Determinants of CO_2 Emissions Growth in South Asia: An Analysis of Seven Key Factors

By

Hassan Aziz

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Faculty Advisor: Dr. Luis Bettencourt

Preceptor: Dr. Brianne Painia

Contents

Abstract

This study examines the influence of seven key variables (economic growth, urbanization, population, energy consumption, fossil fuel use, agricultural production, and forest area) on CO_2 emissions in five South Asian countries (India, Pakistan, Bangladesh, Nepal, and Sri Lanka) from 1990 to 2014. Data on CO_2 emissions are sourced from both World Development Indicators (WDI) and the Global Carbon Budget (GCB).Using fixed effects and random effects models, along with Arellano-White heteroskedasticity-robust standard errors, we conducted regression analysis. The analysis using WDI data reveals that GDP growth, urbanization, energy consumption, and fossil fuel usage contribute positively to CO_2 emissions, while forest area and agricultural production have a negative impact.Conversely, analysis using GCB data indicates that urbanization, population growth, and fossil fuel use are positively correlated with CO_2 emissions, while only forest area shows a negative correlation. The noteworthy impact of urbanization, forest area, and fossil fuel use on CO_2 emissions is consistent across both regression models. However, a more detailed investigation with granular data is suggested to better understand the relationships between population growth and agricultural production and CO_2 emissions in the region.

1 Introduction

While Earth's climate change has been changing throughout history, the rate of climate change and global warming since the mid-20th century is unprecedented. In the last 800,000 years, there have been eight cycles of warmer periods and ice ages, however, the end of the last ice age about 11,000 years ago, marked the beginning of human civilization and the modern climate era. Within this modern climate era, the current trend of climate warming is attributed to human civilization and human activities beginning from the 1800s (IPCC 2023, 36). An increase in atmospheric CO_2 levels is one of the factors behind the increase in climate warming. CO_2, carbon dioxide, is a heat-trapping gas that is produced mainly through the extraction and burning of fossil fuels – which include coal, oil, and natural gas (NASA 2023). Figure 1 shows the graph of atmospheric carbon dioxide (CO_2) from 1979 till 2023 (measured in parts per million (ppm)).

Climate change is a global problem and has affected or is predicted to affect every part of the world. South Asia is one of the most vulnerable regions to climate change (World Bank 2021). 2022 was the year when extreme climatic events served as a reminder of the destruction that climate change could inflict on the region. Pakistan's flooding led to hundreds of deaths, left eight million people displaced, and caused USD 30 billion in losses (World Bank 2022). Similarly, India faced droughts in West Bengal, Bihar, and Uttar Pradesh, while the states of Madhya Pradesh, Andhra Pradesh, Telangana, and Maharashtra faced

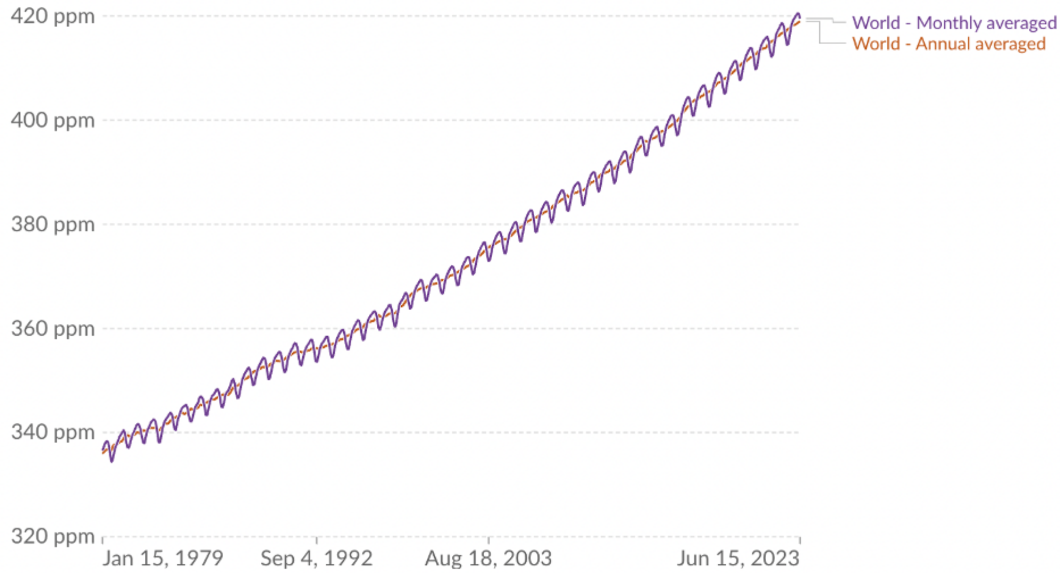

Figure 1: atmospheric CO_2

flooding (Butt 2022). Climate change has been identified as the primary driver of these disasters. Four months of the monsoon supplies the region with 80% of annual rainfall, however, climate change has dramatically affected this cycle, with extreme levels of rainfall taking place in a shorter period, causing flooding, and longer spells of dry months, causing droughts (Asian Development Bank 2014).

South Asia is seriously affected by climate change and while the problem has not been its making, it has become its problem to solve and deal with. The countries that will be the focus of this study include five major countries in the region: India, Pakistan, Bangladesh, Nepal, and Sri Lanka. These countries collectively contribute 8.6% to the global GHG emissions, with India, accounting for 7.1% of this 8.6% contribution (World Bank 2021). South Asia has the highest number and concentration of people in the world and is slowly increasing its share in the global GDP through constant economic growth. Thus, South Asia's absolute CO_2 emissions and its contribution to the CO_2 emissions globally, are bound to increase with time. South Asian countries are currently classified as lower-middle-income countries (LMICs) and for them to grow economically while not contributing further to climate change, they have to identify areas which are contributing the most to CO_2 emissions.

A few important factors that can potentially be considered indirect or direct drivers of increasing GHG and CO_2 emissions include economic growth, urbanization, population growth, energy consumption, agricultural production, and deforestation. These factors have been identified by the literature focusing on climate change and CO_2 emissions. This research study will try to identify the impact of these factors on the growth of CO_2 emissions in South Asia. In essence, the question this study attempts to answer is:

How do economic growth, urbanization, population growth, energy consumption, fossil fuel share, agricultural production, and deforestation impact the CO_2 emissions in South Asia?

The rest of this study will delve into the literature review, then map out a theoretical model, the methods section will then expand on the methodological approach and data sources used in the study, lastly the analysis and discussion sections will focus on analyzing the results of panel data regression analyses and the implications of the results.

2 Literature Review

The relationship between CO_2 emissions and economic growth (proxied by GDP) has been well-researched in the context of industrialized world and OECD countries, however, this section will start with a detailed review of the literature focusing on South Asia and individual South Asian countries and then proceed to review the literature focusing on rest of the world. This literature review section is divided in seven sub sections, each focusing on a variable that will be investigated in this study.

2.1 CO_2 emissions and Economic Growth

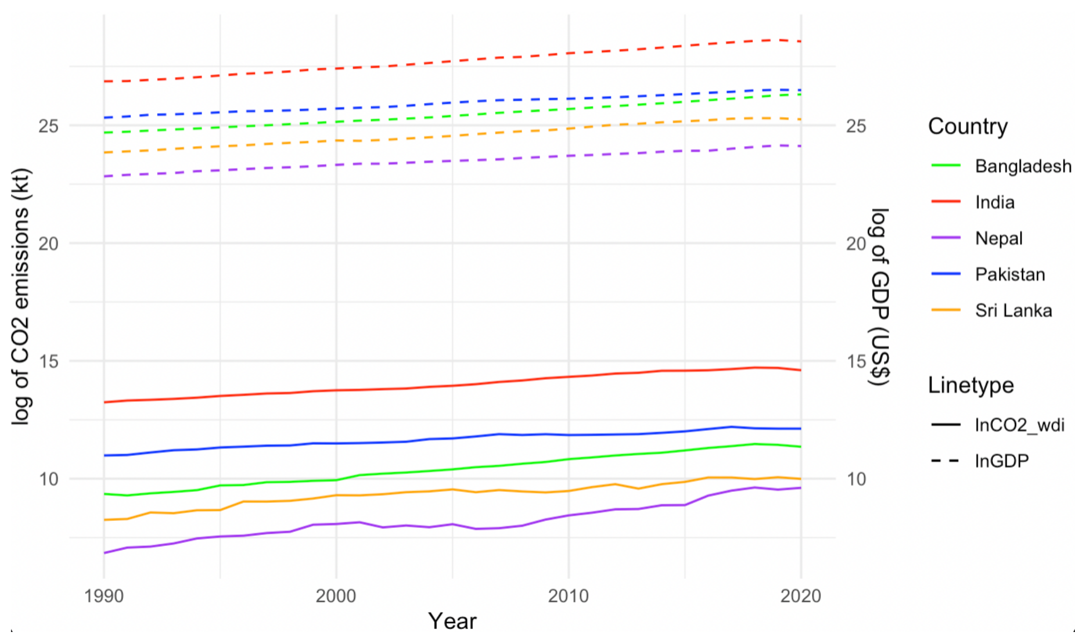

Figure 2: CO_2 emissions and Economic Growth

The link between CO_2 emissions and economic growth in South Asia can be illustrated by a descriptive graph of the two variables from 1990 to 2020, showing how the variables are tracked by each other. The solid lines show the log of CO_2 emissions, and the dotted lines show the log of GDP (current at 2015 US$). Further investigation of this link is merited and has been the subject of much research. In the studies linking CO_2 emissions and economic growth, economic growth is often proxied by GDP. Sharma's (2011) research linking GDP per capita with per capita CO_2 emissions, looking at the time period from 1985 to 2005, showed that the GDP per capita had a positive relation with per capita CO_2 emissions on the global level, however, this relationship was not statistically significant for the panel of high-income countries, while this link existed for middle income and low-income countries. Govindaraju and Tang's (2013) work showed that while there exists a link between CO_2 emissions and economic growth in China, not enough evidence was found for such a link in India. On the other hand, work by Alam et al. (2012) showed that CO_2 emissions Granger caused economic growth both in the short and in the long run, in Bangladesh, however, the study also found that the role of economic growth was largely mediated by energy consumption. Vidyrathi (2014) analyzed data from India, Pakistan, Bangladesh, Sri Lanka and Nepal over the period 1972-2009, and found a long-run equilibrium relationship between economic growth and carbon emissions and unidirectional causality from carbon emissions to GDP. A more recent study further suggested a bidirectional Granger causal relationship between CO_2 emissions and economic growth in the region, using data from 1990 to 2017 (Rahman et al. 2020).

Apart from the South Asian region, research focused on forty-two Belt and Road Initiative (BRI) member nations, showed that higher levels of economic growth exhibit adverse environmental consequences by boosting the CO_2 emission figures of the selected developing BRI member nations (Shakib et al. 2023). Recent work focusing on economic growth and CO_2 emissions showed that the per capita income was the most important driver in explaining the dynamics and variation of CO_2 emissions, in a larger sample of 14 Asian countries for a period ranging from 1972 to 2009 (Parker 2020). Another research study focused on the MENA region showed that the real GDP exhibits a quadratic relationship with CO_2 emissions for the region as a whole (Arouri 2012), suggesting the existence of an Environmental Kuznets Curve. A larger study which included South Asian and Southeast nations found a long-run positive relationship between economic growth and CO_2 emissions, however, the squared economic growth variable showed a negative relationship with CO_2 emissions, again validating the inverted U-shape relationship hypothesis between economic growth and CO_2 emissions (i.e., the existence of an Environmental Kuznets Curve) (Batoon et al. 2022). While, most studies have found a positive relationship between economic growth (measured by GDP, in most cases) and CO_2 emissions, an exception is a study published in 2017, which used time series data from 1971 to 2013 for India, Pakistan, Bangladesh, Nepal, and Sri Lanka; the

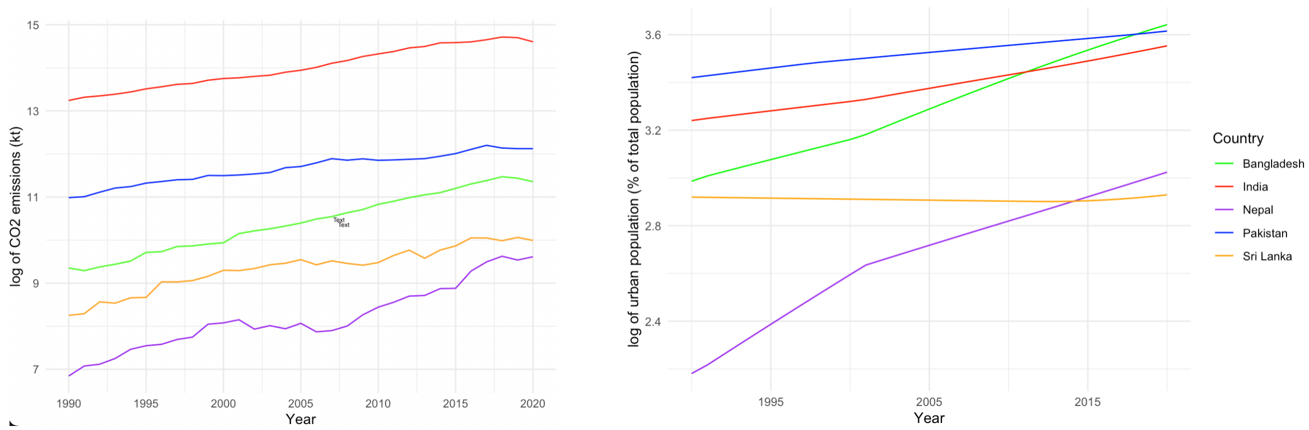

Figure 3: CO_2 emissions and urbanization

findings showed a negative relationship between income per capita (GDP) and CO_2 emissions for the whole group, however, at the country level, this negative relationship was statistically significant only for Sri Lanka and Bangladesh. On the other hand, a positive relationship between GDP per capita and CO_2 emissions existed at a 10% significance level, for Pakistan (Ahmed, Rehman and Ozturk 1143).

2.2 CO_2 emissions and urbanization

The link between CO_2 emissions and urbanization has also been investigated by multiple researchers, due to urbanization's impact on vehicle usage, energy usage and higher consumption of products that are manufactured through processes that lead to higher CO_2 emissions. The share of the urban population is often used as a proxy for urbanization in research studies. A visual inspection of the graphs in figure 3, documenting the log of CO_2 emissions and log of urban population share in South Asia, shows that the relationship between urbanization and CO_2 emissions may not be as linear or straightforward as the relationship between CO_2 emissions and economic growth.

A literature review on the link between urbanization and CO_2 emissions shows that the link is not well and it can vary from one context to another, especially in the magnitude of the impact. Sharma (2011) investigated the impact of urbanization on a global level, as well as in lower-income, middle-income, and high-income countries separately. The results showed that urbanization had a negative effect on per capita CO_2 emissions, on a global level, however, the effect of urbanization on per capita CO_2 emissions was statistically insignificant in lower-income, middle-income, and high-income countries. Li and Lin (2015) investigated the impact of urbanization on CO_2 emissions as mediated by the impact on energy consumption. Their findings revealed a positive link between urbanization and CO_2 emission for low-income and middle-income countries, while the link was not statistically significant for high-income countries, the results showed that urbanization in low-income and middle-income countries is not environmentally sustainable, while the nature of urbanization in higher income countries varied amongst countries enough for it to not have a statistically significant positive relationship with CO_2 emissions. A study by Alam et al. (2007) focusing only on Pakistan from a period of 1971 to 2005, found that urbanization, within Pakistan, led to higher CO_2 emissions. Lastly, an expansive study by Al-Mulali and Ozturk (2015) investigated the link between urbanization, proxied by share of the urban population, and CO_2 emission in 14 MENA (Middle East and North African) countries from 1996 to 2012, and the study showed a positive impact of urbanization on ecological footprint, the region, however, the impact within individual countries was not statistically significant.

2.3 CO_2 emissions and energy consumption

Energy usage is constantly increasing in South Asia, and the energy demand has increased by over 50 percent in the last two decades. A rising population and increasing urbanization alongside an increasing share of the manufacturing sector in GDP, has led to a higher demand for electricity (Chen 2022). While the increase in demand for energy can be considered an essential part of a better lifestyle and an increase in consumption and GDP growth, this energy usage needs to be environmentally sustainable, otherwise, a large population – that resides in South Asia – consuming an increasing amount of energy produced through fossil fuels and other non-renewable sources may lead to significant environmental damage to the world. Thus, it is important to investigate the relationship between energy usage and CO_2 emissions. The graph below, in Figure 4, shows the constant increase in energy consumption in select South Asian countries. Although the growth in energy consumption is not the same for every country, it is easy to see a faster growth rate for Bangladesh, which is also experiencing higher urbanization, an expansion of the manufacturing industry, and higher GDP growth (Yusuf 2021).

Sharma's (2011) work showed that energy consumption, proxied by per capita electric power consumption and per capita total primary energy consumption, has a positive effect on CO_2 emissions. Energy consumption (per capita) is found to be a statistically significant determinant of CO_2 emission for high-income countries, however, per capita energy usage, proxied by per capita electric power consumption and per capita total primary energy consumption, does not have a significant impact on CO_2 emissions for middle income and low-income countries. Alam et al. (2007) posited that economic development in Pakistan leads to higher energy consumption and found a strong relationship between economic growth, proxied by GDP growth, and energy consumption and thus, to higher CO_2 emissions. A paper published

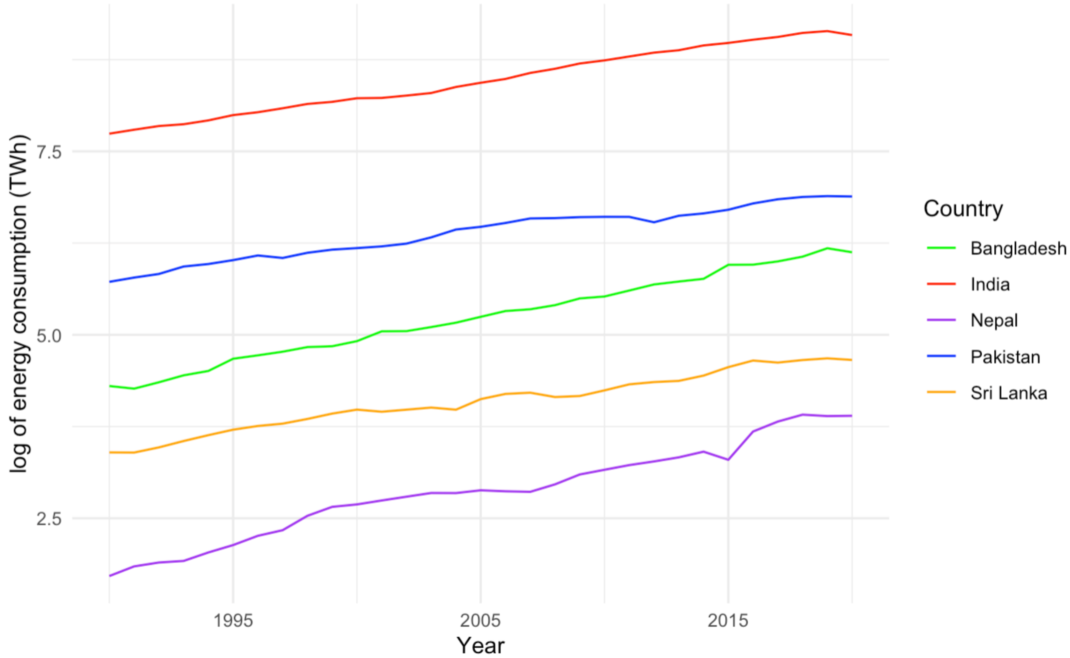

Figure 4: Energy consumption in South Asia

in *Energy & Environment* analyzed data from 1972 to 2017 for South Asian countries and found a positive relationship between energy usage and CO_2 emissions on the regional level and also found a statistically significant relationship between the two variables in Bangladesh, although the relationship was not statistically significant for other countries (Khan et al. 2021). The paper also further confirmed the EKC hypothesis for the region through the negative coefficient associated with the squared term on the GDP variable.

Another study focusing on five member nations of the Association of Southeast Asian Nations (ASEAN), analyzed data for the period 1971-2009 using an Autoregressive Distributed Lag (ARDL) methodology and found a non-linear relationship between the CO_2 emissions and economic growth in Thailand and Singapore, which supports the Environmental Kuznets Curve (EKC) hypothesis. The Granger causality suggested a bidirectional relationship between energy consumption and CO_2 emissions in all five Southeast Asian countries (Saboori and Sulaiman 2013). A study focusing on 17 Southeast Asian and South Asian countries found a cointegrating relation – i.e., a long-run relationship between two non-stationary time series variables – between primary energy consumption and CO_2 emissions (Behera and Dash 2017). The study also used fossil fuel energy consumption in place of primary energy consumption and found a positive relationship between fossil fuel energy consumption and CO_2 emissions in the SSEA region. The literature review shows the existence of a long-run and a short-run relationship between higher energy use and CO_2 emissions; however, the literature also shows that this relationship is mediated by the consumption of fossil fuels. We will include the fossil fuel share as a variable in our model, to investigate the standalone effects of the two variables as well.

2.4 CO_2 emissions and fossil fuel share in energy mix

UNDP's sustainable development goal 7 is about ensuring the access of clean and affordable energy to people ("UNEP Goal 7" 2019). However, as the electricity demand grows, developing countries are starting to fulfil this demand by increasing their consumption of fossil fuels and increasing their share in the fuel mix. This is because of multiple reasons: firstly, electricity production through fossil fuels is a short-term solution to the problem of excess energy demand. The production plants operating on fossil fuels require less investment, can be set up anywhere or at least have fewer geographical limitations on where they can be set up (Tongia 2022). Secondly, fossil fuels (especially coal) are cheaper and thus, more economically viable for developing countries, as it allows them to fulfil their energy demand at lower costs and become more competitive in the export market. Another argument for the fossil fuel consumption put forward by developing countries is that all the developed countries, themselves, use and have used fossil fuels to fuel their economic and industrial growth and thus, it is the only way through which they can quickly grow their economy (Mikulska 2019). However, such an argument may lock us in a bad equilibrium which may lead to a climate crisis and damage the environment even further.

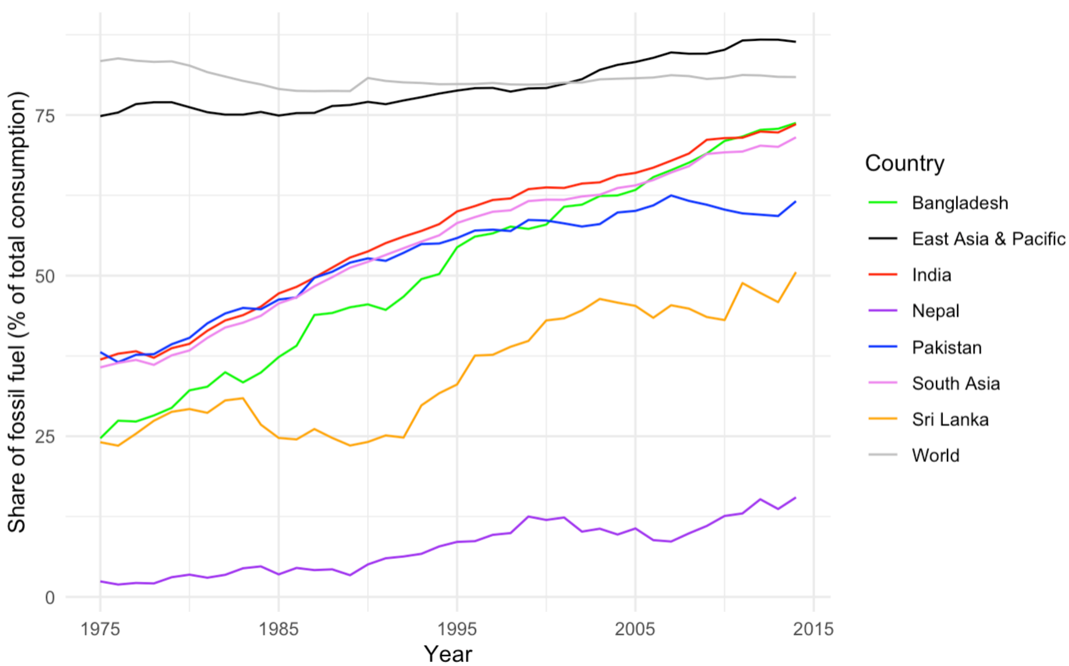

Figure 5: Fossil Fuel share in South Asian countries

The share of fossil fuels in CO_2 emissions is one of the primary indicators of the dependence of a country and could help us see how the dependence on fossil fuels is changing in the region. The graph in Figure 5 above, shows the share of fossil fuels in the energy mix of South Asia, five individual countries from South Asia, the region of East Asia, and the rest of the world. The graph clearly shows that over time, the share of fossil fuels in the energy mix has increased. The share of fossil fuels is the highest where the GDP growth rate has been the highest (i.e., India and Bangladesh). Furthermore, the graph suggests that the share of fossil fuel consumption is still less in South Asia as compared to East Asia and the rest of the world. This may increase in the future as South Asia's fossil fuel share in energy consumption is constantly growing. Thus, it is important to understand the impact of fossil fuel share on CO_2 emissions to understand the climate damage that can be caused in the near future by the current policies. This subsection of the literature review will try to document the impact of fossil fuels on CO_2 emissions and the impact of replacing fossil fuels with renewable energy sources.

In a research study, focused on 49 developing countries, the authors used data from 1995 to 2017, to look at the impact of various factors on CO_2 emissions, the findings showed that renewable energy consumption reduces CO_2 emissions significantly (Haldar and Sethi 2020). Similarly, a research paper, published in 2021, focused on China from 1990 to 2020, used the Autoregressive Distributed Lag (ADRL) model and found that a 1% increase in fossil fuel consumption leads to a per capita increase in CO_2 emission by 0.235% in the long term and a 1% increase in the renewable energy consumption per capita decreases the CO_2 emission per capita by 0.259% in the long run (Li and Haneklaus 2021). A recent study focusing on renewable energy use and CO_2 emission analyzed data from 2000 to 2014, using the linear autoregressive distributed lag technique and found that renewable energy options decrease CO_2 emissions significantly and that the impact of urbanization and industrial development on CO_2 emission is also mediated by higher use of fossil fuels in energy production (Zeng, Stringer, and Lv 2021). Hanif et al. (2019) focusing on fifteen Asian economies, using data from 1990 to 2013 and utilizing an Autoregressive Distributive Lag (ALDR) model found that at the regional level, fossil fuel consumption affects CO_2 emissions strongly and that the impact of fossil fuel use is not sticky, as the CO_2 emissions decrease significantly, in a short period of time, after the decrease in the fossil fuel energy share.

2.5 CO_2 emissions and population growth

South Asia is currently home to 24% of the world's population and the population will grow by 5.8 per cent in 2024. The population growth is expected to slow down to around 5.6 per cent in 2025 and 2026, which still means that the absolute population is still going to grow (Song 2019). This growth in population, alongside economic growth, urbanization and increasing energy demand, will increase CO_2 emissions. The graph in Figure 6 shows how the rising CO_2 emissions per capita coupled with the increase in population, could have a devastating impact on the climate. The graph below shows CO_2 emissions per capita, which illustrates South Asia at a very low level compared to the World, and East Asia & Pacific region. East Asia & Pacific had a significant increase in CO_2 emissions per capita during the decade of 2000s, which is also the decade where the region experienced a high level of GDP growth. However, the impact of population itself, on CO_2 emissions may not be as clear as it seems when conjoined with other variables.

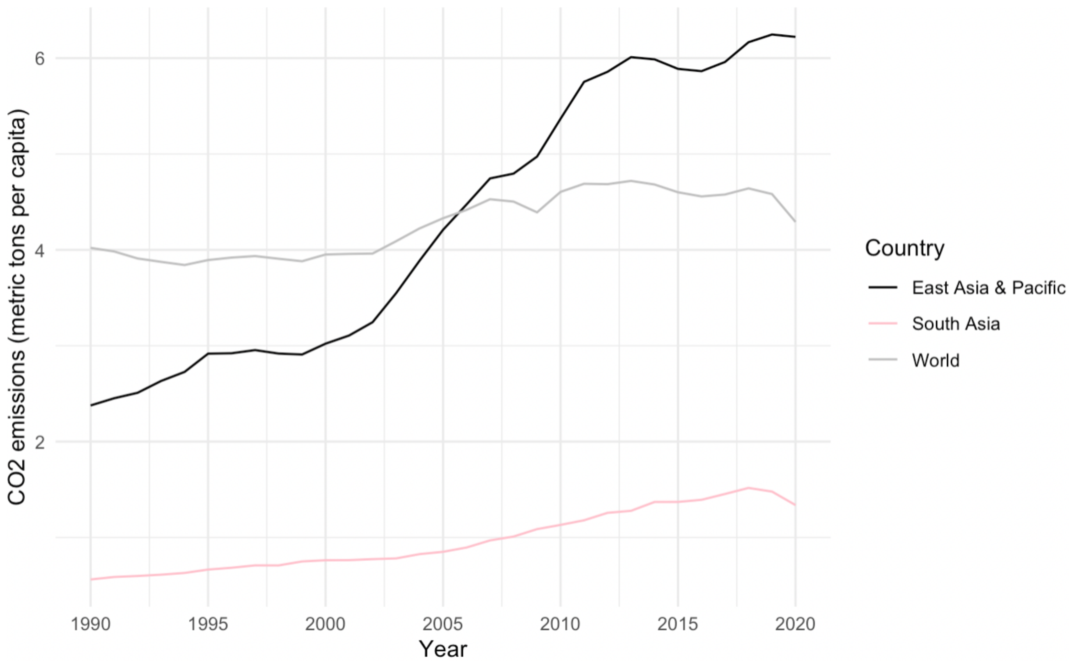

Figure 6: CO_2 emissions (metric tons per capita

There is mixed evidence on the relationship between population and CO_2 emissions, often the relationship is considered conditioned on other factors, and by itself seems to have little explanatory power. A study investigating the determinants of CO_2 emissions in Malaysia showed that while per capita GDP and per capita energy consumption had an impact on per capita CO_2 emissions, the population growth rate did not have a significant impact on per capita CO_2 emissions (Begum et al. 594). However, another study focusing on China and using data from 30 provinces in China, from 1997 to 2012, showed that population size has strong explanatory power on CO_2 emissions in all three regions of China while the ageing population and household size decrease emissions (Wang et al. 324). Similarly, a study of an unbalanced panel dataset of 128 countries, for the period of 1990 to 2014, showed that at both global and regional levels, population size positively and significantly affects CO_2 emissions (Dong et al. 181). The research study by Ahmed, Rehman and Ozturk (2017) showed not only a relationship between population and CO_2 emissions but also unidirectional causality between population and CO_2 emissions.

A study focusing on India, Indonesia, China and Brazil, using data from, 1970 to 2012, and employing an Autoregressive Distributed Lag (ARDL) bounds test approach, found that CO_2 emissions and population have a statistically significant relationship in the case of India and Brazil, however, the relationship was statistically insignificant in China and Indonesia (Alam et al. 2016, 468). Another study focused on the five most populous countries in Asia (i.e., China, India, Pakistan, Indonesia and Bangladesh), using data from 2011 to 2014, found that population growth was an important factor in intensifying CO_2 emissions in all of the individual countries (Rehman and Rehman 2022, 5432). A research study focused on India, used data from 1980 to 2018, and found that there was a uni-directional causal relationship running from population growth to CO_2 emissions, furthermore, results showed that a 1% increase in population growth will lead to a 1.4% increase in CO_2 emissions (Pachiyappan et al. 2021, 8333). Population growth can have an impact on CO_2 emissions through numerous pathways, one such pathway is the transport sector. The transport sector is an important contributor to CO_2 emissions and a research study focused on investigating the impact of population growth on CO_2 emissions through the transport sector in Pakistan, using data from 1975 to 2015, found that a single unit increase in population growth rate led to an increase of 51.39-unit CO_2 emission intensity from the transport sector (Mohsin et al. 2019, 32828). A country-level research study focused on Pakistan that utilized data from 1975 to 2019 and used an ARDL (autoregressive distributed lag) bounds testing technique, showed that population growth had a positive interaction with CO_2 emissions (Hussain and Rehman 2021, 39390).

Outside of Asia, a recent study analyzed data from 1980 to 2016 on seven East African countries, to examine the nexus between CO_2 emissions and population growth. The study found that population growth positively affects CO_2 emissions at the regional level, however, the relationship is unclear at the level of individual countries (Namahoro et al. 2021, 2). A one-way directional causation, on the other hand, was found between population growth and CO_2 emissions in Kenya and Sudan (Namahoro et al. 2021, 17). The literature review shows that the relationship between population and CO_2 emissions requires more investigation and thus, this study will try to illuminate the relationship between the two variables.

2.6 CO_2 emissions and agricultural production

Agriculture is a significant contributor to greenhouse gas emissions, especially CO_2 emissions. According to the US Environmental Protection Agency, agriculture produces 10% of the total CO_2 emissions in the US (US EPA 2015). Similarly, East Asia has the largest share of greenhouse gas emissions coming from agriculture compared to any other region in the world (Aryal 2022). The graph in Figure 7 shows how cereal production has grown over the last 45 years. While, in the last five years, agricultural production growth has started to plateau in East Asia and the world at large, this is not the case with South Asia. As the economy grows, the consumption of food per capita will also grow, and consequently, it will affect the cereal production in the region. The graph in Figure 8 helps us to see how the agricultural Nitrous oxide emissions, which are a product largely of higher fertilizer use, are changing in the region and around the globe (Aryan 2022). Agricultural Nitrous oxide emissions may increase as South Asia tries to increase its agricultural productivity through increased fertilizer use. Thus, the impact of agricultural production on CO_2 emissions and climate change needs to be investigated and mitigated, if a significant negative impact is found.

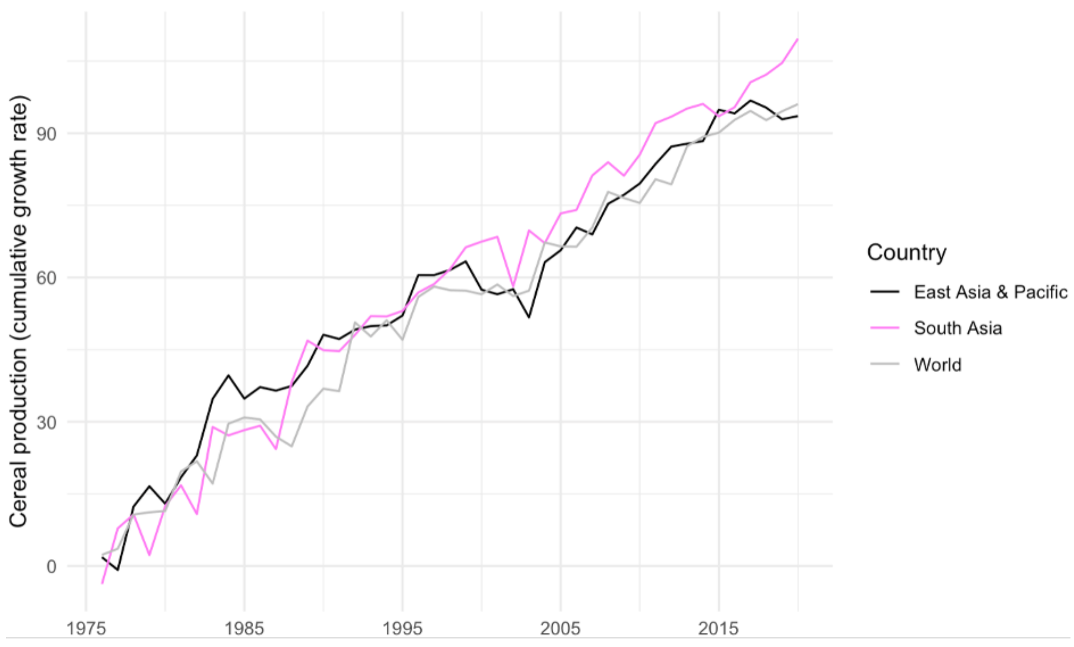

Figure 7: Agricultural production

The literature on the connection between agricultural production and CO_2 emissions has been investigated on the regional level; however, a clear connection has not been estbalished between the two variables. The research has been largely seen in the context of how an increase in agricultural produce is driven by an increase in agricultural productivity, which in turn increases energy consumption and makes

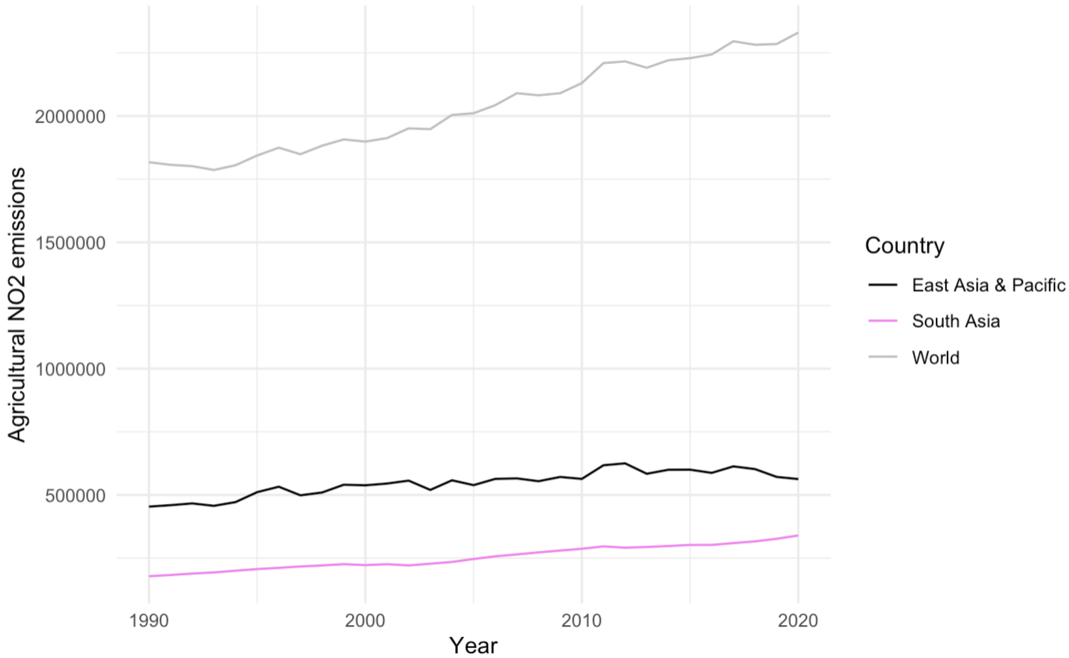

Figure 8: NO_2 emissions

the agricultural production more energy intensive and thus, leads to a higher level of CO_2 emissions. It is important to see the impact of agricultural production on CO_2 emissions, as it allows us to see how energy efficiency and other factors directly and indirectly related to agricultural production affect the CO_2 emissions in South Asia. A research study by Ugur Pata (2021) investigated the determinants of the ecological footprint and CO_2 emissions in BRIC countries (Brazil, Russia, India, and China), using data from 1971 to 2016, except for Russia for which the data is available from 1990 onwards, and did not find enough evidence to establish a relationship between CO_2 emissions and agriculture, which was measured through the agricultural value-added as a % of GDP.

A similar result was found in a research paper studying Nigeria, using data from 1981 to 2014, which found a statistically insignificant association between agricultural value added and CO_2 emissions (Agboola and Bekun 2019, 27663). On the contrary, a study focusing only on China and for the period ranging from 1971 to 2010, found that there is a long-term relationship between agriculture and CO_2 emissions, using ARDL methods and bound tests for determining cointegration; thus, it could partially be a regional and context-specific phenomenon (Dogan 2019, 267). Within South Asia, however, an important agricultural research study focusing on Pakistan, showed that cropped area and fertilizer uptake have a positive and statistically significant association with CO_2 emissions (Rehman et al. 2019, 1692). Thus, it would not be wrong to say that the relationship between the two variables in understudied and further investigation is merited, especially in the context of South Asia.

2.7 CO_2 emissions and forest area share

Forests help in stabilizing the climate, regulating the ecosystems, protecting biodiversity and more importantly, from the perspective of this research study, play a central role in the carbon cycle (Baig et al. 2015). Forests act like carbon sinks, absorbing CO_2 from the surroundings, a research paper published in the *Nature*, found that between 2011 and 2019, forests absorbed twice as much CO_2 as they emitted (Harris et al. 2021, 234). However, as forests can absorb CO_2, deforestation can also lead to CO_2 emissions and a higher atmospheric concentration of CO_2 (as CO_2 stored in the trees is released in the atmosphere), thus, having a large forest area can be a double-edged sword. The graph in Figure 9 below, shows how the share of forest in the total land in the country, has changed from 1990 to 2020. The graph shows that forest area share has changed by much only in Sri Lanka and India. The graph, obtained from World Development Indicators, shows a conservative estimate of deforestation and other estimates show a higher level of deforestation in the selected countries, however, the WDI estimates have been used in other works and the data is considered reliable for academic research (Utility Bidder 2023).

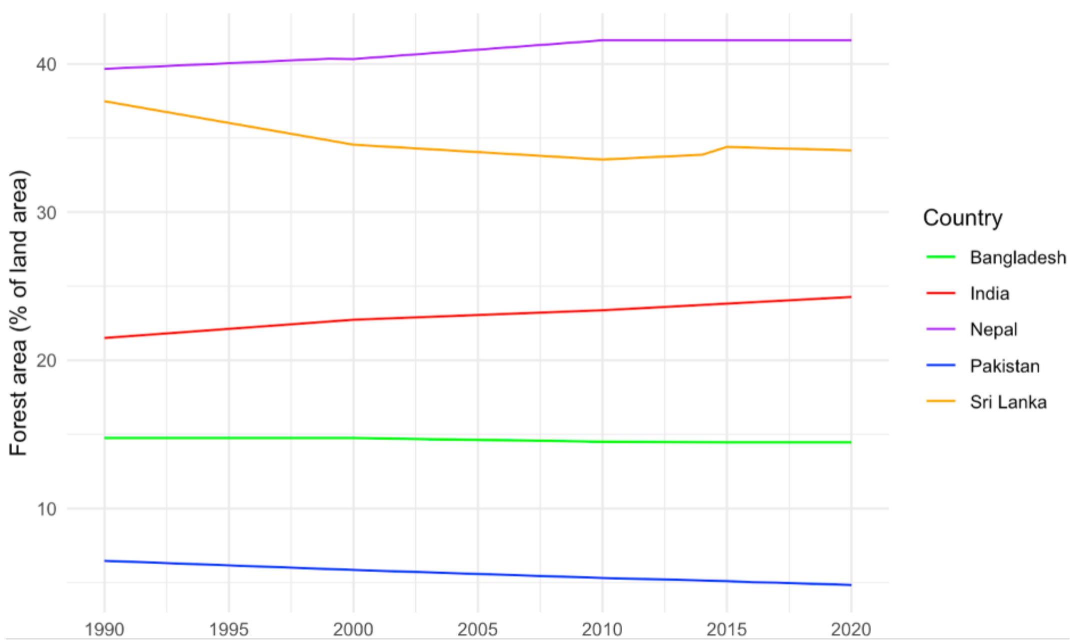

Figure 9: Forest area (as a percentage of total land area) in South Asia

Forest area's impact on CO_2 emissions is relatively under-researched as compared to other variables in this research study, however, increasing urbanization, the widespread use of wood as a domestic fuel and increasing agricultural production can lead to deforestation and a decrease in forest area in South Asia. On the other hand, to counter the threat of deforestation, afforestation efforts have been the focus of numerous international environmental non-governmental organizations in the region (World Wildlife

Fund 2023). Recently, a project named Billion Tree Tsunami was launched in Pakistan in 2014, which aimed at planting a billion new trees in the country while China restored more than 70 million hectares of forests and committed to planting and conserving 70 billion trees by the year 2030, as part of the Trillion Tree campaign (International Union for Conservation of Nature 2017). In this scenario, it is important to investigate and establish the impact and effect of forest area share on CO_2 emissions (Becker 2022).

3 Theoretical Model

3.1 Conceptual framework

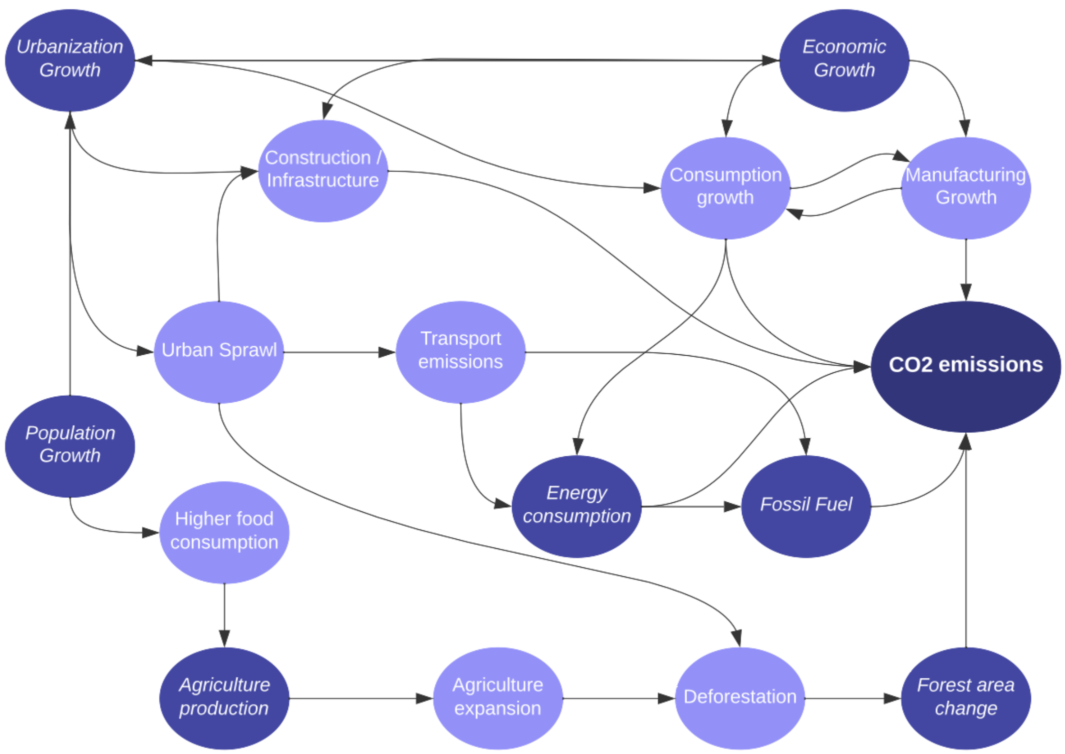

Figure 10: Systems framework

The conceptual framework this study follows has been mapped out in the form of a systems diagram. The diagram focuses on the seven major determinants (in dark blue circles) of the CO_2 emissions and pathways that connect these seven determinants forming a system that collectively contributes to the growth in CO_2 emissions. Furthermore, the factors through which these seven factors affect CO_2 emissions are also added as intermediaries (in purple shaded circles), most of the major factors cause CO_2 emissions through energy consumption, which itself causes growth in CO_2 emissions through a higher use of fossil fuels. The conceptual mapping of such a system allows us to identify the root causes of growth in CO_2

emissions and will also help us in making sense of the empirical findings.

3.2 Empirical Model

The form of the proposed mathematical model based on the literature is as follows:

$$C = f(Y, U, P, E, F, A, FA) \tag{1}$$

Equation (1) states that GDP (Y), urbanization (U), total population (P), energy consumption (E), fossil fuel share in the energy mix (F), agricultural production (A), forest area (FA) can potentially determine CO_2 emissions (C). Since our study is a panel study, we have to take into account the time and individual (country) effects for the mathematical model, resulting in the following equation:

$$\begin{aligned} CO_2emissions_{it} = \beta_0 \, + \, \beta_1 \, GDP_{it} + \beta_2 \, urbanization_{it} + \beta_3 \, total\ population_{it} \\ + \beta_4 \, energy\ consumption_{it} + \beta_5 \, fossil\ fuel\ share_{it} \\ + \beta_6 \, agricultural\ production_{it} + \beta_7 \, forest\ area_{it} + \epsilon_{it} \end{aligned} \tag{2}$$

where i represents country (in our study, we have 5 countries), t represents time (our time frame is 1990–2014).

4 Data and Estimation Methods

4.1 Data source and descriptive statistics

The population of this study is five selected countries in South Asia: India, Pakistan, Bangladesh, Sri Lanka, and Nepal. The primary data source for our analysis is the World Development Indicators, created by The World Bank (2023). The data for CO_2 emissions is in kilo tons, the data for economic growth is in GDP (constant 2015 US$), urbanization is measured by the percentage of urban population out of the total population, energy consumption data is in Terawatt hours and is acquired from Energy Institute Statistical Review of World Energy (2023), fossil fuel share data represents the share of fossil fuel in total energy produced, and the forest area is the forest area as a percentage of total area. The cereal production data is acquired from the WDI as well and is used as a viable proxy for agriculture production. The data for CO_2 emissions is acquired from two different sources: the Global Carbon Budget, and the World Development Indicators (Friedlingstein et al. 2022). The data from the Global Carbon Budget

	Bangladesh (N=25)	India (N=25)	Nepal (N=25)	Pakistan (N=25)	Sri Lanka (N=25)	Overall (N=125)
CO2 emissions (million ton)						
Mean (SD)	30.8 (17.2)	1130 (468)	3.11 (1.61)	109 (30.6)	10.6 (4.02)	257 (487)
Median [Min, Max]	27.3 [10.8, 66.3]	985 [564, 2150]	2.81 [0.939, 7.13]	102 [59.0, 154]	11.4 [3.84, 17.5]	27.3 [0.939, 2150]
CO2 emissions (GCB)						
Mean (SD)	34.6 (16.2)	1170 (472)	3.11 (1.66)	117 (32.4)	10.1 (3.88)	267 (500)
Median [Min, Max]	32.0 [14.1, 66.0]	1020 [578, 2190]	2.64 [0.721, 7.59]	113 [67.5, 157]	10.9 [3.83, 17.7]	32.0 [0.721, 2190]
GDP (USD trillion)						
Mean (SD)	101 (39.4)	1010 (456)	14.8 (4.45)	169 (49.0)	44.4 (17.5)	268 (427)
Median [Min, Max]	91.1 [52.8, 183]	871 [465, 1950]	14.1 [8.25, 23.4]	155 [99.5, 258]	38.7 [22.7, 81.7]	91.1 [8.25, 1950]
Urban population (% of total population)						
Mean (SD)	25.6 (4.26)	28.6 (2.11)	13.8 (2.90)	33.3 (1.58)	18.4 (0.109)	23.9 (7.50)
Median [Min, Max]	24.8 [19.8, 33.5]	28.2 [25.5, 32.4]	14.2 [8.85, 18.2]	33.4 [30.6, 35.8]	18.3 [18.2, 18.5]	24.8 [8.85, 35.8]
Population (mil)						
Mean (SD)	133 (15.2)	1090 (135)	24.7 (2.53)	162 (29.3)	19.2 (1.24)	287 (414)
Median [Min, Max]	134 [107, 156]	1100 [870, 1310]	25.3 [19.6, 27.5]	163 [115, 208]	19.1 [17.2, 21.2]	126 [17.2, 1310]
Energy Consumption (TWh)						
Mean (SD)	172 (76.6)	4380 (1630)	15.9 (7.20)	553 (158)	54.8 (16.1)	1040 (1840)
Median [Min, Max]	156 [71.3, 318]	3870 [2300, 7660]	16.3 [5.54, 30.2]	514 [305, 776]	53.5 [29.8, 85.1]	156 [5.54, 7660]
Fossil fuel energy consumption (% of total)						
Mean (SD)	60.7 (8.89)	64.5 (5.81)	10.2 (2.74)	58.1 (2.82)	40.2 (7.76)	46.7 (21.0)
Median [Min, Max]	61.0 [44.7, 73.8]	64.3 [53.8, 73.6]	9.93 [5.05, 15.5]	58.6 [52.3, 62.5]	43.4 [24.1, 50.5]	55.1 [5.05, 73.8]
Agriculture production (mil metric tons)						
Mean (SD)	39.3 (9.78)	239 (31.6)	7.15 (1.23)	30.2 (6.33)	3.14 (0.717)	63.8 (90.3)
Median [Min, Max]	39.3 [26.3, 55.2]	236 [193, 296]	7.22 [4.90, 9.56]	29.0 [21.0, 41.9]	2.89 [2.10, 4.84]	27.7 [2.10, 296]
Forest area (% of land area)						
Mean (SD)	14.7 (0.108)	22.7 (0.659)	40.7 (0.675)	5.77 (0.413)	34.8 (1.25)	23.7 (12.9)
Median [Min, Max]	14.7 [14.5, 14.8]	22.9 [21.5, 23.7]	40.6 [39.7, 41.6]	5.74 [5.14, 6.47]	34.3 [33.5, 37.5]	22.9 [5.14, 41.6]

Table 1: Summary statistics

allows us to eliminate any bias that may enter our results due to the use of a single source for data, and while the difference between the data from both sources is not very high, it still adds to the validity of our findings. Table 1 below shows the descriptive statistics for all variables and for all countries in the dataset.

4.1.1 Data Collection

In the summary statistics, we find that the CO_2 emissions are the highest for India, followed by Pakistan, Bangladesh, Sri Lanka and Nepal. The standard deviation is high for the variable within each country, which shows the high level of variation in the CO_2 emissions over time. The CO_2 emissions data from Friedlingstein et al. (2022), labelled as CO_2 emissions (GCB), are in close alignment with the CO_2 emissions data from World Development Indicators, adding to the validity of both datasets, as both datasets use different methodologies for calculating CO_2 emissions. The GDP is in a trillion USD units, the minimum value for GDP is USD 8.25 trillion, while the highest value is USD 1,950 trillion, which shows the range of GDP values in the dataset, which allows for a better analysis of the effect of GDP on CO_2 emissions. The energy consumption variable measures the energy consumption in Terawatt hours and shows that the mean energy consumption is 4,380 TWh for India, which is more than 275 times more than the mean energy consumption in Nepal, where it is 15.9 TWh. Fossil fuel share in the energy mix is the most consistent variable and has the smallest standard deviation to mean value ratio, much lower than compared to other variables. Similarly, the fossil fuel share in the energy mix is also similar across countries, except for Nepal where it is exceptionally low, and the fossil fuel share ranges between 58% to 65% in the three biggest energy-consuming countries in the region: India, Pakistan, and Bangladesh.

4.2 Econometric methodology

In this sub-section, we describe the econometric models and techniques used to analyze panel data, focusing on both random effects and fixed effects models. This section outlines the methodologies employed and the underlying assumptions. Panel data is structured with multiple observations on entities (e.g., countries) over time periods (e.g., years). This design allows us to examine changes within entities over time, providing a comprehensive view of dynamic phenomena. The data will have to be transformed to make the analysis more meaningful. The stability of time-series data or panel data is essential to meaningful regression analysis, and transformations such as logarithms can help to stabilize the variance of a time series. Thus, we will apply a natural log transformation to the equation (2), changing the equation to the following form:

$$\begin{aligned} ln\, CO_2 emissions_{it} = \beta_0 \;+\; &\beta_1\, ln\, GDP_{it} + \beta_2\, ln\, urbanization_{it} + \beta_3\, ln\, total\ population_{it} \\ &+ \beta_4\, ln\, energy\ consumption_{it} + \beta_5\, ln\, fossil\ fuel\ share_{it} \\ &+ \beta_6\, ln\, agricultural\ production_{it} + \beta_7\, ln\, forest\ area_{it} + \epsilon_{it} \end{aligned} \tag{3}$$

4.3 Stationarity of data

To further check the stability of the data, the root test of the data is conducted to check the stationarity of the data. A stationary time series is characterized by properties that remain consistent regardless of when the series is observed. In contrast, time series exhibiting trends or seasonality are considered non-stationary, as these patterns can impact the series' values at various points in time. Stationary time series exhibit consistent statistical properties, making statistical inference more reliable and simplifying modelling. This stability also enhances forecasting accuracy and ensures data comparability, facilitating meaningful comparisons. To check for the stationarity of the data, an Augmented Dickey-Fuller (ADF) test was conducted. The results of these tests are presented in the table 2.

Variable	**ADF Statistic**	**p-value**	**Stationarity**
CO_2	-2.4034	0.4089	False
CO_2 (GCB)	-2.4112	0.4057	False
GDP	-2.3776	0.4196	False
Urbanization	-2.3346	0.4375	False
Population	-2.3338	0.4378	False
Energy consumption	-2.3785	0.4193	False
Fossil fuel share	-2.1149	0.5288	False
Agricultural production	-2.4673	0.3824	False
Forest area	-2.0776	0.5443	False

Table 2: Root unit tests on level forms of variables

Since all the variables are non-stationary in their level form, they need to be made stationary for analysis. A commonly used method for making the variables stationary is to differentiate the variable in question. Differencing can help stabilise the mean of a time series by removing changes in the level of a time series and therefore eliminating (or reducing) trend and seasonality. The differenced series is the change between consecutive observations in the original series and can be written as:

$$\alpha' = \alpha_t - \alpha_{t-1} \tag{4}$$

The differenced series will have only $t-1$ values since it is not possible to calculate a difference α' for the first observation.

After first differencing, agricultural production, GDP, energy consumption, fossil fuel share and both CO_2 emissions variables become stationary, however, other variables needed to be differenced a second time for them to become stationary. The order of differentiation needed to make each variable stationarity is provided below in Table 3, alongside the ADF test values associated with the variable. The change in the definition of the variable after the first-order and second-order differentiation is provided in Table 4, this definition will also help us in interpreting the results of our analysis. The equation (5) is the final equation after differentiating the equation 3.

$$\begin{aligned} ln\,\Delta\, CO_2 emissions_{it} = \beta_0 \,+\, &\beta_1\, ln\,\Delta\, GDP_{it} + \beta_2\, ln\,\Delta^2\, urbanization_{it} + \beta_3\, ln\,\Delta^2 total\ population_{it} \\ &+ \beta_4\, ln\,\Delta\, energy\ consumption_{it} + \beta_5\, ln\,\Delta\, fossil\ fuel\ share_{it} \\ &+ \beta_6\, ln\,\Delta\, agricultural\ production_{it} + \beta_7\, ln\,\Delta^2 forest\ area_{it} + \epsilon_{it} \end{aligned} \tag{5}$$

Variable	ADF Statistic	p-value	Differentiation order	Stationarity
CO_2	-2.4034	0.4089	1	True
CO_2 (GCB)	-2.4112	0.4057	1	True
GDP	-2.3776	0.4196	1	True
Urbanization	-2.3346	0.4375	2	True
Population	-2.3338	0.4378	2	True
Energy consumption	-2.3785	0.4193	1	True
Fossil fuel share	-2.1149	0.5288	1	True
Agricultural production	-2.4673	0.3824	1	True
Forest area	-2.0776	0.5443	2	True

Table 3: Root units tests after differencing

Variable	Definition	Differentiation order
CO_2	CO_2 emissions growth rate	1
GDP	GDP growth rate	1
Urbanization	Rate of growth in the share of urban population	2
Population	Rate of population growth	2
Energy consumption	Energy consumption growth	1
Fossil fuel share	Growth in the share of fossil fuel in energy mix	1
Agricultural production	Growth in agricultural production	1
Forest area	Rate of change of forest area share	2

Table 4: Variable definitions after differencing

4.4 Multicollinearity

Apart from stationarity, another important aspect of regression analysis is collinearity amongst the independent or explanatory variables, i.e., multicollinearity. Multicollinearity makes it difficult to distinguish the individual effects of explanatory variables. It's important to address multicollinearity because it can lead to unstable and unreliable parameter estimates. In panel data, it can obscure the relationships between variables, hinder the identification of causal factors, and affect the model's predictive accuracy (Hsiao 2005, 145). To identify multicollinearity, a correlation matrix is used, which allows us to see the level of correlation between independent variables. Table 7 (in the appendix) contains the correlation matrix, and it shows that there is less than 0.50 correlation score between the variables, which indicates low multicollinearity. None of the variables have a particularly high correlation with another, the highest correlation value is between fossil fuel and energy use, which is an acceptable 0.417. Thus, we can safely say there is low multicollinearity in our variables.

4.5 Statistical techniques

Panel data often exhibits unobserved heterogeneity and time-related variations that pose unique challenges for researchers. Unobserved heterogeneity refers to individual-specific or entity-specific factors that affect the outcomes but are not directly observable. These factors can introduce bias and complicate the analysis. Time-related variations, on the other hand, capture changes that occur over different periods within the panel. Addressing unobserved heterogeneity and modelling time-related variations is essential for accurate and meaningful analysis of panel data.

Random effects and fixed effects models are statistical techniques used in panel data analysis to account for unobserved heterogeneity and time-related variations in the data. Fixed effects models, also known as within-effects models, control for unobserved individual-specific factors by including entity-specific fixed effects. These fixed effects differentiate each entity's constant unobservable characteristics, eliminating them from the analysis. In contrast, random effects models, or between-effects models, assume that unobserved heterogeneity follows a random distribution, and they estimate population averages for entity-specific effects. Random effects models effectively capture time-related variations in the data, considering both within-entity and between-entity variations. In addition to addressing the problem of unobserved heterogeneity, Random effects and fixed effects models in panel data analysis can also help address the problem of endogeneity.

The decision of whether a fixed effects or random effects model should be used for a panel dataset can be made using the Hausman test. The Hausman test compares the coefficient estimates from a fixed effects model (which assumes no endogeneity) and a random effects model (which allows for endogeneity). If the test suggests that the fixed effects model is preferable (i.e., the coefficients differ significantly between the two models), it implies the presence of endogeneity, as the random effects model violates the assumption that the unobserved individual-specific effects are uncorrelated with the independent variables. The result of the Hausman test shows that the fixed effects are the preferred method, however, results from both models are shown and interpreted in the regression tables. Using the Breusch-Pagan test, we detected the presence of heteroskedasticity in the regression analysis (Breusch and Pagan 1979). To solve this problem, we used the Arellano-White heteroskedasticity-robust covariance matrix, which is a statistical technique (MacKinnon and White 1985). This method provides robust standard errors for the estimated coefficients in panel data regression models, ensuring that statistical inference remains valid even when the assumption of constant variance is violated.

5 Results and Discussion

The following section will delineate the results of the regression analysis and also discuss the explanations for the results, with the help of the conceptual model outlined above and a thorough survey of the literature.

Table 5: Regression results (Data source: WDI)

	Dependent variable:	
	CO_2 emissions	
	Fixed effects	Random effects
	(1)	(2)
GDP	0.331***	0.306***
	(0.110)	(0.093)
Urbanization	2.438**	2.691**
	(1.114)	(1.117)
Population	-1.337	-0.987
	(1.228)	(1.573)
Energy Consumption	0.383***	0.404***
	(0.140)	(0.148)
Fossil fuel	0.859***	0.846***
	(0.133)	(0.128)
Agriculture	-0.245**	-0.242**
	(0.106)	(0.109)
Forest area	-6.552**	-6.659**
	(2.787)	(2.771)
Constant		0.013***
		(0.005)
Observations	115	115
R^2	0.602	0.609
Adjusted R^2	0.559	0.583
Note:	*p<0.1; **p<0.05; ***p<0.01	

5.1 Impact of GDP growth

The results for regression with CO_2 emissions data taken from world development indicators, presented in Table 5, show a positive impact of GDP growth on CO_2 emissions, in both fixed effects and random effects models. The impact is statistically and practically significant (at 1% significance level), with a 1% change in GDP growth leading to a 0.331% increase in growth in CO_2 emissions, for the fixed effects model. According to the random effects model, the impact is again statistically and practically significant (at 1% significance level), with a 1% change in GDP growth leading to a 0.306% change in CO_2 emissions

Table 6: Regression results (Data source: GCB)

	Dependent variable:	
	CO_2 emissions	
	Fixed effects	Random effects
	(1)	(2)
GDP	0.181*	0.086
	(0.110)	(0.093)
Urbanization	5.063***	4.631***
	(1.114)	(1.117)
Population	4.466***	3.808**
	(1.228)	(1.573)
Energy Consumption	0.112	0.151
	(0.140)	(0.148)
Fossil fuel	0.833***	0.855***
	(0.133)	(0.128)
Agriculture	-0.153	-0.153
	(0.106)	(0.109)
Forest area	-5.157*	-6.145**
	(2.787)	(2.771)
Constant		0.036***
		(0.005)
Observations	115	115
R^2	0.490	0.503
Adjusted R^2	0.435	0.470
Note:	*p<0.1; **p<0.05; ***p<0.01	

growth. However, the regression results in Table 6 show that the impact of GDP growth on CO_2 emissions growth is not statistically significant. The result is surprising; however, it shows the variability in the results due to a difference in the data source of a variable.

The positive impact of GDP growth on CO_2 emissions growth is not surprising as this result is aligned with the literature on the subject. This result shows the importance of making GDP growth more sustainable, as GDP growth is expected to keep increasing in South Asia in the near future. Figure 11 shows the carbon intensity (i.e., CO_2 emission (kg per \$)) in South Asia compared to East Asia and the rest of the world. The carbon density, while being low and on the decline in South Asia, is still not enough to cover for the increased absolute CO_2 emissions growth, due to a higher level of GDP growth. The carbon density of GDP has decreased drastically since the 1990s both, around the world and in East Asia. This decline is less in South Asia, however, as GDP increases, it is important to decrease the carbon intensity of its GDP, to make sure that the absolute impact of GDP growth on CO_2 emissions is lowered.

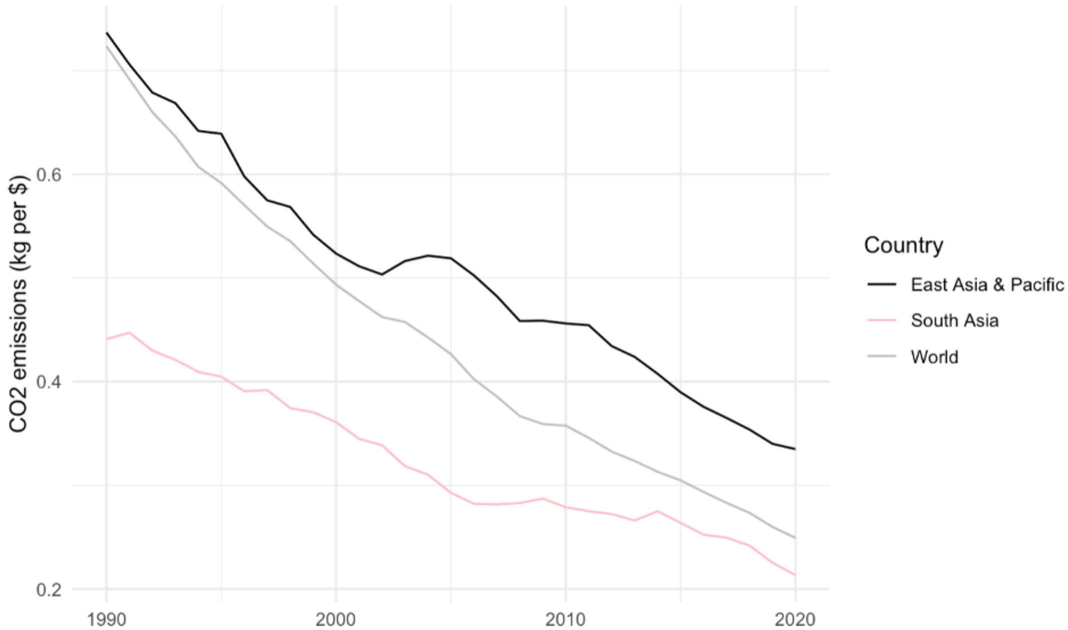

Figure 11: Carbon intensity

5.2 Impact of urbanization growth

Growth in urbanization (i.e., in the share of people living in urban areas) rate has a statistically significant positive impact on CO_2 emissions in both fixed effects and random effects models in both Table 5 and Table 6. The impact is much higher according to the results displayed in Table 6. According to the fixed effects model, in Table 6, a 1% increase in the growth in urbanization rate leads to a 5.063% increase in CO_2 emissions growth, while according to the random effects model, a 1% increase in the growth in urbanization rate leads to a 4.631% increase in CO_2 emissions growth. The regression results in Table 5, also show a positive relationship between the growth of urbanization and CO_2 emissions growth. In Table 5, according to the fixed effects model, a 1% increase in urbanization growth leads to a 2.438% increase in the growth of CO_2 emissions, while the random effects model shows that a 1% increase in urbanization growth rate leads to a 2.691% increase in the CO_2 emissions growth.

Urbanization can lead to an increase in CO_2 emissions, through an increase in urban sprawl which, in turn, leads to an increase in CO_2 emissions from transport, construction and industry (Glaeser and Kahn 2010, 405). The contribution of each of these factors in CO_2 emissions is not captured in our regression model and thus, the urbanization coefficient can capture the impact on CO_2 emissions from these factors. Apart from these intermediary factors, as urban sprawl takes place it leads to land use change, which leads to an increase in CO_2 emissions due to a 'heat island effect' (Liang et al. 2020). The mode of urban development has a fundamental relationship with CO_2 emissions, through the intermediate factors outlined above. While, urban sprawl leads to higher CO_2 emission, high-density urban development improves the energy utilization efficiency, thus decreasing the CO_2 emissions (Fang et al. 2015, 521). In the absence of data documenting the total urban area in South Asian countries, it is hard to ascertain the increase in urban sprawl in the region or specific countries. However, it is pertinent for the countries in the Global South at large, and in South Asia, to encourage urban growth without urban sprawl to minimize the damage to the environment and increase in CO_2.

5.3 Impact of population growth rate

The results for the population variable vary the most in our regression models. The rate of population growth had a negative impact on the growth of CO_2 emissions, according to the regression models with data from World Development Indicators, however, this result is statistically insignificant at 10% significance level. On the other hand, the results in Table 6, i.e., regression results with data from Global Carbon Budget show that the rate of population growth has a positive impact on the growth of CO_2 emissions. According to the fixed effects model, a 1% increase in the rate of population growth leads to a 4.466% increase in the growth of CO_2 emissions. The results from the random effects model show that a 1% increase in the rate of population growth leads to an increase of 3.808% increase in the growth of CO_2 emissions. The result from the fixed effects model is statistically significant at 10% significance level, while the result from the random effects model is statistically significant at 5% significance level.

The results from the two data sources vary quite a lot, which means that we should be cautious while interpreting them. However, with the help of the literature, we can explain the results seen in Table 6. The positive impact of the rate of population growth on the growth of CO_2 emissions can be explained by three major intermediaries. Firstly, an increasing rural population puts pressure on agricultural land, thus leading to migration to urban areas increasing the share of the urban population, which increases CO_2 emissions (Caldwell 1968, 361). As discussed above, the pathways through which population and urbanization increase the overall CO_2 emissions, intersect quite a bit. The increase in population, increased employment in manufacturing, total consumption, and urban sprawl may lead to an increase in CO_2 emissions as well. Apart from this, the increase in population may put pressure on a country's agricultural needs as well, this may lead to a higher use of fertilizers in search for a higher yield, leading to a higher release of greenhouse gases (Zhang et al. 2015, 89). Population growth, thus by itself, cannot be labelled as a problem that is causing damage to the climate, rather the pathways through which it is causing this damage need to be identified, which this study has tried to do. However, further investigation of the impact of population growth on CO_2 emissions is required.

5.4 Impact of energy consumption and fossil fuel share

The growth in energy consumption has a positive impact on the growth of CO_2 emissions as well, according to results in both regression tables. The results in Table 5 are highly statistically significant (i.e., statistically significant at a 1% significance level), while the results in Table 6 are not statistically significant. According to the fixed effects model in Table 5, a 1% increase in energy consumption growth leads to a 0.383% increase in CO_2 emissions, while according to the random effects model, a 1% increase in energy consumption growth leads to a 0.404% increase in the CO_2 emissions growth. This impact is high and practically more significant than the impact of the population growth rate because energy consumption is increasing in South Asia, on a per capita basis as well as on an absolute basis. The energy consumption growth has the same impact on CO_2 emissions growth in percentage terms, as the growth in GDP, this is an interesting insight into the nature of economic growth, and the two might be linked to some extent as well.

Energy consumption directly affects CO_2 emissions if the energy is produced through methods that produce CO_2 emissions. As is clear from Figure 5, in the literature review section, the share of fossil fuels in the energy mix is growing constantly in South Asia, thus, it is no surprise that energy consumption has a positive impact on the growth of CO_2 emissions. To further illuminate the impact of the growth of the share of fossil fuels on the growth of CO_2 emissions, we can look at the beta coefficient values associated with the fossil fuel share variables in Table 5 and Table 6. The random effects and the fixed effects models in both tables show that a 1% growth in the share of fossil fuel in the energy mix leads to an increase in the growth of CO_2 emissions, ranging from 0.833% to 0.859%. Fossil fuel share in the energy mix has the biggest impact out of all the first-order difference variables in our regression model, which is good news from a policy perspective because fossil fuel share can be decreased through investment in renewable energy sources.

5.5 Impact of agricultural growth

The regression results from Table 5 show that agricultural production (proxied by cereal production) has a negative impact on CO_2 emissions. For a 1% increase in agricultural production growth, there is a 0.245% decrease in the growth rate of CO_2 emissions, according to the fixed effects model, while according to the random effects model, there is a 0.242% decrease in the growth rate of CO_2 emission, for a 1%

increase in agricultural production growth. This result is also significant at a significance level of 5%. Table 6 also shows a negative effect of agricultural production on CO_2 emissions, although, the impact is smaller. According to Table 6 regression results, for a 1% increase in agricultural production growth, the CO_2 emissions decreased by 0.153%, however, the result is statistically significant at a 10% significance level only.

The negative impact of agricultural production growth on CO_2 emissions can have multiple explanations. One explanation could be the employment of particular agricultural practices that lead to lesser CO_2 emissions. These practices include the lesser use of fertilizer per hectare of arable land. South Asia had an average fertilizer consumption of 165.7 kg per hectare of arable land, as compared to East Asia, where the average in 2017 was 327.8 kg per hectare (World Bank Open Data 2023). The amount of energy and the source of energy used in agriculture are other important determinants of the impact of agriculture on CO_2 emissions, however, we have included these variables in the regression model separately already.

Another explanation for this negative impact on agricultural production could be the choice of crops that are grown. Different cereal crops have different environmental impacts. For example, rice cultivation is associated with methane emissions due to flooded fields, on the other hand, wheat has been shown to act as a carbon sink, as it absorbs more carbon than it releases (Veeck et al. 2022, 901). The high level of wheat production in the South Asia region might partially explain this negative effect of agricultural production on CO_2 emissions in South Asia. Conceptually, higher agricultural growth also shows substitution away from manufacturing and industrial growth in the company. The growth in these sectors of the economy may cause a higher level of CO_2 emissions than agricultural production and thus, agricultural production, on net, has a negative impact on CO_2 emissions.

5.6 Impact of change in forest area share

According to the results in both regression tables, the rate of change in the share of forest area has a negative effect on the growth of CO_2 emissions. According to the fixed effects model, in the regression analysis conducted using data from WDI, a 1% increase in the rate of change in the share of forest area is associated with a 6.552% decrease in the growth of CO_2, while according to random effects model, it is associated with a 6.659% decrease in the of CO_2 emissions. These results are also statistically significant at a 5% significance level. On the other hand, according to the results of CO_2 emissions data from Friedlingstein et al. (2022), a 1% increase in the rate of change in the share of forest area leads to 5.157% and 6.145% decrease in the growth of CO_2 emissions level. There are two pathways through which this effect of forest area on CO_2 emissions can be explained. Firstly, afforestation can lead to a decrease in atmospheric CO_2 levels, as forests can act as carbon sinks and can capture and store atmospheric CO_2. Secondly, deforestation can also lead to an increase in atmospheric CO_2 levels. Deforestation can be a result of multiple factors, including agriculture expansion (through conversion of forests to cropland and pasture), urbanization (through urban sprawl), and the use of wood as a domestic fuel (My NASA data 2018). These factors are intimately linked with the factors we have outlined in our conceptual model and thus, can be considered a part of a larger system.

6 Conclusion

This study tried to illuminate the impact of seven major factors on CO_2 emissions in South Asia: GDP growth, urbanization growth, population growth, energy consumption growth, change in fossil fuel share in the energy mix, agricultural production growth, and change in share of forest area. We used from five South Asian countries: India, Pakistan, Bangladesh, Nepal, and Sri Lanka, from 1990 to 2014. We used two different sources for the data on CO_2 emissions, World Development Indicators (WDI) and Global Carbon Budget (GCB) and relied on a fixed effects model and a random effects model, for conducting an empirical analysis. The four models found that an increase in urbanization growth, an increase in agriculture production growth, an increase in the share of fossil fuel share in the energy mix, and a decrease in the forest area share growth led to an increase in the growth of CO_2 emissions. The evidence on growth in energy consumption and GDP growth increase was fixed, with a regression model using data from WDI, showing a positive relation between the two variables and CO_2 emissions, while data from GCB, showed a statistically insignificant relationship between the two variables and CO_2 emissions. Lastly, the evidence for the increase in population growth is also mixed, with data from WDI showing an insignificant relationship, while data from GCB, showing a positive relationship between change in population growth and CO_2 emissions growth. The results were analyzed in light of the conceptual model formed through a thorough literature review, which delineated the possible explanations and factors which explain the relationships found between the explanatory variables and the CO_2 emissions.

7 References

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8 Appendix

Table 7: Correlation matrix

	GDP	Urbanization	Population	Energy use	Fossil fuel	Agriculture	Forest
GDP	1	0.180	-0.071	0.261	0.220	0.122	-0.095
Urbanization	0.180	1	0.107	-0.030	0.306	-0.080	-0.050
Population	-0.071	0.107	1	-0.047	0.016	-0.084	0.141
Energy use	0.261	-0.030	-0.047	1	0.416	0.074	-0.107
Fossil fuel	0.220	0.306	0.016	0.416	1	-0.078	0.059
Agriculture	0.122	-0.080	-0.084	0.074	-0.078	1	-0.151
Forest	-0.095	-0.050	0.141	-0.107	0.059	-0.151	1

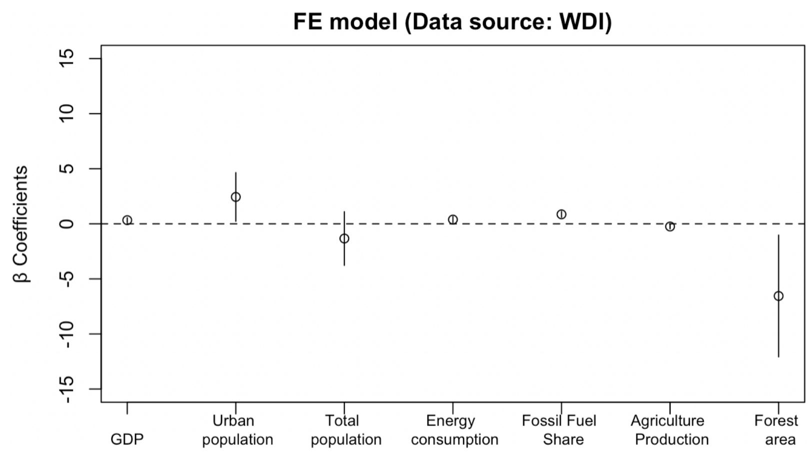

Figure 12: β coefficients with standard errors for Fixed Effects model with WDI data

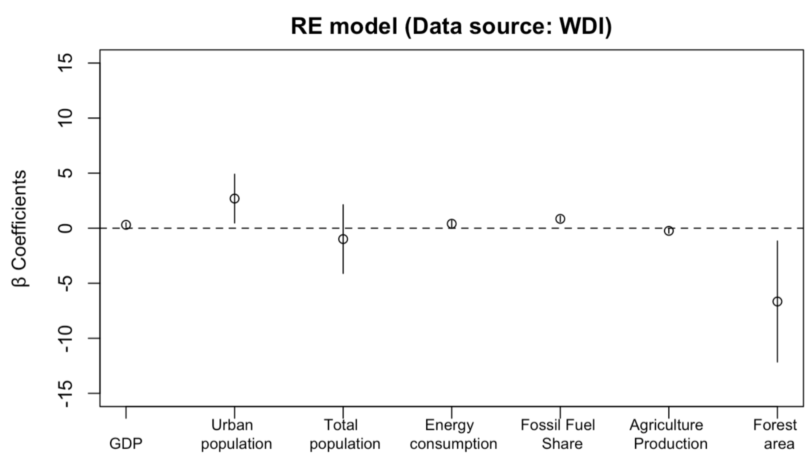

Figure 13: β coefficients with standard errors for Random Effects model with WDI data

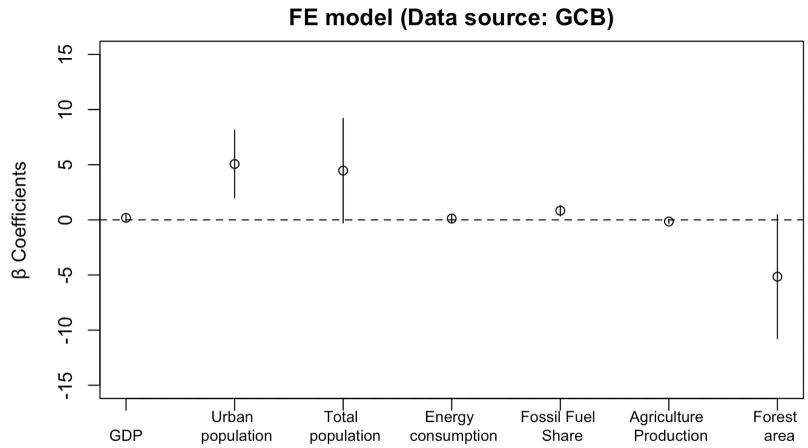

Figure 14: β coefficients with standard errors for Fixed Effects model with GCB data

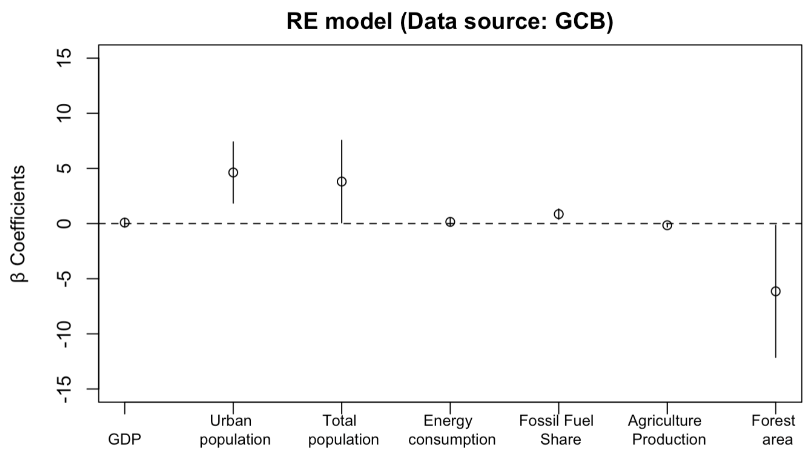

Figure 15: β coefficients with standard errors for Random Effects model with GCB data

8.1 Code availability

The code for this study can be found on this link.