissions from human sources
P = Population size
G = Gross Domestic Product (GDP)
E = Energy consumption

The ratios $\frac{G}{P}$, $\frac{E}{G}$ and $\frac{C}{E}$ denote the GDP per capita, energy intensity of GDP and emissions intensity of the energy supply respectively.

Therefore, the equation 2.1 can also be expressed as:

CO_2 emissions from human sources =
Population size × GDP per capita × Energy intensity × Emissions intensity

This identity primarily breaks down the emissions into the per capita impact of CO_2 emissions and *population.* The per capita emissions is further determined by *income* and *technology*. *Income* is described by the GDP per capita and *technology* is denotes how much CO_2 is emitted for every dollar of expenditure. This *technology* is further determined through *energy intensity* and *carbon intensity* defined as the amount of energy consumed per unit of GDP and the amount of CO_2 emitter per unit of energy respectively.

Chapter 3

Data and methods

The central goal of this thesis is to analyse the various components of CO_2 emissions in India and environmental damage using the *Environmental Kuznets Curve* and *Kaya Decomposition*. For the analysis carried out in this thesis, a combination of both theory-based and data-based approach has been considered. Historical data has been obtained from *The World Bank*, *Our World in Data* and *Air Quality Life Index*. This data has been used to see if it supports existing theory and then to predict possible trends in the future. This prediction helps in understanding the ability of India to fulfill the pledges the country has made through its NDCs.

The predictions do not aim to be an accurate forecast of future environmental and economic conditions. They are rather an attempt to understand possible trends in the various factors that contribute to the CO_2 emissions in the country.

The following sections in this chapter expand upon the data sources of the variables used for this analysis, summarises the data obtained and explains the statistical models that have been key in analysing and predicting the data.

3.1 Environmental Kuznets Curve

For this analysis 2 *Environmental Kuznets Curves* (EKCs) are plot. Three variables are of primary importance for these plots - the annual CO_2 emissions and the GDP per capita of India, and for a closer look, particulate pollution level of the National Capital Territory (NCT) of Delhi. One EKC is based on the annual CO_2 levels for the entire country of India whereas the second one is based of the particulate pollution level of NCT of Delhi for a closer look of the second most polluted city in the world (IQAir (2022)). The annual CO_2 emissions and particulate pollution level of the NCT of Delhi represent the environmental degradation which are plot along the y-axis against GDP per capita which represents the stage of economic development India is in - plotted along the x-axis. These plots (partially) depict the inverted U-shaped curve as seen in Figure 2.10.

3.1.1 Source of data

The World Development Index maintained by the World Bank has been used for this analysis. After removing partially available data, annual data from 1960 to 2018 is available for CO_2 emissions measured in metric tonnes per capita and the GDP per capita measured at constant 2015 prices expressed in U.S. dollars. The dollar expression of the GDP is converted from the domestic currency, Indian National Rupee (INR) in this case using 2015 official exchange rates. The GDP data has been sourced from World Bank and OECD National Account data files. The data for particulate pollution level in the NCT of Delhi is measured in μg per m^3 is available from 1998 to 2018 after removing partially unavailable data. This data has been obtained from Air Quality Life Index *(AQLI)* maintained by *University of Chicago*.

3.1.2 Summary

The dataset for the country-level EKC contains three columns: "Year", "CO2emissionsmetrictonspercapita" and "GDPpercapitaconstant2015US$". These variables have been referred to as "Year", "CO2emissions" and "GDPpercapita" respectively for brevity in the tables used below.

Table 3.1 below summarises the dataset obtained from World Bank that has been used for plotting the EKC. The CO_2 emissions ranges between 0.2676 and 1.7998 measured in metric tonnes per capita and the GDP per capita ranges between US$302.7 to US$1915.4 (in constant 2015 prices) during the 58 years time-span described in the data.

Table 3.1: Summary of data for Environmental Kuznets Curve

	Year	CO_2 emissions	GDPpercapita
Minimum	1960	0.2676	302.7
1st Quartile		0.3929	366.8
Median		0.6441	515.4
Mean		0.7551	690.2
3rd Quartile		0.9382	871.5
Maximum	2018	1.7998	1915.4

In Figure 3.1, we see a steep upward trend in both CO_2 emissions as well as GDP per capita over the 58 years span described by the data.

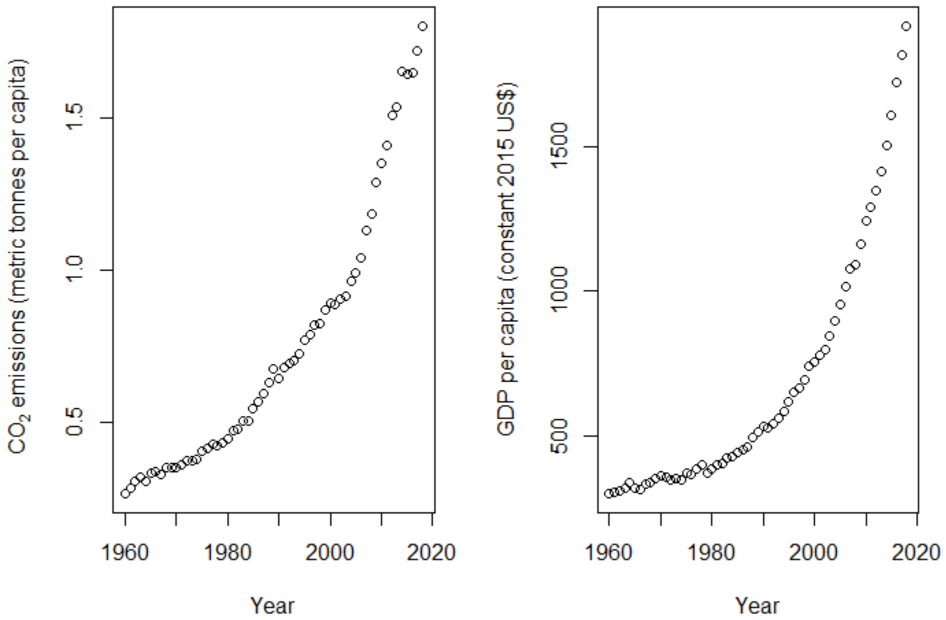

Figure 3.1: Trends in CO_2 emissions and GDP per capita

Indicated by the similarities in the trends of both the curves, a high degree of correlation is observed between the variables as seen in Table 3.2.

Table 3.2: Correlation matrix between the variables in the EKC dataset

	Year	CO2emissions	GDPpercapita
Year	1	0.941	0.894
CO2emissions	0.941	1	0.988
GDPpercapita	0.894	0.988	1

The dataset for the EKC for NCT of Delhi contains three columns: "Year", "Particulate Pollution ($\mu g/m^3$)" and "GDPpercapitaconstant2015US$". These variables have been referred to as "Year", "Particulate Pollution" and "GDPpercapita" respectively for brevity in the tables used below.

Table 3.3 below summarises the dataset obtained from World Bank and Air Quality Life Index *(AQLI)* that has been used for plotting the EKC. The particulate pollution ranges between 72.99 and 123.51 measured in micro-grams per metre-cube ($\mu g/m^3$) and the GDP per capita ranges between US$694.7 to US$1915.4 (in constant 2015 prices) during the 21 years time-span described in the data.

Table 3.3: Summary of data for Environmental Kuznets Curve for NCT of Delhi, India

	Year	GDPpercapita	Particulate Pollution
Minimum	1998	694.7	72.99
1st Quartile		845.3	89.79
Median		1093.1	101.07
Mean		1175.0	99.18
3rd Quartile		1415.8	108.54
Maximum	2018	1915.4	123.51

In Figure 3.2, we see a general upward trend in particulate pollution levels and a steep upward trend in GDP per capita over the 21 years span described by the data.

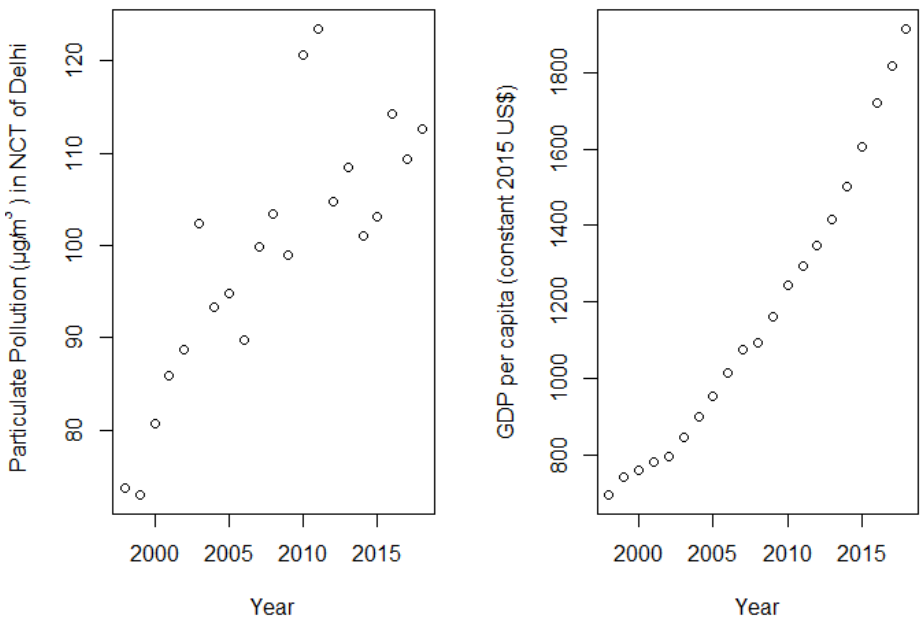

Figure 3.2: Trends in Particulate Pollution in NCT of Delhi and GDP per capita

The correlation matrix for the variables in the dataset is shown in Table 3.4.

Table 3.4: Correlation matrix between the variables in the EKC for NCT of Delhi dataset

	Year	GDPpercapita	Particulate Pollution
Year	1	0.982	0.816
GDPpercapita	0.982	1	0.747
Particulate Pollution	0.816	0.747	1

3.1.3 Methods

As observed previously in Figure 2.10, the *EKC* depicts a quadratic relationship between environmental degradation (represented here by CO_2 emissions and particulate pollution) and GDP per capita owing to the inverted U-shaped nature of the curve. A regression analysis of order 2 is then conducted on historically available data to establish a regression model. The results of this analysis has been reported and discussed in the next chapter.

3.2 Kaya decomposition

For the purpose of *Kaya Decomposition*, the individual components for the calculation, *i.e.*, *population*, *GDP per capita*, *energy intensity* and *emissions intensity* are considered. The data has been obtained from Our World In Data which has further compiled from multiple sources and put together. The sources for each specific variable has been described below.

3.2.1 Sources

The dataset used for this analysis contains the following variables that have been gathered from the sources cited:

1. Annual CO_2 emissions : CO_2 emissions based on annual production, measured in tonnes. This is based on territorial emissions, which don't take into consideration emissions from traded goods.
2. Annual CO_2 emissions per unit energy (kg/kWh) : CO_2 emissions based on annual production, measured in kilograms per kilowatt-hour of primary energy usage. Production-based emissions are calculated using territorial emissions, which exclude emissions from traded goods.
3. Annual CO_2 emissions per GDP $(kg/\$PPP)$: CO_2 emissions based on annual production, estimated in kilos per dollar of GDP (2011 international-\$). Production-based emissions are calculated using territorial emissions in this case as well - excluding emissions from traded goods.
4. Energy per GDP $(kWh/\$)$: Primary energy consumption per unit of GDP - in kilowatt-hours per international-$.
5. GDP per capita : Real GDP per capita in 2011$.
6. Population : The data on population estimates for the time-period used in this analysis has been obtained from UN Population Estimates.

For this analysis, we use the data for *population*, *GDP per capita*, *energy per GDP* and *annual* CO_2 *emissions per unit energy*.

3.2.2 Summary

The variables used from the dataset has been summarised in the table below. These variables have been referred to by the following names for easy of use: “Population”, “GDPpercapita”, “Energyintensity” and “Carbonintensity”.

Table 3.5: Summary of data for Kaya decomposition

	Population[1]	GDPpercapita[2]	Energyintensity[3]	Carbonintensity[4]
Minimum	$4.991e+08$	1215	1.006	0.2291
1st Quartile	$6.830e+08$	1494	1.111	0.2453
Median	$9.274e+08$	2101	1.196	0.2570
Mean	$9.344e+08$	2684	1.195	0.2578
3rd Quartile	$1.183e+09$	3351	1.278	0.2668
Maximum	$1.393e+09$	6806	1.379	0.2863

As we plot the trends for the different variables, we see that *population* and *GDP per capita* have a steady increase over the years. However, *energy intensity of GDP* and *emissions intensity of energy* sees relatively uneven trends over the time-period of the observations.

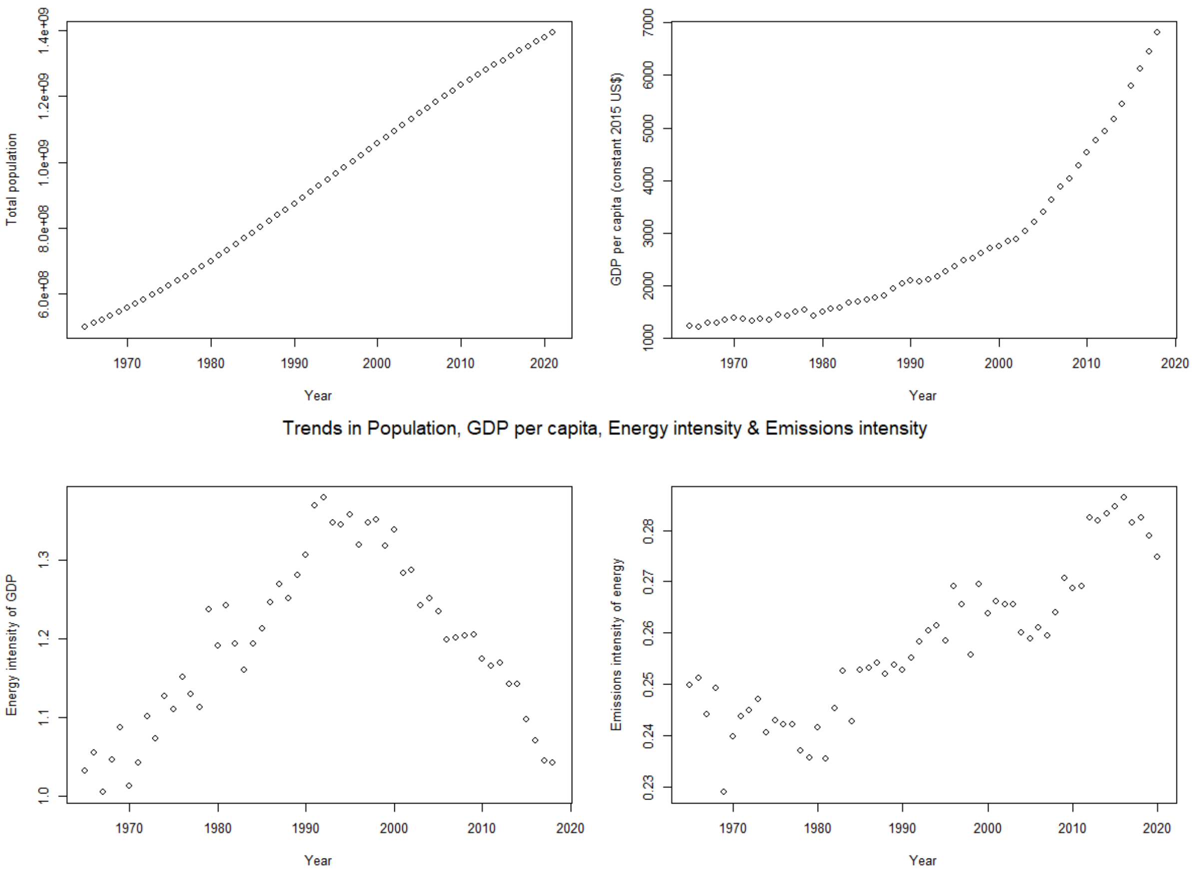

Figure 3.3: Trends in *population*, *GDP per capita*, *energy intensity* and *Carbonintensity*

[1]available for the time-period 1965 – 2021
[2]available for the time-period 1965 – 2018
[3]available for the time-period 1965 – 2018
[4]available for the time-period 1965 – 2020

Upon checking for correlation between the variables observed here, we find a strong correlation between *Year*, *Population*, *GDPpercapita* and *Carbonintensity* as shown in Table 3.6. Correlation between *Year* and *Energyintensity* however is much lower than the other variables.

Table 3.6: Correlation between the variables in the dataset

	Year	Population	GDPpercapita	Energyintensity	Carbonintensity
Year	1	0.999	0.911	0.290	0.891
Population	0.999	1	0.918	0.270	0.899
GDPpercapita	0.911	0.918	1	−0.097	0.894
Energyintensity	0.290	0.270	−0.097	1	0.119
Carbonintensity	0.891	0.899	0.894	0.119	1

3.2.3 Methods

Given the strong correlation between *Year*, *Population*, *GDPpercapita* and *Carbonintensity* we explore univariate regression models for all the variables including *Energyintensity* with *Year* as the independent variable and the others as dependent variables. First and second order regression models are tested and the fit is assessed based on error metrics such as mean square error (MSE), root mean square error ($RMSE$) and mean absolute percentage error ($MAPE$). The model error comparisons are provided in the tables below.

Table 3.7: Model errors for *Population*

	Models	MSE	RMSE	MAPE
1	Regression - 1	1.559236e+14	12486937.92	1.356848e-02
2	Regression - 2	1.245095e+14	11158380.66	1.137189e-02
3	Regression - 3	5.722925e+11	756500.18	6.439128e-04
4	Regression - 4	5.722925e+11	756500.18	6.439128e-04
5	Regression - 5	5.722925e+11	756500.18	6.439128e-04

Table 3.8: Model errors for *GDPpercapita*

	Models	MSE	RMSE	MAPE
1	Regression - 1	389957.095	624.46545	0.22840676
2	Regression - 2	39051.957	197.61568	0.07016555
3	Regression - 3	5083.268	71.29704	0.02683388
4	Regression - 4	5083.268	71.29704	0.02683388
5	Regression - 5	5083.268	71.29704	0.02683388

Table 3.9: Model errors for *Energyintensity*

	Models	MSE	RMSE	MAPE
1	Regression - 1	0.010061302	0.10030604	0.07170094
2	Regression - 2	0.001677013	0.04095134	0.02763345
3	Regression - 3	0.001205297	0.03471739	0.02414209
4	Regression - 4	0.001205297	0.03471739	0.02414209
5	Regression - 5	0.001205297	0.03471739	0.02414209

Table 3.10: Model errors for *Carbonintensity*

	Models	MSE	RMSE	MAPE
1	Regression - 1	4.016550e-05	0.006337626	0.01946777
2	Regression - 2	3.373834e-05	0.005808471	0.01870769
3	Regression - 3	3.073686e-05	0.005544083	0.01758008
4	Regression - 4	3.073686e-05	0.005544083	0.01758008
5	Regression - 5	3.073686e-05	0.005544083	0.01758008

From the tables above we see a significant drop in errors for regression models of third order for *Population*, *GDPpercapita*, *Energyintensity* and *Carbonintensity*. While the change in error is much lower for the variables in tables 3.9 and 3.10 that the other two variables, the model fit in the case of a third order regression is still significantly better compared to the first and second order regression models. For higher order models, no change in accuracy is observed.

Based on these evaluations, we move forward with third order regression models to predict trends in the case of all four variables considered for this analysis. The results of these analyses have been reported in the next chapter.

Chapter 4

Results

In this chapter of the thesis, the key results of the approaches and methods that have been discussed in the previous chapter have been presented. For every approach, the model parameters, error statistics and relevant plots can be found below. Additional information has been included in the Appendix.

4.1 Environmental Kuznets Curve

The quadratic relationship between CO_2 emissions per capita and GDP per capita has been derived from the regression model summarised in Table A.1. The fitted regression model is given by the equation 4.1.

$$\hat{y} = (-2.827e - 07) \times x^2 + (1.540e - 03) \times x + (-1.209e - 01) \tag{4.1}$$

The variables x and y in equation 4.1 denote the GDP per capita in constant 2015 US$ and CO_2 emissions (measured in metric tonnes) per capita respectively. The overall regression was statistically significant with Adjusted $R^2 = 0.9894$, $F(2, 56) = 2713$, p $< 2.2e - 16$).

Over the years we see an increase in GDP per capita for India from 1960 until 2018. The same is seen in the CO_2 emission levels as depicted in the Figure 3.1.

As we plot the Environmental Kuznets Curve with the GDP per capita on the X-axis and CO_2 emission levels on the Y-axis we notice a steep rise in environmental degradation indicating the country to be transitioning from a pre-industrial to a post-industrial stage of economic development. The curve - as the trend gets less steep by 2018 with a recorded GDP per capita of 1915.43 USD (indicated by the vertical line in Figure 4.1 and 1.7998 metric tonnes per capita of CO_2 emissions during the same time.

Upon extrapolation of the regression curve depicted by the equation 4.1 - we obtain the curve observed in Figure 4.1. The pattern is similar to the U-shaped curve seen in 2.10 as proposed by Kuznets in 1984.

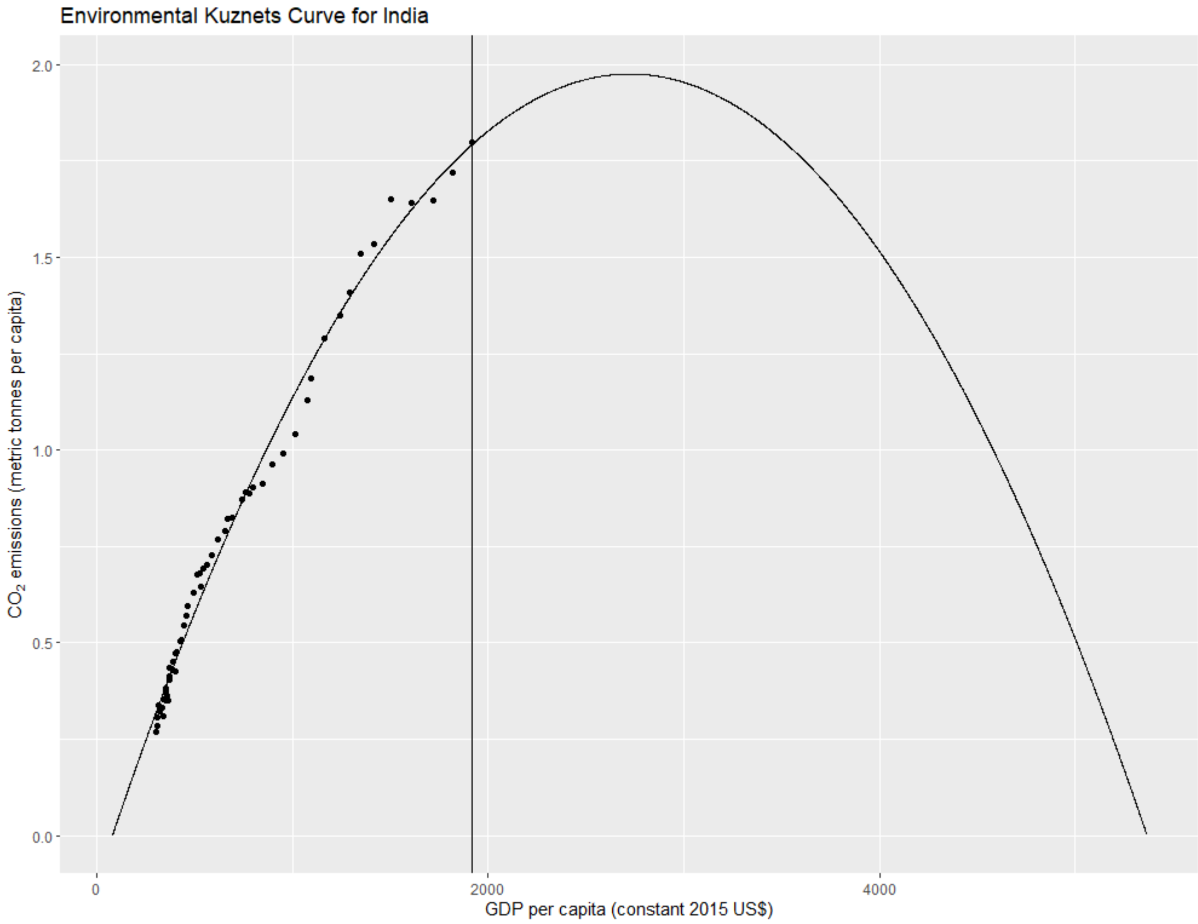

Figure 4.1: Environmental Kuznets Curve of India

The Environmental Kuznets Curve thus obtained for India indicates that while the curve is getting less steep, it does not appear to have reached the maxima of the curve.

As economic growth is paving way for rising pollution through "scale effect" (Smith, 1776) as increase in use of resources consequently increases generation of waste. In Figure 2.3, we see that India made a push for an industry and services-based economy in 2014 and tried to shift away from an agriculture-based economy. This corresponds to the points on the EKC curve above getting less steep as we notice this shift in the dominant activities of the economy from agriculture to manufacturing and services. This shift in the principal economic activity, as of 2021, stands at agriculture standing accounting for 16.38% of the total economic activity whereas manufacturing and services make up for the rest.

The quadratic relationship between particulate pollution ($\mu g/m^3$) and GDP per capita has been derived from the regression model summarised in Table A.2. The fitted regression model is given by the equation 4.2.

$$\hat{y} = (-4.406e - 05) \times x^2 + (0.1391) \times x + (2.492) \tag{4.2}$$

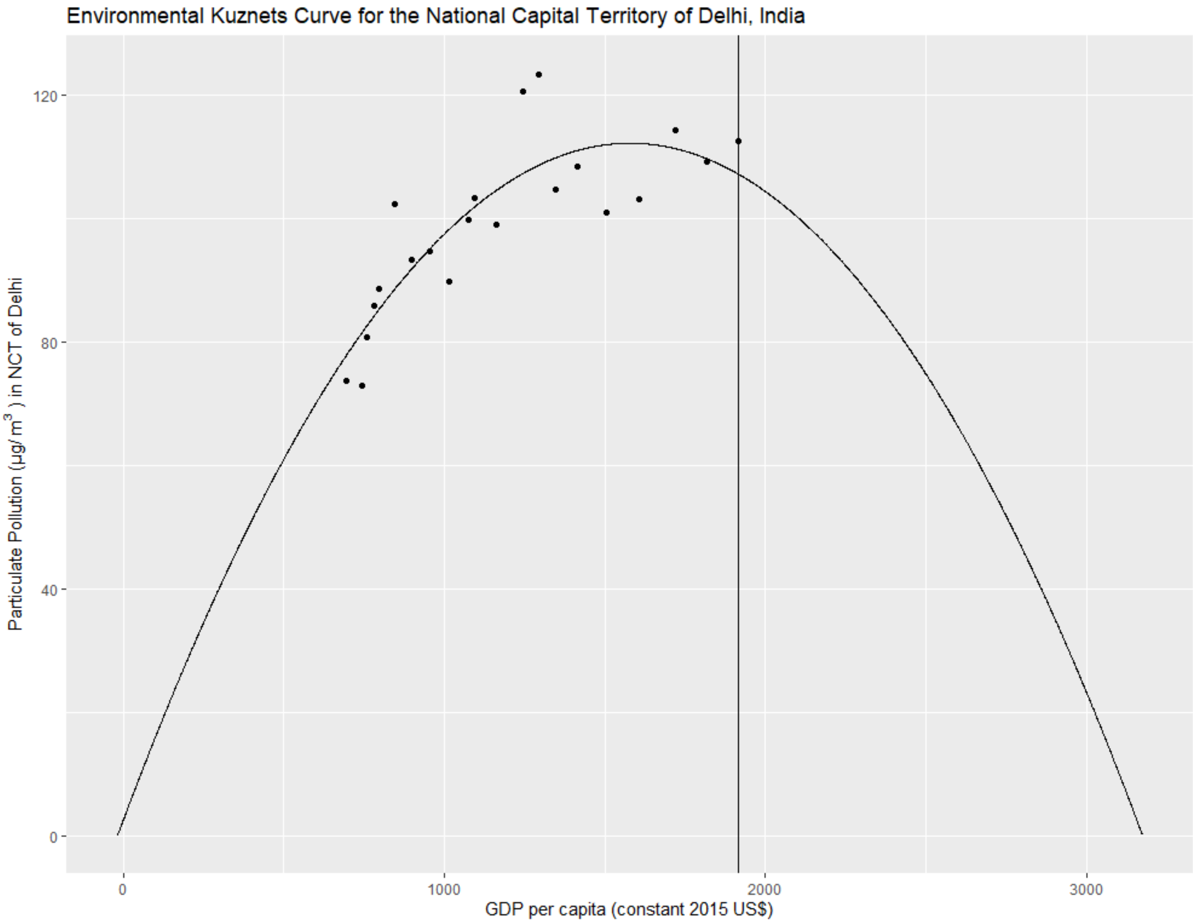

Figure 4.2: Environmental Kuznets Curve for NCT of Delhi, India

4.2 Kaya decomposition

In this section, we discuss the results of the cubic regression models we have deployed for the analysis of each variable of the *Kaya equation*. Below, each subsection describes the regression models with appropriate statistics, figures and interpretation.

The detailed output of each of the regression models discussed below has been provided in the Appendix. The predictions made using these models, along with the original data used for the analysis has also been provided in the table B.1.

4.2.1 Population

The cubic relationship between *year* and *population* has been derived from the regression model summarised in Table A.3. The fitted regression model is given by the equation 4.3.

$$\hat{y} = (-3.188e+03) \times x^3 + (1.908e+07) \times x^2 + (-3.806e+10) \times x + (2.529e+13) \quad (4.3)$$

Figure 4.3 shows how the fitted model described by the equation 4.3 performs against the available data.

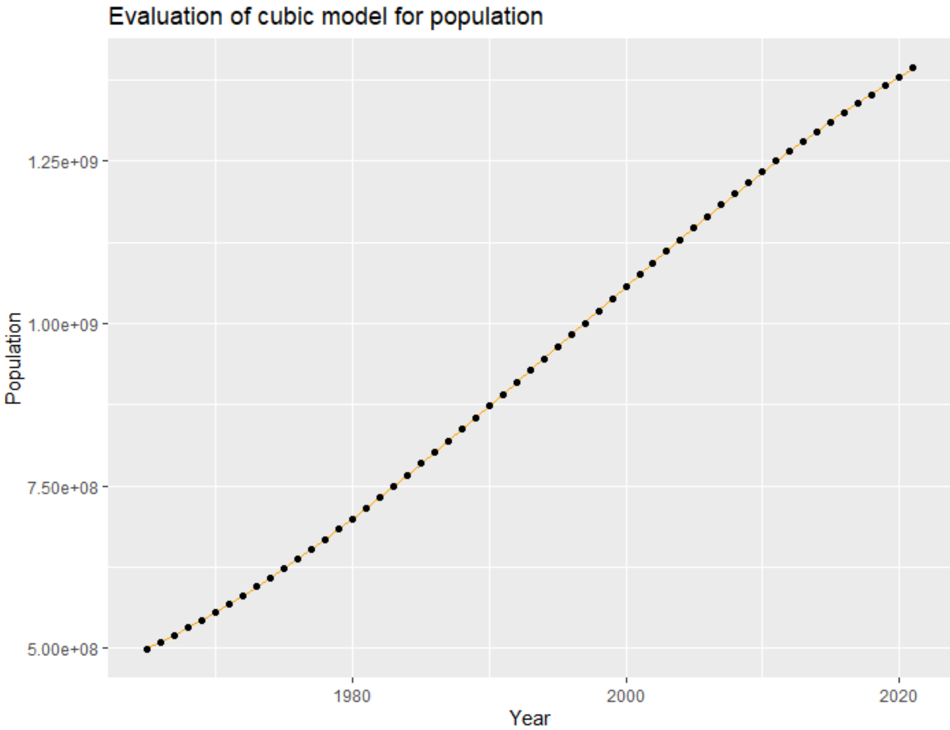

Figure 4.3: Evaluation of predicted model for population

The variables x and y in equation 4.3 denote the *year* and *population* respectively. The overall regression was statistically significant with Adjusted $R^2 = 1$ and $p < 2.2e-16$.

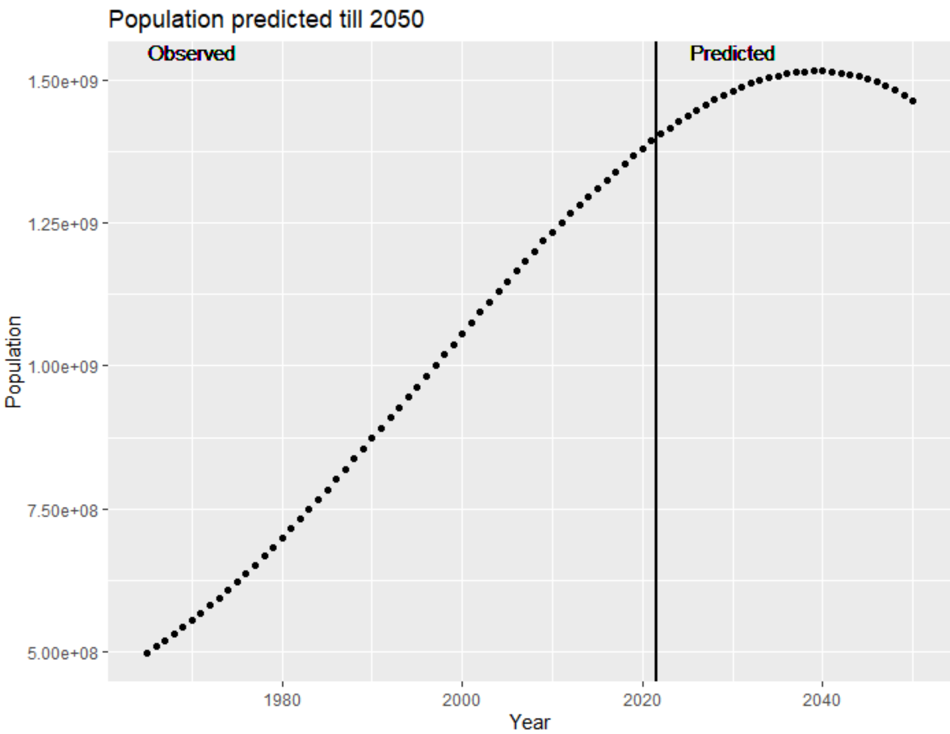

Figure 4.4: Population predicted till 2050

The regression model predicts the population to reach approximately *1.48 billion* by 2030 and almost *1.46 billion* by the year 2050.

4.2.2 GDP per capita

The cubic relationship between *year* and *GDP per capita* has been derived from the regression model summarised in Table A.4. The fitted regression model is given by the equation 4.4.

$$\hat{y} = (6.208e - 02) \times x^3 + (-3.682e + 02) \times x^2 + (7.279e + 05) \times x + (-4.797e + 08) \quad (4.4)$$

Figure 4.5 shows how the fitted model described by the equation 4.4 performs against the available data.

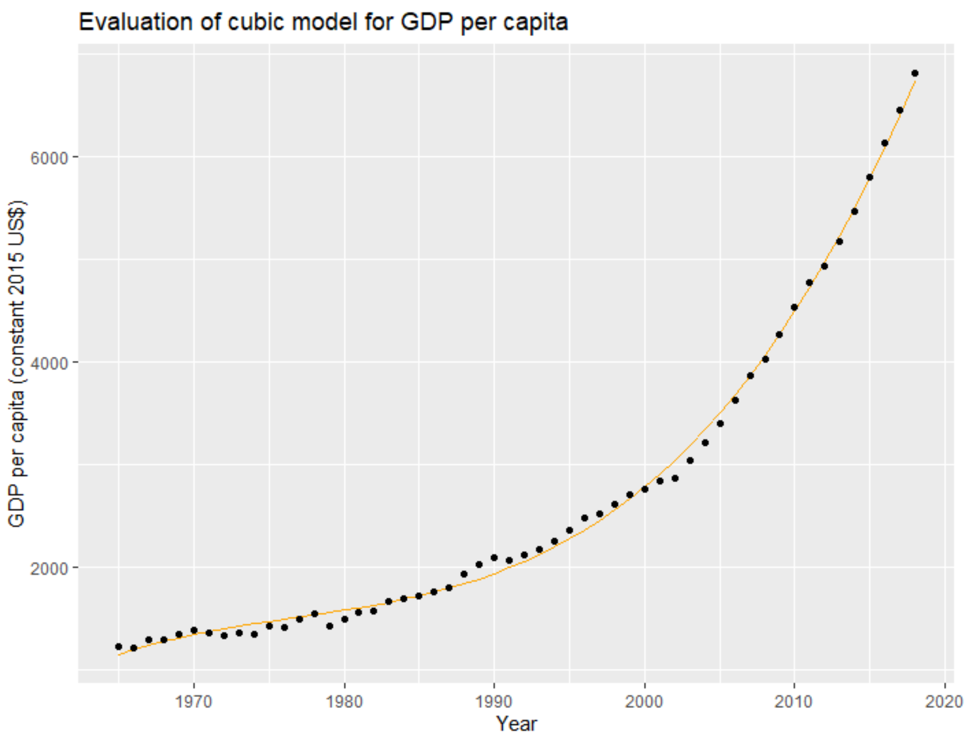

Figure 4.5: Evaluation of predicted model for GDP per capita

The variables x and y in equation 4.4 denote the *year* and *GDP per capita* respectively. The overall regression was statistically significant with Adjusted $R^2 = 0.9977$ and $p < 2.2e - 16$.

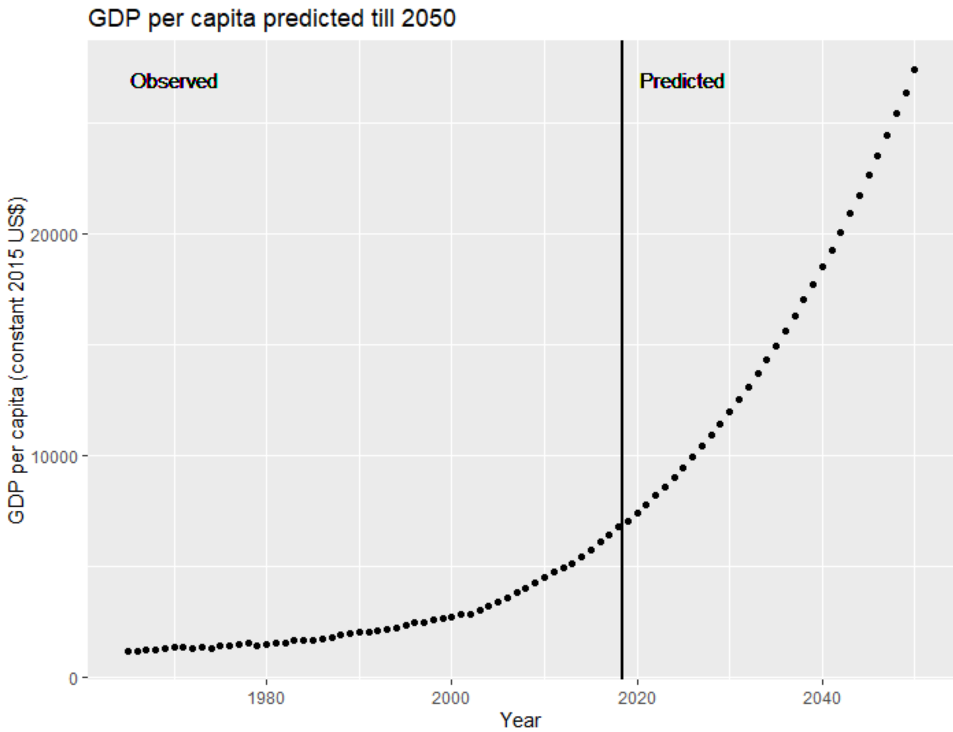

Figure 4.6: GDP per capita predicted till 2050

The regression model described by the equation 4.4 predicts the GDP per capita to reach approximately \$11981.51 in 2030 and \$27392.87 in US 2011\$.

However, it is important to note that the available data only covers observations till the year 2018 and therefore does not take into account effects of negative externalities such as the COVID-19 pandemic. Such externalities result as sharp contractions in the growth rate of the GDP as observed in Figure 2.1.

This essentially means this model assumes that India continues to have growth rates similar to what was there before the pandemic.

4.2.3 Energy intensity

The cubic relationship between *year* and *energy intensity of the GDP* has been derived from the regression model summarised in Table A.5. The fitted regression model is given by the equation 4.5.

$$\hat{y} = (-4.216e-04) \times x^2 + (1.681e+00) \times x + (-1.675e+03) \tag{4.5}$$

Figure 4.7 shows how the fitted model described by the equation 4.5 performs against the available data.

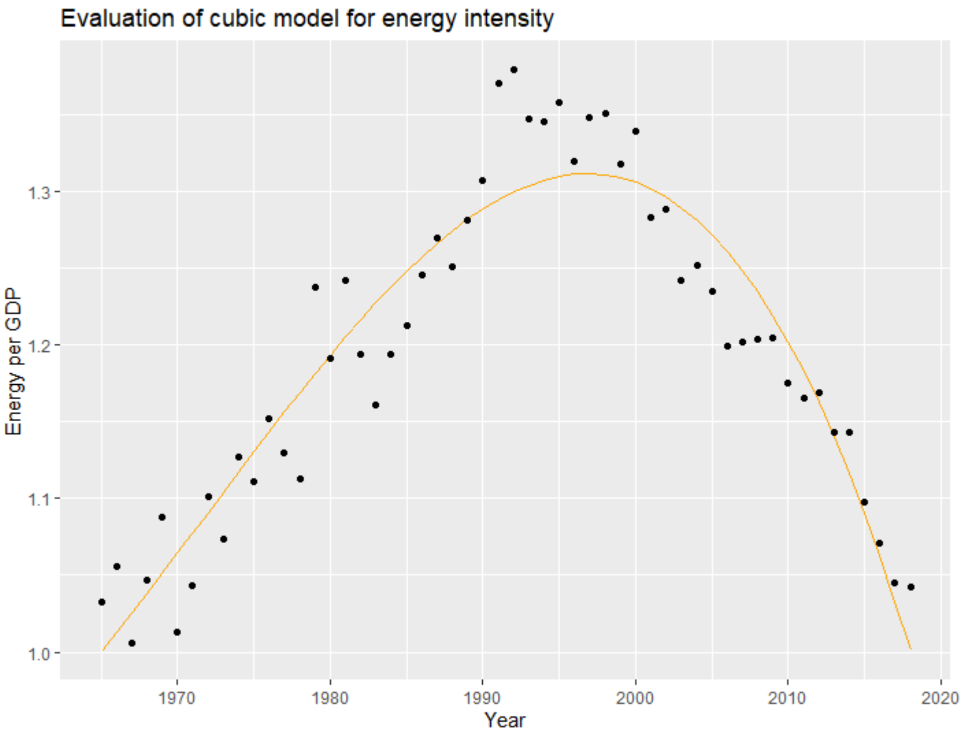

Figure 4.7: Evaluation of predicted model for energy intensity

The variables x and y in equation 4.5 denote the *year* and *energy intensity of the GDP* respectively. The overall regression was statistically significant with Adjusted $R^2 = 0.8837$, $p < 2.2e-16$).

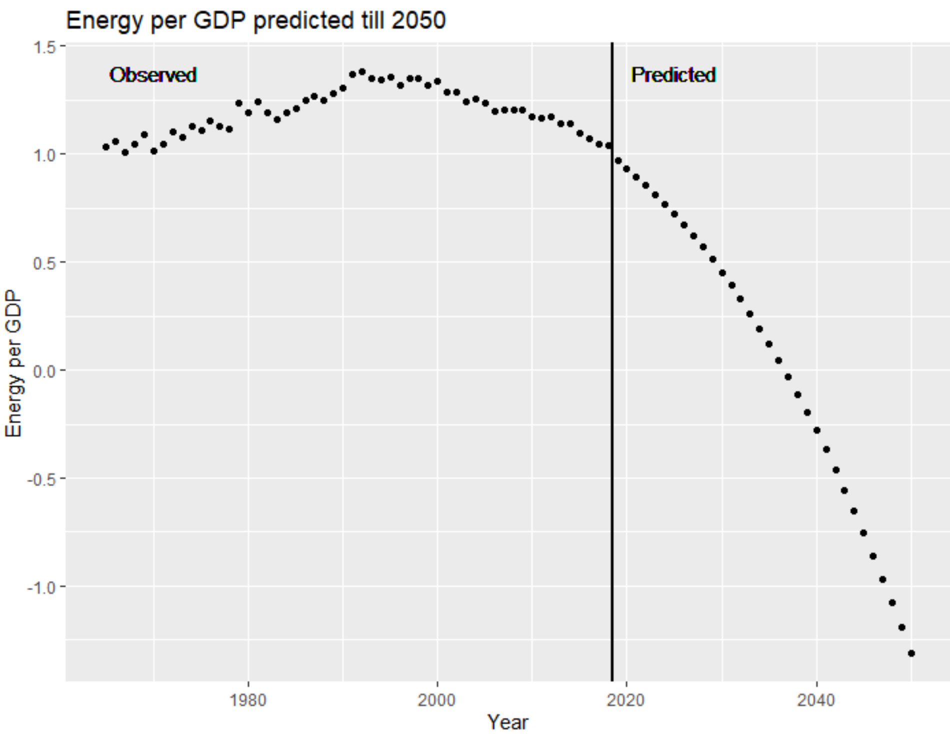

Figure 4.8: Energy intensity predicted till 2050

The regression model described by the equation 4.5 predicts the energy intensity of GDP to decrease to $0.453kWh/\$$ in 2030 and $-1.3092kWh/\$$ by 2050. It is interesting to note that the prediction for the year 2050 points towards a negative value for energy intensity of the GDP. This is an unlikely case and therefore points towards a limitation of the methodology used here.

It should also be noted that this regression model is not built using data that accounts for fluctuations in energy production and consumption as a result of the pandemic. Therefore, the model presented here does not account for externalities caused by events since 2018. This could be a contributing factor to any possible inaccuracies in the predictions.

4.2.4 Carbon intensity

The cubic relationship between *year* and *carbon intensity of energy* has been derived from the regression model summarised in Table A.6. The fitted regression model is given by the equation 4.6.

$$\hat{y} = (-2.827e-07) \times x^2 + (1.540e-03) \times x + (-1.209e-01) \tag{4.6}$$

Figure 4.9 shows how the fitted model described by the equation 4.6 performs against the available data.

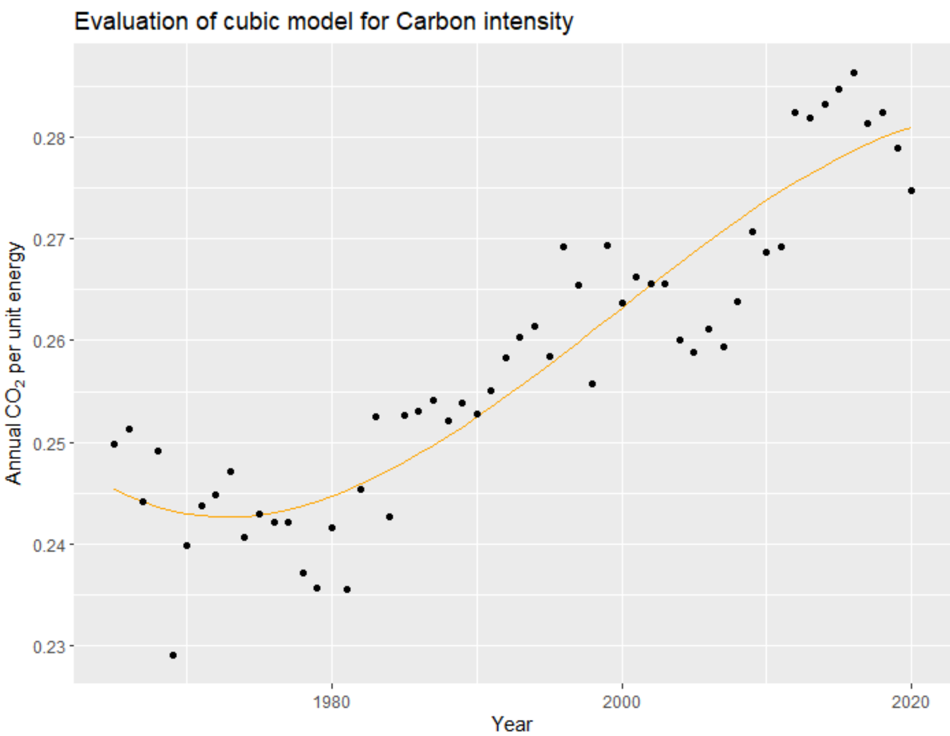

Figure 4.9: Evaluation of predicted model for Carbon intensity

The variables x and y in equation 4.6 denote the *year* and *carbon intensity of energy* respectively. The overall regression was statistically significant with Adjusted $R^2 = 0.8422$, $p < 2.2e-16$).

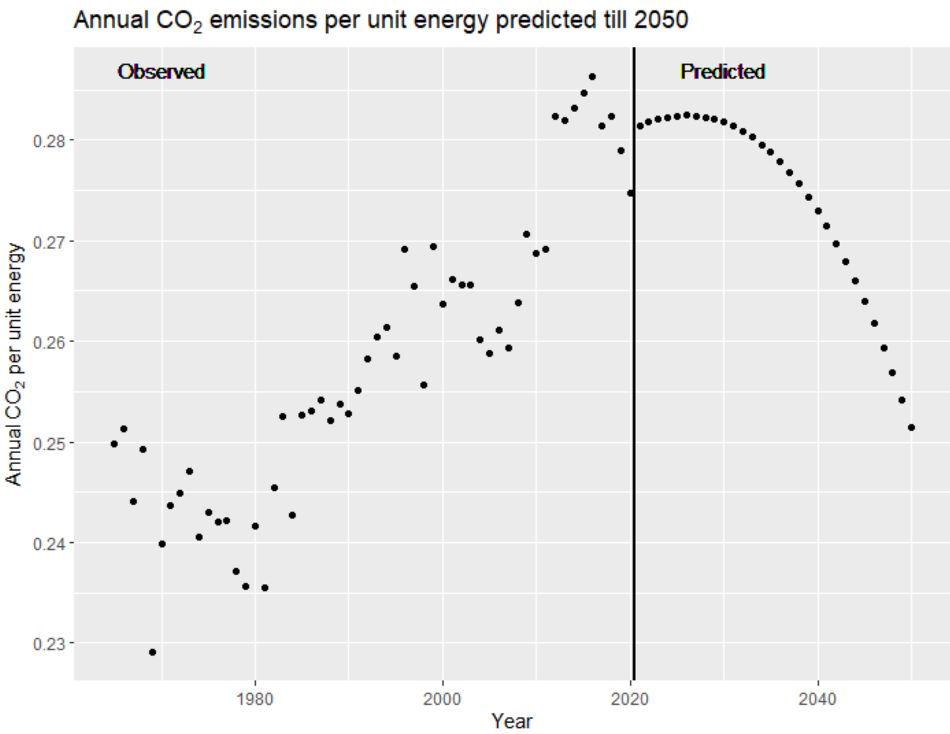

Figure 4.10: Carbon intensity predicted till 2050

The regression model described by the equation 4.6 predicts the carbon intensity of energy to keep increasing in the future. The outcome of the analysis predicts such increases to be $0.2818 kg/\$PPP$ in 2030 and $0.2514 kg/\$PPP$ by 2050.

This regression model is made using data till 2020 and therefore does not account for changes in emissions and energy supply during the pandemic-induced lockdowns.

Table 4.1: Percentage change in Carbon intensity between 2005 and 2030

Year	Calculated Carbon intensity (in kg/kWh)	Percentage change
2005	0.2588	-
2030	0.2818	+8.16%

As the table 4.1 indicates Carbon intensity while on a relative downward trend, will still be 8.16% higher than its 2005 levels in the year 2030.

4.2.5 Total CO_2 emissions - calculated

Using both the data used for the analysis and the predictions made using the regression models above, we obtain the total year-wise CO_2 emissions by the identity described in the equation 2.1. The calculated figures have been reported in the table B.1. The calculated data has been plot against their corresponding year as shown in Figure 4.11.

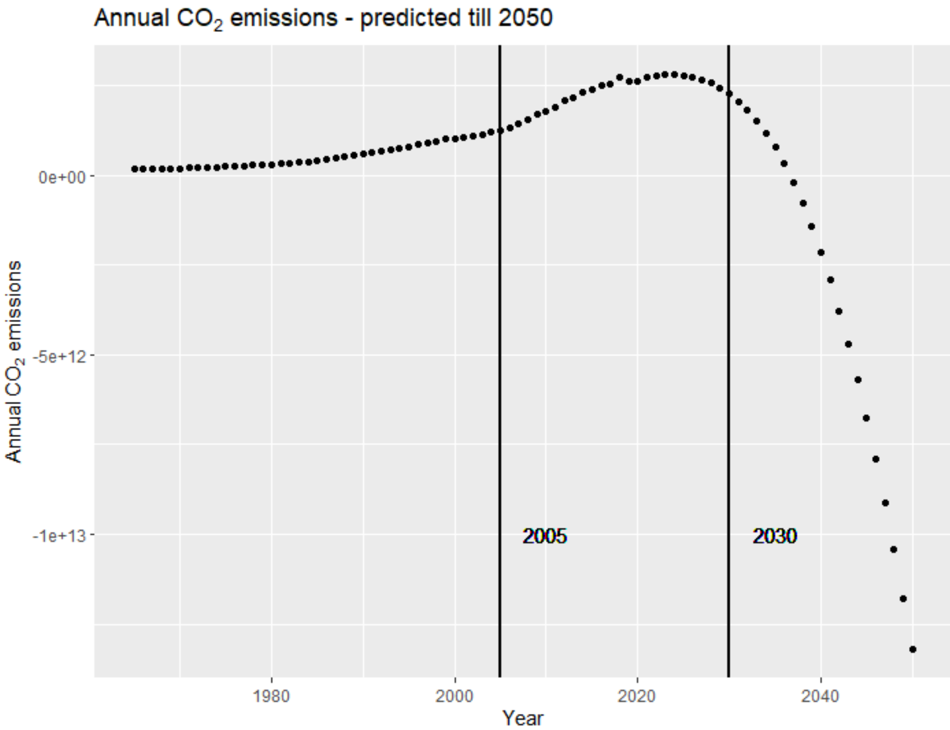

Figure 4.11: CO_2 emissions - predicted till 2050

It is interesting to note that the CO_2 emissions have been predicted to be negative from the year 2037 - which is unlikely. Such figures point towards the limitations of the methodology used for this analysis as the error keeps increasing for all successive years.

Table 4.2: Percentage change in CO_2 emissions between 2005 and 2030

Year	Calculated CO_2 emissions (in kilograms)	Percentage change
2005	1245879828862.43	-
2030	2264181805194.05	+81.73%

As the table 4.2 indicates CO_2 emissions will go up 81.73% from its 2005 levels in the year 2030.

Chapter 5

Discussions

To understand India's position in the global economic stage, we first take a look its economic advantages. Countries with increased interconnection can more easily access and arbitrage using a nation's natural or comparative advantage. One of its natural advantages is through agribusiness foreign direct investment (FDI) and international supply-chain agreements with Indian farms are driven by India's advantages in low-cost agricultural labor and nine months of sunshine (Gulati et al. (2007)).

Interconnectedness contributes to and enhances national benefits. It sprouts and encourages the development of industry agglomerations, networks of auxiliary or feeder enterprises, and clusters of skills and knowledge. This is where India's created advantages are observed. The growth of India's pharmaceutical industry after the Trade Related Aspects of Intellectual Property Rights (TRIPS) agreement is one such observation (Kamiike (2020)). The services sector continues to be the key engine of India's overall economic growth and one of the most alluring for FDI inflows. Global value chains (GVCs) give developing nations like India - the chance to participate more fully in the global economy. They can more affordably integrate into the global economy since they just need to specialize in a portion of the manufacturing process rather than having to produce the full good. This is especially noticeable in India's increased participation in the GVC through its IT and manufacturing industry (Pattnayak et al. (2019)).

China and India are essential to the expanding South-South commerce since they are the two largest developing nations in the world in terms of both population and economy. The various comparative advantages of developing nations offer justification for robust economic exchange. Other developing nations' exports to China have mostly consisted of extractive goods, minerals, and petroleum, especially from African nations. A significant amount of raw materials are needed to fuel China's resource-intensive economic model, which is supported by significant infrastructure investment and its manufacturing infrastructure. In a similar vein, India purchased a variety of inputs from other emerging nations, including metals from Sub-Saharan Africa and petroleum from Latin America. As the two economies with the greatest rates of growth in the world, both export a significant amount of manufactured goods, and they may continue to do so for many years to come as the conduits for the world's demand for these items. The quantity and spatial distribution of future global CO_2 emissions will be impacted by these developments in addition to their significant effects on global economic development (Meng et al. (2018)).

In the next section, we discuss what the results reported in the previous chapter means for India with respect to the NDCs pledged at the Glasgow climate summit.

5.1 India's promises

As we take a closer look into their air quality of one of the most polluted regions of India and use it as a component of the Environmental Kuznets Curve, we see a developing downward trend. The relative reduction of particulate pollutants in the citiy's air can be attributed to several steps taken by the Delhi government under public pressure. These steps included shutting down the Badarpur coal-fired power plant in the southeastern outskirts of Delhi and introduction of electric public transport buses in the transportation sector (Patel (2019)).

On a global level, we begin with a comparison of India with the US, European Union and China. On comparison of the respective Environmental Kuznets Curves, we see that service based economies like that of the US (Figure 5.1A) and the European Union (Figure 5.1B) show a downward trend in their curves indicating towards a reduction in their levels of environmental degradation.

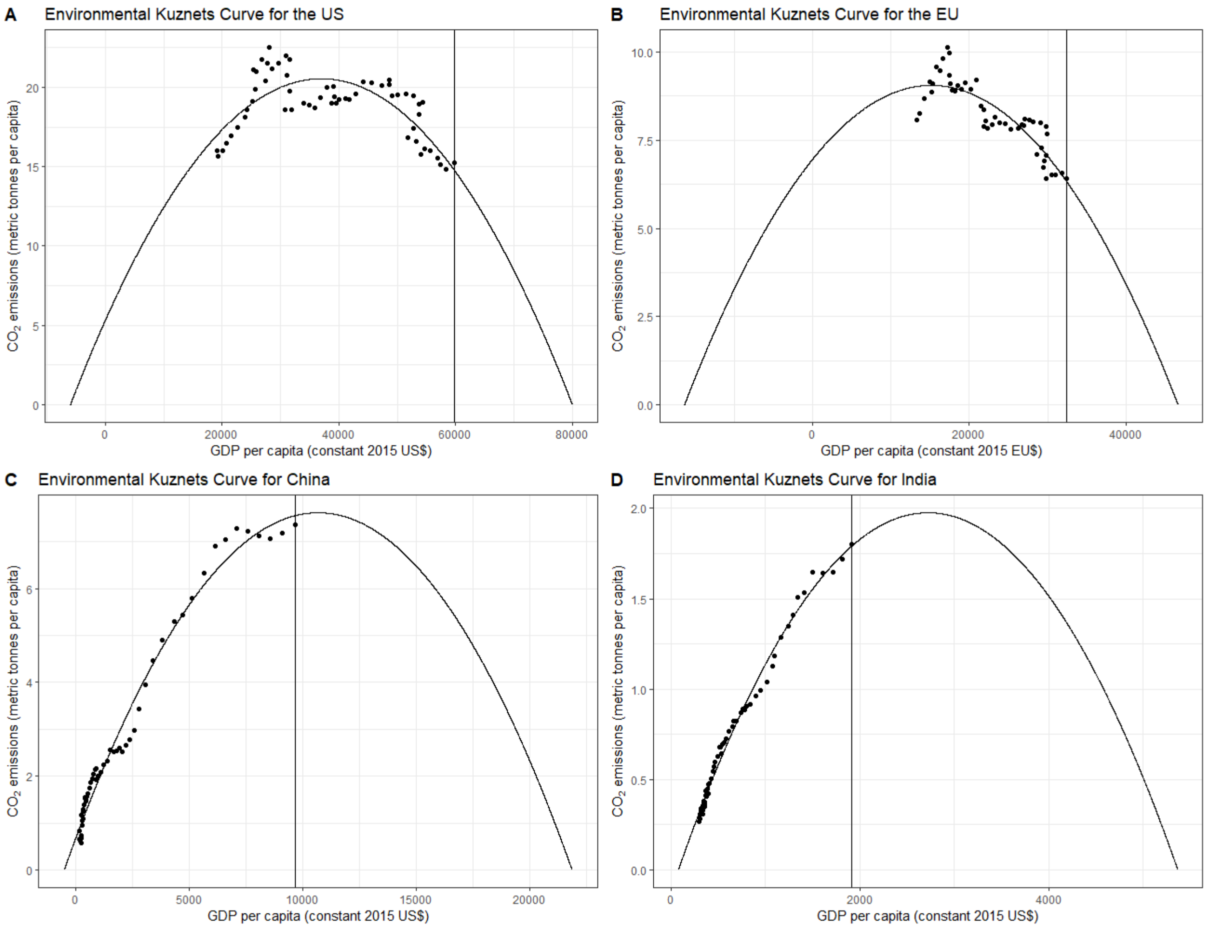

Figure 5.1: Comparison of Environmental Kuznets Curve for the United States, European Union, China and India

In the case of China (Figure 5.1C) we see that the industrial economy is almost at the maxima of the EKC with the local trend of the curve pointing upwards. While India (Figure 5.1D), another industry-based economy is yet to reach the maxima of the EKC is also trending upwards both globally and locally through the curve. This points towards a possible increase in environmental degradation for India in the future. However, it might be different for China considering the economy is at the maxima of the curve already.

Table 5.1: Required percentage change to reduce Carbon intensity of the economy 45% below 2005 emission levels

Year	Carbon intensity (in kg/kWh)	% change required by 2030
2005	0.2588*	-55%
2022	0.2818**	-49.49%
2030	0.1423***	-

*Historic observed value; **Current calculated value; ***Required projected value

This analysis demonstrates that a reduction by at least 49.49% of the 2022 levels of CO_2 emissions is required for India to be able to match the target of 45% below 2005 levels of Carbon intensity that it has pledged in the NDCs declared during the Glasgow climate summit in November 2021. To attain the promised reduction of cumulative CO_2 emissions by 1 billion tonnes by 2030, the target level would be $1,773,269,347.57$ tonnes - 63.94% lower than the current calculated level in 2022.

Going by the above-mentioned figures, a reduction in emissions by 1 billion tonnes for 2030 requires 27.68% less emissions than the calculated emission levels for 2030. To reach a Carbon intensity (lower than 45% of the 2005 level, a reduction of about 230.42% of projected 2030 level of emissions needs to be attained.

As discussed previously in this chapter, India has positioned itself as an important player in the global value chain in services and manufacturing. Since these two sectors are key drivers of the economy, it is least likely to slow down in the near future. As suggested by the calculations presented in Tables B.1, 4.1 and 5.1, the CO_2 emissions and Carbon intensity for such continued economic activities are far from their required level. This means that it is not realistic for India to reduce its emissions to the levels declared in its NDCs.

The COVID-19 pandemic has made the Indian renewable energy industry vulnerable. Massive losses, project delays, and excessively ambitious plans are now doomed to failure. The dramatic drop in electricity usage across the nation is a glaring illustration of the pandemic's effects (Shekhar et al. (2021)). India's ability to fulfil its promise increasing its power generation capability without relying on fuels and meeting 50% of its energy demands through renewable energy looks bleak in the face of such lack of progress.

5.2 Policy effects and implications

India witnessed a slew of air pollution and control legislation for environmental protection. In this section we discuss the policies that have been put in place for such purposes.

Some of the most notable control legislation for environmental protection are discussed below:

- *The Air (Prevention and Control of Pollution) Act, 1981* - the first law created specifically to address the prevention, control, and mitigation of air pollution. It was created to serve the purposes of boards, which include granting and delegating authority to them over the relevant issues (Central Pollution Control Board (2021)).

- *The Environment (Protection) act, 1986* - this law went into effect to address issues related to environmental protection, improvement, and related things. Numerous more laws and norms are encapsulated under this legislation (Central Pollution Control Board (2021)).

- *The Ozone Depleting Substances (Regulation and Control) Rules, 2000* - India is classified as being under the Montreal Protocol Regulation's Article 5 Paragraph 1 regarding the production and consumption of ozone depleting compounds. This law addresses the ban on new investments using ozone depleting substances, the regulation of the import, export, and sale of goods created with or containing ozone depleting substances, as well as the monitoring and reporting requirements related to these issues (Central Pollution Control Board (2021)).

- *National Ambient Air Quality Standards* - the 2009 notification of the *The Environment (Protection) act, 1986* covers Indian cities are suffering from severe particulate pollution, with 63 cities (or 52 percent) reaching critical levels (exceeding 1.5 times the limit), 36 cities (or 1 to 1.5 times the standard) and only 19 cities (or 50 percent below the standard) at moderate levels. Since the new criteria are stricter than the old ones, more cities in India will become severely or highly polluted, which will damage India's reputation on the global stage. Additionally, it includes the implementation of Continuous Ambient Air Quality Monitoring Stations for large scale industries (Central Pollution Control Board (2021)).

Despite having several regulations in place to check environmental pollution, there is no policy developed or put in place on the basis of economic loss attributed to air pollution.

In India, chronic obstructive pulmonary disease and acute lower respiratory infections cause 400,000–550,00 premature deaths as a result of indoor air pollution (Smith (2000)). Indians have started to see air pollution as an issue in recent years, and the government is starting to act. 2019 saw the central government establish the National Clean Air Programme (NCAP) and vow a "war on pollution". By 2024, the programme hopes to have cut particle pollution by 20 to 30 percent compared to 2017 levels. Despite the fact that the NCAP's goals are not legally enforceable, if India were to achieve and maintain this reduction, it would have a remarkable positive impact on the country's health: a reduction of 25% nationwide, the midpoint of the NCAP's target, would extend the country's life expectancy by 1.8 years and by 3.5 years for Delhi residents (AQLI (2022)).

5.2.1 Carbon pricing in India

In 2021, India priced a total of 58.1% CO_2 emissions from energy use. India does not levy an explicit carbon price. Fuel excise taxes - an implicit method of carbon pricing covered 58.1% of emissions in 2021, remaining constant from 2018 OECD (2021).

As of July 16, 2021, government estimates place the overall excise duty incidence as a percentage of retail sales on gasoline and diesel at 32.4% and 35.4%, respectively. According to the Petroleum Minister Hardeep Singh Puri, the central government's different development initiatives are funded by the money raised by levying these fees (Animesh Singh (2021)). However, it is important to note that such funds are not channeled towards environmental protection projects.

As the government works to enhance local gasoline supply to meet rising demand and boost federal revenues, India has slapped windfall tax on oil producers and refiners who increased product exports to benefit from greater international margins (Verma et al. (2022)). Russian petroleum is being avoided by many Western consumers in response to the country's invasion of Ukraine, but private Indian refiners like Reliance and Nayara have been among the top consumers of discounted Russian supplies this year. They are making significant profits by cutting back on domestic sales and aggressively increasing gasoline exports, notably to customers in Europe, which is currently snubbing Russian energy imports. Private refiners have decreased their market share of domestic fuel sales from 10% in the fiscal year to March 2022 to 7% in April to allow dramatically increasing fuel exports and earn a bigger share of the increasing global demand owing to the Russia (Verma and Maguire (2022)).

Chapter 6

Conclusions

6.1 Summary

6.2 Limitations of this study

6.3 Scope of future work

However, the environmental performances of other densely populated cities like Mumbai, where protection of forests are being taken away are yet to be seen and studied (Jyotsna Mohan (2022)).

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Appendices

Appendix A

Statistical model details

This section summarises the statistical models used in this thesis. The tables and figures presented below are obtained using *R*. The codes used to obtain these outputs have also been provided.

A.1 Environmental Kuznets Curve

Table A.1: Regression model statistics for EKC

Residuals:				
Min	1Q	Median	3Q	Max
-0.108512	-0.025767	0.001053	0.026051	0.094302
Coefficients:				
term	estimate	std.error	t value	$Pr(>\|t\|)$
(Intercept)	-1.21e-1	2.43e-2	-4.98	$6.51e-6^{***}$
poly(GDPpercapita, 2, raw = T)1	1.54e-3	6.36e-5	24.2	$2.40e-31^{***}$
poly(GDPpercapita, 2, raw = T)2	-2.83e-7	3.21e-8	-8.80	$3.85e-12^{***}$
Residual std. error (on 56 DF)			0.04477	
Multiple R^2			0.9898	
Adjusted R^2			0.9894	
F-statistic (2, 56)			2713	
p-value			$< 2.2e-16$	
Number of obs.			59	

Significance codes: $^{***}p < 0$; $^{**}p < 0.01$; $^{*}p < 0.05$; $.p < 0.1$; $p < 1$

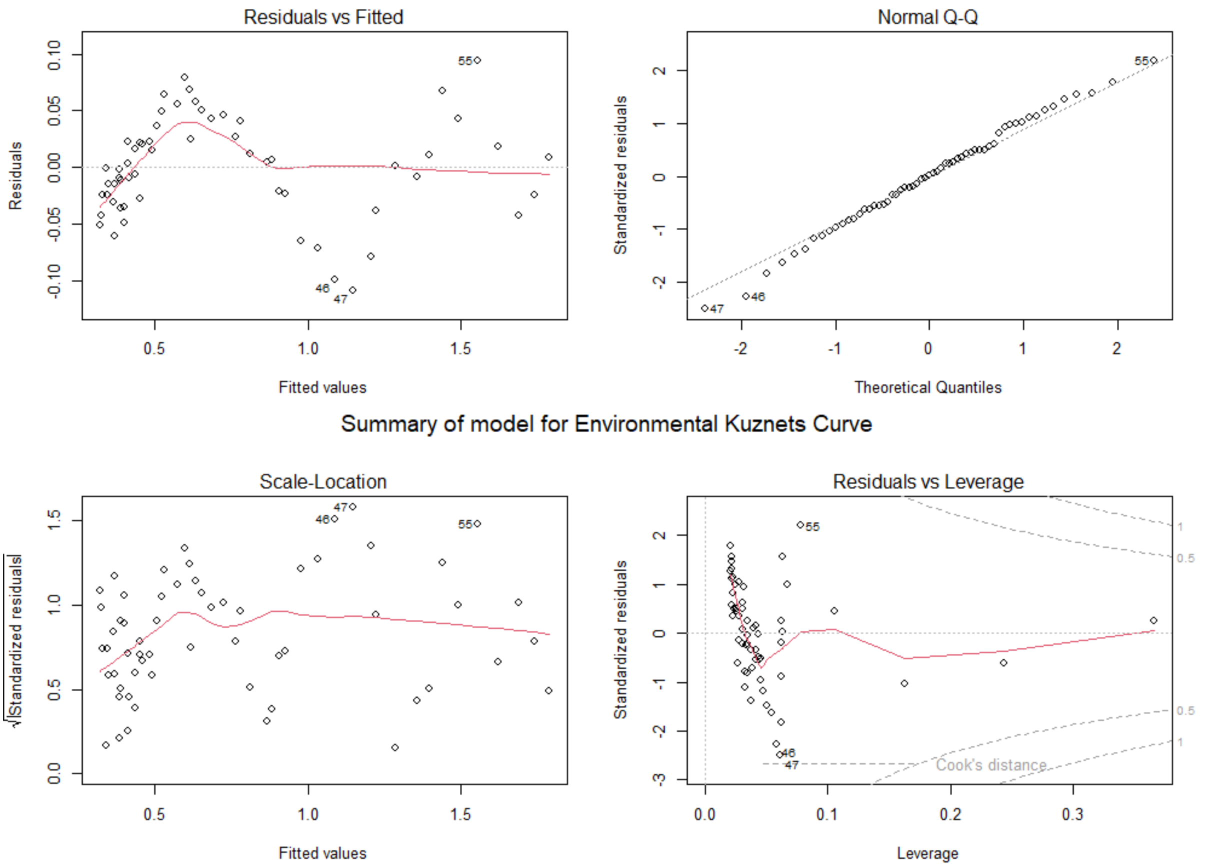

Figure A.1: Model statistics for Environmental Kuznets Curve of India

Table A.2: Regression model statistics for EKC for NCT of Delhi

Residuals:				
Min	1Q	Median	3Q	Max
-10.9622	-5.1829	-0.4389	2.9238	14.8250
Coefficients:				
term	estimate	std.error	t value	$Pr(>\|t\|)$
(Intercept)	2.492e+00	2.080e+01	0.120	0.905974
poly(GDPpercapita, 2, raw = T)1	1.391e-01	3.501e-02	3.973	0.000892***
poly(GDPpercapita, 2, raw = T)2	-4.406e-05	1.371e-05	-3.215	0.004805**
Residual std. error (on 18 DF)			7.745	
Multiple R^2			0.7188	
Adjusted R^2			0.6875	
F-statistic (2, 18)			23	
p-value			$1.1e-05$	
Number of obs.			21	

Significance codes: $^{***}p < 0$; $^{**}p < 0.01$; $^{*}p < 0.05$; $.p < 0.1$; $p < 1$

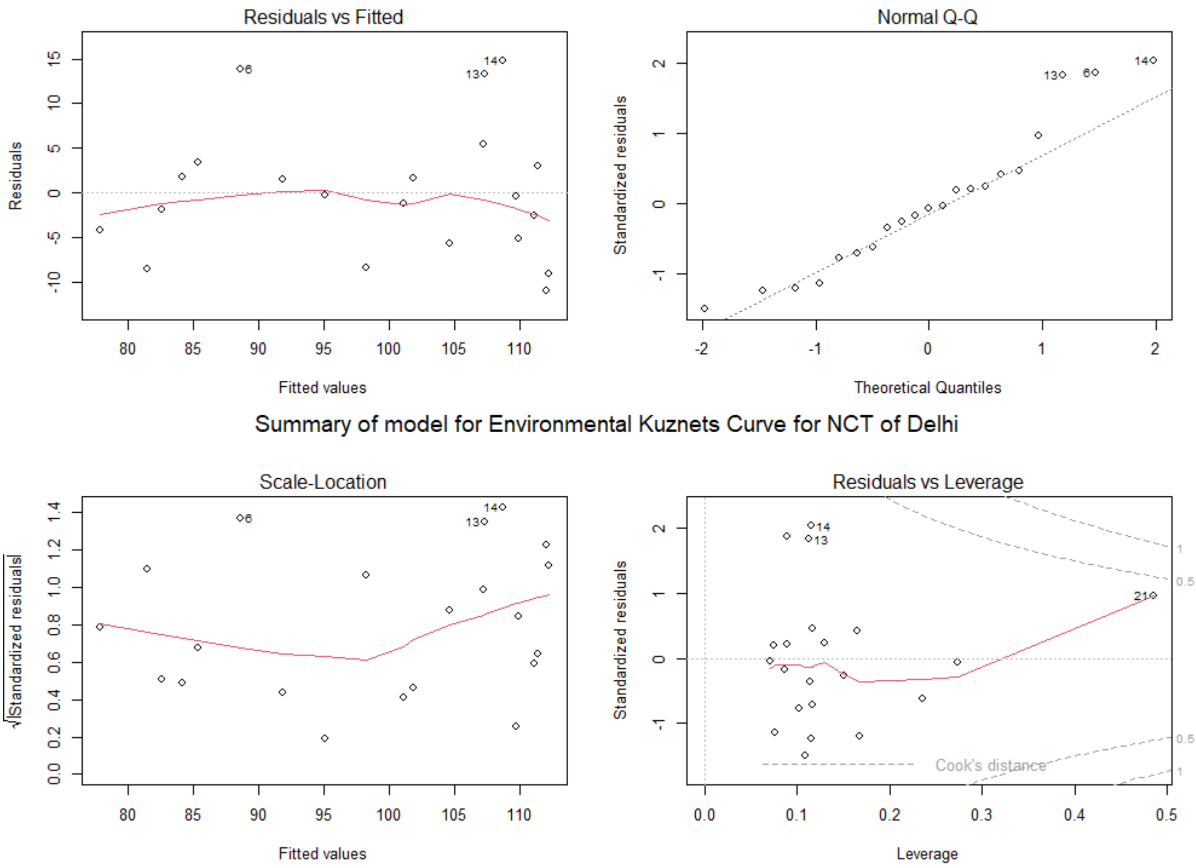

Figure A.2: Model statistics for Environmental Kuznets Curve of NCT of Delhi

A.2 Kaya decomposition

A.2.1 Population

Table A.3: Regression model statistics for *Population*

Residuals:				
Min	1Q	Median	3Q	Max
-1210407	-480895	-31472	531147	1739163
Coefficients:				
term	estimate	std.error	t value	$Pr(>\|t\|)$
(Intercept)	$2.529e+13$	$2.355e+11$	107.4	$< 2e-16^{***}$
poly(kayac$Year, 3, raw = T)1	$-3.806e+10$	$3.546e+08$	-107.3	$< 2e-16^{***}$
poly(kayac$Year, 3, raw = T)2	$1.908e+07$	$1.779e+05$	107.3	$< 2e-16^{***}$
poly(kayac$Year, 3, raw = T)3	$-3.188e+03$	$2.976e+01$	-107.1	$< 2e-16^{***}$
Residual std. error (on 54 DF)			784500	
Multiple R^2			1	
Adjusted R^2			1	
F-statistic (2, 54)			$2.386e+06$	
p-value			$< 2.2e-16$	
Number of obs.			56	

Significance codes: $^{***}p < 0$; $^{**}p < 0.01$; $^{*}p < 0.05$; $.p < 0.1$; $p < 1$

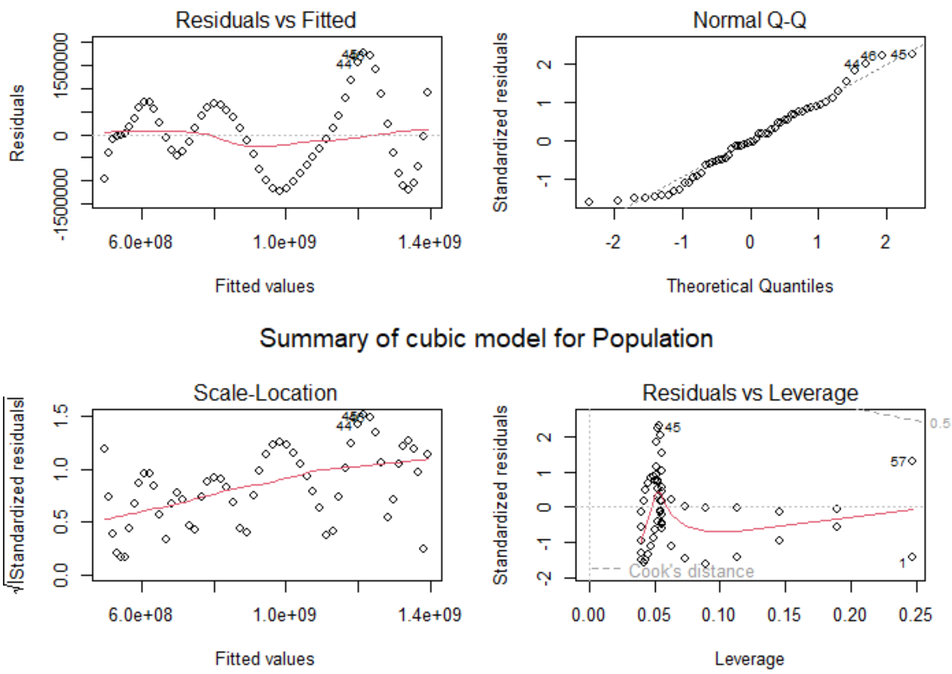

Figure A.3: Model statistics for Kaya decomposition: Population

A.2.2 GDP per capita

Table A.4: Regression model statistics for *GDP per capita*

Residuals:				
Min	1Q	Median	3Q	Max
-383.85	-138.49	12.67	143.80	516.34
Coefficients:				
term	estimate	std.error	t value	$Pr(>\|t\|)$
(Intercept)	$-4.797e+08$	$2.682e+07$	-17.88	$< 2e-16^{***}$
poly(kayac$Year, 3, raw = T)1	$7.279e+05$	$4.041e+04$	18.01	$< 2e-16^{***}$
poly(kayac$Year, 3, raw = T)2	$-3.682e+02$	$2.029e+01$	-18.14	$< 2e-16^{***}$
poly(kayac$Year, 3, raw = T)3	$6.208e-02$	$3.396e-03$	18.28	$< 2e-16^{***}$
Residual std. error (on 51 DF)			74.09	
Multiple R^2			0.9978	
Adjusted R^2			0.9977	
F-statistic (3, 50)			7540	
p-value			$< 2.2e-16$	
Number of obs.			54	

Significance codes: $^{***}p < 0$; $^{**}p < 0.01$; $^{*}p < 0.05$; $.p < 0.1$; $p < 1$

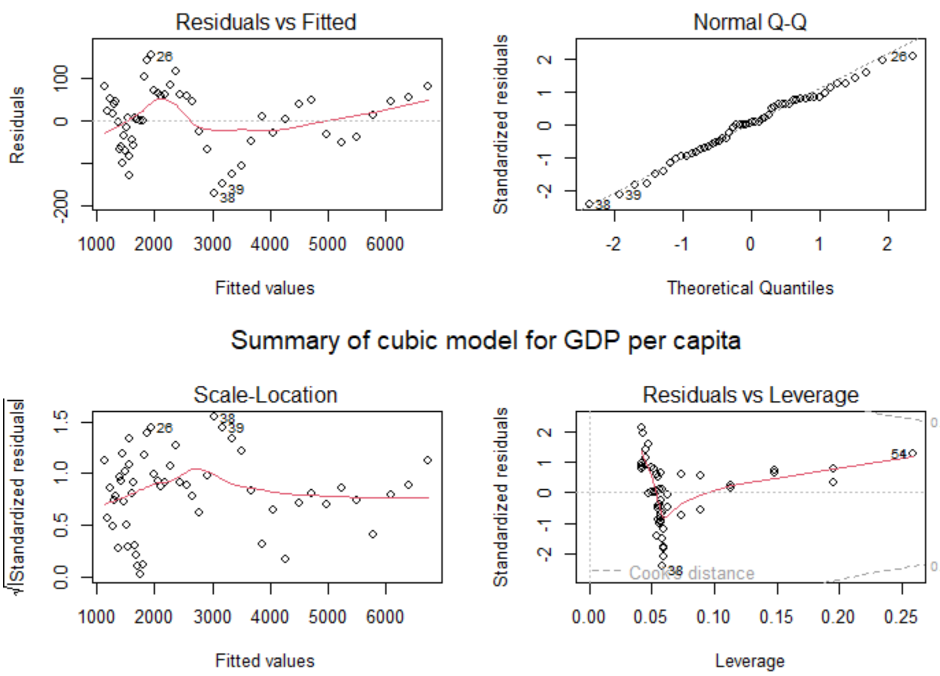

Figure A.4: Model statistics for Kaya decomposition: GDP per capita

A.2.3 Energy intensity

Table A.5: Regression model statistics for *Energy intensity*

Residuals:				
Min	1Q	Median	3Q	Max
-0.066454	-0.026684	0.003262	0.030856	0.079327

Coefficients: term	estimate	std.error	t value	$Pr(>\|t\|)$
(Intercept)	$5.610e+04$	$1.306e+04$	4.295	$8.03e-05***$
poly(kayac$Year, 3, raw = T)1	$-8.536e+01$	$1.968e+01$	-4.338	$6.97e-05^{***}$
poly(kayac$Year, 3, raw = T)2	$4.329e-02$	$9.881e-03$	4.381	$6.05e-05^{***}$
poly(kayac$Year, 3, raw = T)3	$-7.316e-06$	$1.654e-06$	-4.424	$5.25e-05^{***}$

Residual std. error (on 50 DF)	0.03608
Multiple R^2	0.8903
Adjusted R^2	0.8837
F-statistic (3, 50)	135.3
p-value	$< 2.2e-16$
Number of obs.	54

Significance codes: $^{***}p < 0$; $^{**}p < 0.01$; $^{*}p < 0.05$; $.p < 0.1$; $p < 1$

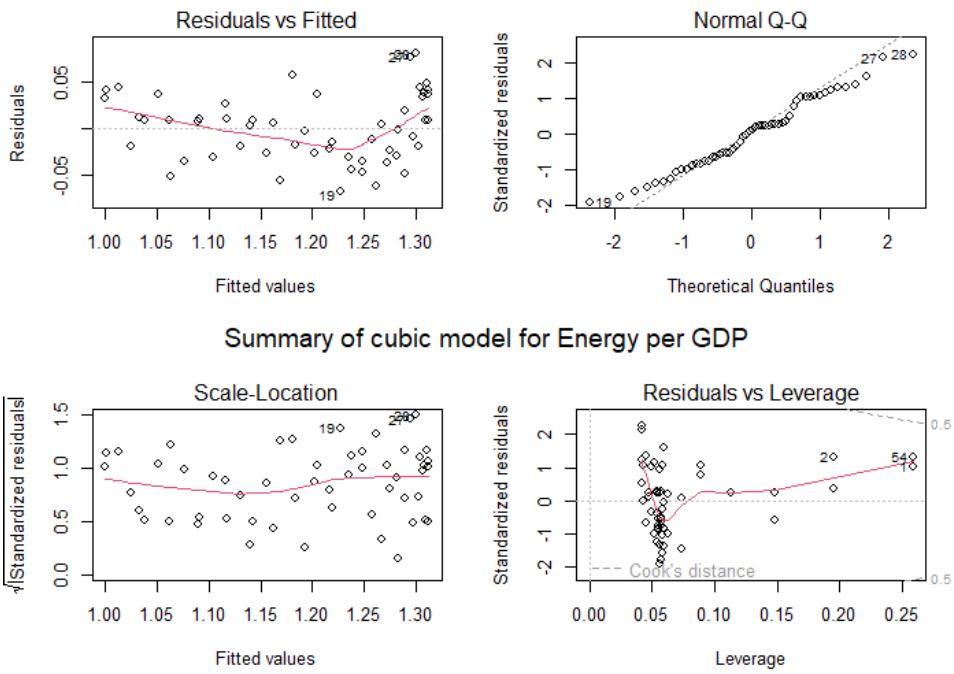

Figure A.5: Model statistics for Kaya decomposition: Energy intensity

A.2.4 Carbon intensity

Table A.6: Regression model statistics for *Carbon intensity*

Residuals:				
Min	1Q	Median	3Q	Max
-0.0141778	-0.0034528	0.0006655	0.0044948	0.0104437
Coefficients:				
term	estimate	std.error	t value	$Pr(>\|t\|)$
(Intercept)	$4.180e+03$	$1.836e+03$	2.276	0.0270*
poly(kayac$Year, 3, raw = T)1	$-6.273e+00$	$2.765e+00$	-2.269	0.0275*
poly(kayac$Year, 3, raw = T)2	$3.138e-03$	$1.388e-03$	2.261	0.0280*
poly(kayac$Year, 3, raw = T)3	$-5.232e-07$	$2.322e-07$	-2.253	0.0285*
Residual std. error (on 52 DF)			0.005753	
Multiple R^2			0.8508	
Adjusted R^2			0.8422	
F-statistic (3, 52)			98.84	
p-value			$< 2.2e-16$	
Number of obs.			56	

Significance codes: $***p < 0$; $**p < 0.01$; $*p < 0.05$; $.p < 0.1$; $p < 1$

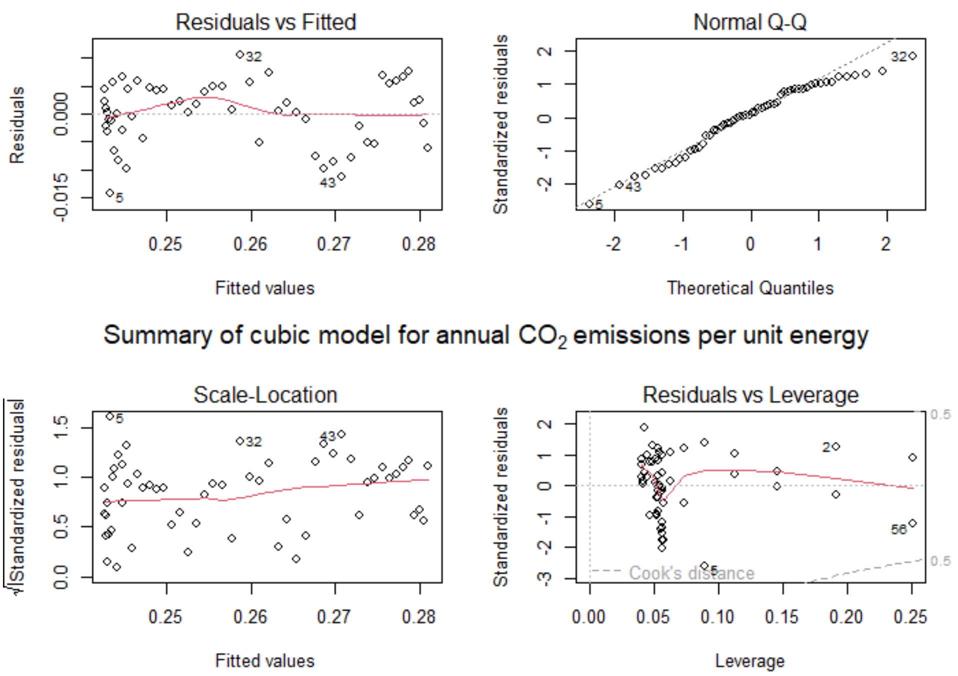

Figure A.6: Model statistics for Kaya decomposition: Carbon intensity

Appendix B

Data

Table B.1: Kaya decomposition

	Year	P	G/P	E/G	C/E	C - *Calculated*
1	1965	499123328	1229	1.033	0.249 8	158289645628.439
2	1966	509631509	1215	1.056	0.2513	164319443721.54
3	1967	520400577	1286	1.006	0.2441	164340459956.576
4	1968	531513834	1290	1.047	0.2492	178895329580.163
5	1969	543084333	1347	1.088	0.2291	182342898763.98
6	1970	555189797	1384	1.013	0.2399	186731359764.762
7	1971	567868021	1364	1.043	0.2437	196880008925.309
8	1972	581087255	1329	1.101	0.2449	208229585774.062
9	1973	594770136	1360	1.074	0.2471	214666902212.564
10	1974	608802595	1344	1.127	0.2406	221868323994.696
11	1975	623102900	1430	1.111	0.243	240555971687.031
12	1976	637630085	1417	1.152	0.2421	251991515693.646
13	1977	652408766	1494	1.13	0.2422	266761387424.025
14	1978	667499815	1540	1.113	0.2371	271268014602.084
15	1979	682995348	1427	1.238	0.2357	284394992956.883
16	1980	698952837	1495	1.191	0.2416	300675302164.129

17	1981	715384997	1557	1.242	0.2355	325792399106.27
18	1982	732239498	1570	1.194	0.2454	336846228556.67
19	1983	749428958	1663	1.161	0.2525	365356065450.588
20	1984	766833411	1690	1.194	0.2427	375544870673.056
21	1985	784360012	1720	1.213	0.2527	413532773516.598
22	1986	801975250	1755	1.246	0.2531	443862314957.266
23	1987	819682095	1793	1.27	0.2541	474279249647.279
24	1988	837468938	1938	1.251	0.2521	511861701462.635
25	1989	855334675	2024	1.281	0.2538	562843084266.623
26	1990	873277799	2087	1.307	0.2528	602181661551.254
27	1991	891273202	2062.310303	1.37	0.2551	642385731526.91
28	1992	909307018	2115.257324	1.379	0.2583	685113338300.82
29	1993	927403866	2176.427734	1.347	0.2604	707981205886.315
30	1994	945601828	2254.898926	1.345	0.2614	749658121686.214
31	1995	963922586	2355.963135	1.358	0.2585	797206744782.401
32	1996	982365248	2475.568115	1.32	0.2692	864165368014.988
33	1997	1000900028	2514.021729	1.348	0.2655	900563095835.229
34	1998	1019483586	2611.781494	1.351	0.2557	919820649987.65
35	1999	1038058154	2707.740479	1.318	0.2694	998025696327.498
36	2000	1056575548	2753.085449	1.339	0.2637	1027095800612.63
37	2001	1075000094	2837.855469	1.283	0.2662	1041917861004.66
38	2002	1093317187	2870.923584	1.288	0.2656	1073771176590.18
39	2003	1111523146	3035.922607	1.242	0.2656	1113163284176.66
40	2004	1129623466	3212.510986	1.252	0.2601	1181742917447.78
41	2005	1147609924	3396.648682	1.235	0.2588	1245879828862.43
42	2006	1165486291	3629.411133	1.199	0.2611	1324248200636.55
43	2007	1183209471	3870.698975	1.202	0.2594	1427991012867.77
44	2008	1200669762	4030.654297	1.204	0.2639	1537676586119.62
45	2009	1217726217	4270.708008	1.205	0.2707	1696386619742.97
46	2010	1234281163	4525.745605	1.175	0.2687	1763639318607.68
47	2011	1250287939	4768	1.165	0.2692	1869593844004.54
48	2012	1265780243	4932	1.169	0.2824	2060917391513.78
49	2013	1280842119	5172	1.143	0.2819	2134496381427.23

50	2014	1295600768	5458	1.143	0.2832	2288991645293.95
50	2014	1295600768	5458	1.143	0.2832	2288991645293.95
51	2015	1310152392	5794	1.098	0.2847	2372958331674.7
52	2016	1324517250	6125	1.071	0.2863	2487565532546.92
53	2017	1338676779	6449.113281	1.045	0.2814	2538727685684.32
54	2018	1352642283	6806.498535	1.042	0.2824	2709187891392.61
55	2019	1366417756	7071.21389234066	0.967815127893118	0.2789	2608064883043.62
56	2020	1380004385	7431.65734255314	0.932143712147081	0.2748	2627034318107.14
57	2021	1393409033	7808.17283290625	0.894377933531359	0.28141808244618	2738426661459.33
58	2022	1404508374.61328	8201.13286793232	0.854473895269621	0.281770207039699	2773269347567.94
59	2023	1415987091.65234	8610.90995287895	0.812387700592808	0.282051437604423	2793830146613.25
60	2024	1426938328.36719	9037.87659281492	0.76807545273914	0.282258635047583	2795907074896.45
61	2025	1437342957.89844	9482.40529292822	0.721493254895904	0.282388660260949	2776888536502.88
62	2026	1447181853.41797	9944.86855810881	0.672597210315871	0.282438374163576	2734015170773.67
63	2027	1456435888.08594	10425.6388934255	0.62134342212812	0.282404637649961	2664388679567.16
64	2028	1465085935.07422	10925.0888041854	0.567687993643631	0.282284311622789	2564983208327.32
65	2029	1473112867.53516	11443.5907949805	0.511587027998758	0.282074256992018	2432659469515.9
66	2030	1480497558.61328	11981.5173712373	0.452996628497203	0.281771334654877	2264181805194.05
67	2031	1487220881.51172	12539.2410381436	0.391872898326255	0.281372405516777	2056238364651.68
68	2032	1493263709.36719	13117.1343002915	0.328171940629545	0.280874330484039	1805464573366.76
69	2033	1498606915.31641	13715.569663167	0.261849858696223	0.280273970459348	1508470052010.06
70	2034	1503231372.58594	14334.9196317792	0.192862755713577	0.279568186342658	1161869122843.69
71	2035	1507117954.24609	14975.5567110181	0.121166734905273	0.27875383904211	762315029164.135
72	2036	1510247533.57031	15637.8534058332	0.046717899509531	0.277827789462208	306537961070.155
73	2037	1512600983.61719	16322.1822215319	-0.0305276472936384	0.276786898495629	-208613046374.267
74	2038	1514159177.64062	17028.9156634808	-0.11061380225874	0.27562802706143	-786124307943.31
75	2039	1514902988.71094	17758.4262359142	-0.193584462205763	0.274348036055017	-1428767786793.6
76	2040	1514813290.07422	18511.0864444971	-0.279483523903764	0.272943786373617	-2139047546107.32
77	2041	1513870954.80078	19287.2687940001	-0.368354884165456	0.271412138937194	-2919142460402.78
78	2042	1512056856.16016	20087.3457899094	-0.460242439687136	0.269749954635699	-3770845345471.76
79	2043	1509351867.21094	20911.6899368763	-0.555190087288793	0.267954094375455	-4695498737350.19
80	2044	1505736861.21484	21760.6737400889	-0.653241723797692	0.266021419067329	-5693927615872.66
81	2045	1501192711.24219	22634.6697044373	-0.754441245982889	0.263948789606729	-6766369450407.38

82	2046	1495700290.52344	23534.0503355861	-0.85883255067165	0.26173306689725	-7912402043303.86
83	2047	1489240472.14453	24459.1881380081	-0.96645953450934	0.259371111846121	-9130869724826.29
84	2048	1481794129.37109	25410.4556167126	-1.07736609439598	0.256859785359666	-10419808589733.3
85	2049	1473342135.29297	26388.2252771258	-1.19159612707153	0.2541959483342	-11776371543882
86	2050	1463865363.07422	27392.8696240187	-1.30919352934143	0.251376461676955	-13196754102466.8