ESTIMATING CO_2 EMISSIONS FROM ENERGY CONSUMPTION IN PAKISTAN

By
Aysha Malik
(Reg# 00000171486)
A thesis submitted in partial fulfillment of requirements for the degree of
Master of Science
In
Environmental Science

Institute of Environmental Sciences and Engineering (IESE)

School of Civil and Environmental Engineering (SCEE)

National University of Sciences and technology (NUST)

Islamabad, Pakistan

(2019)

THESIS ACCEPTANCE CERTIFICATE

It is certified that the copy of MS/MPhil thesis entitled by Ms. Aysha Malik Registration No. 00000171486 of **IESE (SCEE)** has been vetted by undersigned, found complete in all aspects as per NUST Statutes/Regulations, is free of plagiarism, errors, and mistakes and is accepted as partial fulfillment for award of MS/MPhil degree. It is further certified that necessary amendments as pointed out by GEC members have also been incorporated in the said thesis.

Signature with stamp: __________________

Name of the Supervisor: Dr. M. Fahim Khokhar

Date: ________________

Signature of HoD with stamp: ________________

Date: ________________

Countersign by

Signature (Dean/Principal): ________________

Date: ________________

CERTIFICATE

It is certified that the contents and form of the thesis entitled

"Estimating CO_2 Emissions in Pakistan from Energy Consumption"

Submitted by:

Aysha Malik

have been found satisfactory for the requirement of the degree

Supervisor: ___________________

Dr. Muhammad Fahim Khokhar

Professor

IESE, SCEE, NUST

Member: ______________________

Dr. Zeshan Sheikh

Assistant Professor

IESE, SCEE, NUST

Member: ______________________

Dr. Sofia Baig

Assistant Professor

IESE, SCEE, NUST

DEDICATION

This thesis is dedicated to my affectionate parents.

Acknowledgements

This research work would not have been possible without the guidance of Allah Almighty, the most beneficent and merciful.

I would like to express my utmost gratitude to my Supervisor, Dr. M. Fahim Khokhar for his understanding, wisdom and patience and for pushing me farther than I thought I could go. I would also like to express my gratitude to my GEC members, Dr. Sofia Baig and Dr. Zeshan Sheikh. Their guidance and expertise generously helped me during my research. To Dr. Salman Atif and Dr. Iftikhar Hussain Adil, I am extremely grateful for their assistance and expert opinions that helped me in my research work.

My friends, family and C-CARGO group for helping me in stressful times and not letting me give up. To Fatimah Mahmood for always listening and giving me words of encouragement. Lastly, I would like to thank my parents for their unconditional love, support and encouragement.

Table of Contents

Chapter 1: Introduction

Chapter 2: Literature Review

Chapter 3: Materials & Methods

Chapter 4: Results & Discussion

Chapter 5: Conclusions & Recommendations

List of Abbreviations

ADF	Augmented Dickey Fuller
ARIMA	Auto-Regressive Integrated Moving Average
ARMA	Auto-Regressive Moving Average
AIRS	Atmospheric Infrared Sounder
BAU	Business as usual
CDIAC	Carbon Dioxide Information Analysis Centre
CO_2	Carbon Dioxide
CPEC	China Pakistan Economic Corridor
ECCAD	Emissions of Atmospheric Compounds and Compilation of Ancillary Data.
EDGAR	Emission Database for Global Atmospheric Research
GDP	Gross Domestic Product
GHGs	Greenhouse Gases
INDCs	Intended Nationally Determined Contributions
IPCC	Inter-governmental Panel on Climate Change
MW	Megawatt
OCO-2	Orbiting Carbon Observatory-2
OLS	Ordinary Least Squares
PPM	Parts Per Million
REAS	Regional Emission Inventory in Asia
UNFCCC	United Nations Framework Convention on Climate Change
VIF	Variance Inflation Factor

List of Figures

List of Tables

Abstract

The main culprit behind the changing climate is carbon dioxide (CO_2) along with other greenhouse gases and the impacts so far have been extremely severe. The forecast of CO_2 emission is very crucial, especially for Pakistan as it is one of the top victims of climate change and extreme weather events. This study includes the forecast of CO_2 emissions by using Auto-Regressive Integrated Moving Average (ARIMA) models and regression analysis. The emission data was obtained from globally available emission inventories and the forecast was done till 2030. This is the business as usual (BAU) scenario. Five other scenarios have also been developed for CO_2 emission in the country till 2020, predicting it further by the end 2030. The scenarios developed are CPEC scenario, 20% increase and decrease from BAU scenarios and 40% increase and decrease from the BAU scenarios. These attempt to estimate the impactful emissions reduction percentage, which the country needs to adopt and other necessary changes in the existing policies of the country. The study clearly indicates that the emissions are going to increase by approximately 60% when the high priority energy projects under China Pakistan Economic Corridor (CPEC) will get operational, roughly by 2020. Under these situations the forecast shows increased CO_2 emissions and the country would not be able to meet its NDCs pledge at COP21, by 2030. Additionally, regression was carried out with the help of three independent variables; fossil fuel consumption, cement production and energy production. Regression results clearly indicate that the CO_2 emissions will steadily increase with the increase in all the variables. This relation was found to be statistically significant with minimum error.

Chapter 1

Introduction

1.1. Background

Climate Change has emerged as a global challenge since the late twentieth century. Continuous rise in temperature, shift in seasons, rise in sea level, and changed patterns of rainfall impacts the ecosystem, biodiversity and different human activities (Fang et al., 2017). The greenhouse gases (GHGs) are the potent causal agents for the climate change (Nordhaus & William, 2006). Globally the policymakers are striving hard to address the issue of climate change.

Main reason behind climate change is the increasing concentration of CO_2 along with the other GHGs in the atmosphere. These concentrations are increasing due to ever increasing usage of fossil fuels (Mir *et al.*, 2017), (Seinfeld & Pandis, 2006). Globally fossils fuels are being used to meet the energy demand and are the major source of CO_2 emissions along with the other pollutants. According to International Energy Agency, electricity and heat production has been the biggest CO_2 emissions source in 2016 as its contribution was 42% in the global emissions. After energy sector the industry was reported to be the largest emitter, then the buildings and constructions and lastly the transport sector (IEA, 2018). Therefore CO_2 emissions are a major concern for all the countries including both developed and developing and require utmost attention. Out of all the greenhouse gases, CO_2 contributes approximately 63% to the greenhouse effect, making it a main contributor of the global warming (Sun *et al.*, 2017).

The developing nations are generally more vulnerable to climate changes, despite being small emitters. Most of these countries have the requisite potential to curb the emissions in different sectors.

1.2. Study Area: Climate Change and Development Scenario in Pakistan

Pakistan CO_2 emissions are minimum but it ranks seventh most vulnerable country to climate change, in the world as per the Global Climate Risk Index 2018. The country has the potential and imminent need to switch to green alternative measures in order to decrease their emissions (Yousuf *et al.,* 2014). Map of climate change and related spatial diversity for Pakistan is shown in figure 1.1.

Pakistan is the sixth most populous country with a population of 207.7 million as per 2017 census. The annual growth rate comes out to be 2.4%, therefore the population is bound to increase in the coming years (UNFPA). This will increase the energy demand in the coming years. Pakistan is already an energy deficit country, which has impeded the development and badly impacted the economy over the years. In 2016 the power generating capacity was 17,000 megawatts (MW) and the demand was 22,000 MW, making demand supply gap of approximately 5000 MW (Rafique & Rehman, 2017).

Keeping in mind the energy scenario of the country, the pledges made in the submitted INDCs by Pakistan were not well grounded. Even the climate experts of the country believed that the targets pledged could have been more tangible and well defined (INDC, 2015). The country committed that by 2030 the emissions will reduce by 5% or 18% of the 2012 level, subject to the financial support from developed countries (Ebrahim, 2015).

The energy crisis situation in the country is changing now, due to the ongoing CPEC mega-project that include numerous energy projects. The CPEC will contribute towards the development and economic stability of the country. Investment in infrastructure, energy and industry sectors will increase the GDP growth rate (Ashraf et al. 2017). The worrisome aspect is that a sizeable chunk of energy mix of Pakistan is already based on thermal power plants. Natural gas used for electricity production, contributes more than 50% of the CO_2 emissions in the country (Mohiuddin et al., 2016). The fuel is mostly imported (60% of its total foreign exchange) and is already a stress on the economy (Rafique and Rehman, 2017). Now under CPEC, 10,187 MW generating capacity, energy projects have already been started. About 68% (6900 MW) of the 10,187 MW are coal based power plants (Amin, 2018). Therefore the CO_2 emissions are bound to increase at a higher rate in the near future and will further aggravate the impacts of climate change in the country.

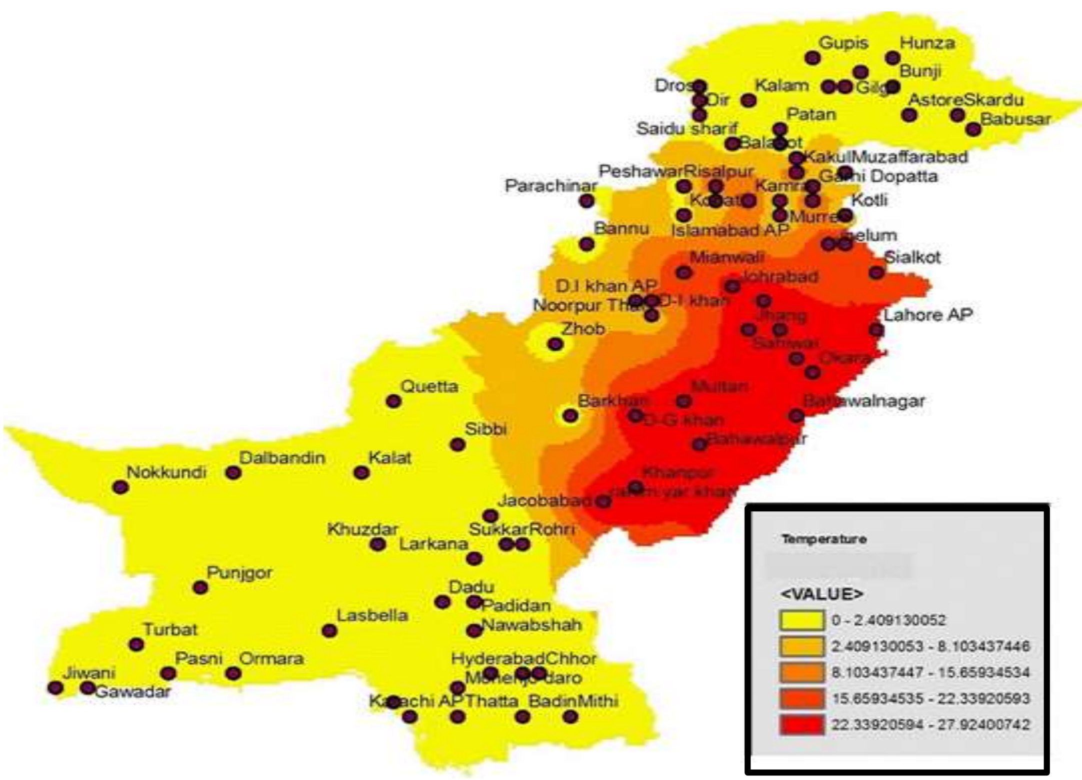


Figure 1.1. Map of Climate change and related spatial diversity shown for Pakistan

(Source: Ali, 2018)

The CO2 emissions forecast in this study will give an estimation to where the country will stand in 2030, if the emissions situation remains the same as in the base years; BAU scenario. Also the CO_2 emissions situation if we increase our emissions especially in the wake of CPEC and if we start to lower the emissions. It would ultimately tell us if the country will be successful in achieving the goals as pledged and it will also aid the policy makers, for appropriate mitigation actions and green planning regarding energy consumption.

1.3. Objectives

1. To study the trends of CO_2 emissions from energy consumption in Pakistan during last decades.
2. To forecast CO_2 emissions from energy consumption, in Pakistan.

1.4. Justification of Topic Selection

Pakistan is gradually shifting from agriculture based economy to industry based economy. This shift along with high energy demand is bound to increase the air pollution in the country. Energy sector is the country's major contributor of adding CO_2 in the atmosphere. With increasing population, increase in transport system and consequently vehicular emissions are also increasing. According to Baber (2008), a Pakistani vehicle emits 25 times higher CO_2 than vehicles in US.

As for now the Pakistan's global CO_2 contribution is 0.8% but the country is highly vulnerable to climate change and the now frequent episodes of flood, heat waves, and abnormal precipitation patterns are undeniable proofs. If the CO_2 emissions are not limited then this is going to cause havoc in the region.

CPEC mostly consists of coal based energy projects. Coal has high carbon content and it will have severe implications on the environment and will prove to be a major setback for the carbon reduction pledge at the COP21 (Lin & Ahmed, 2017).

Pakistan being the vulnerable country is facing potential threats to its water, food and national security:

- Pakistan has faced extreme weather events and these events have become more frequent in the recent past.
- Due to rise of sea-level, saline water penetrates into the Indus Delta.
- With the depletion of Hindu Kush Himalaya glacier increased amount water flows into Indus River System.
- With the increase in temperature country has faced reduced crop productivity, impacting agriculture.

(Source: National Climate Change Policy, 2012.)

This study will help the concerned policy makers in understanding not only of the current scenario but will also get a clear picture of the future trends of CO_2 emissions in the country. They would realize the needs to strategize the future plans and would modify their existing policies accordingly. The best answer to fight the rising CO_2 emissions and to reduce the climatic impacts would be pursued.

1.5. Relevance to National Needs

- It has been found that this region has faced changed monsoon rainfall patterns and the intensity of rainfall has increased. These changed patterns have resulted in massive floods in the country. Recent examples include floods of 2003, 2007, 2010, 2011 and these events have continued to occur on regular basis, killing many people and rendering many homeless and also impacting country's economy (Rasul *et al.,* 2012).

- Heat waves are one of the major causes of weather related casualties in Pakistan. The incidence of heat waves in the country will increase with global warming. Some of the highest temperatures were recorded in the country in recent years. In 2015 a severe heat wave struck Sindh province especially Karachi, with estimated death toll of 1200 (Chaudhary *et al.*, 2015).
- Other impacts include Saline water incursion leading to increased salinity and water logging, vulnerabilities of Indus Delta, droughts, coastal erosion, increased crop water requirement (Rasul *et al.,* 2012).

1.6. Significance of the Study

- This study will create a database of energy consumption and CO_2 emissions for further analysis.
- The forecast will present a clear picture of the emissions till 2030. The CO_2 scenarios, especially the CPEC scenario will help the policy makers to see if the existing policies are enough to achieve the targets pledged (NDCs).
- It will enable decision makers and concerned people to decide which power project will be more suitable for Pakistan i.e. coal power projects or renewable energy projects.
- The concerned people will recognize the vulnerable climatic situation in the country and timely actions will be taken in order to cope with the life threatening events, which are occurring and are likely to intensify in future.

1.7. Areas of Application

The large beneficiaries for this proposed study include academia, policy-makers and decision-makers in the areas of energy sector and climate change. Especially involved in planning and implementation of adaptation and mitigation strategies. Specific audience include both; national and international atmospheric science communities, climate change departments, research centers and cells, energy sector, industry sector, environment department, tourism department, ecologists, division planners and policy-makers.

Outcomes of this study may lead to more reliable air quality parameters, low vulnerability to climate change, incorporation of green environmental practices and technology and the development of effective abatement and mitigation strategies of GHGs.

Chapter 2

Literature Review

2.1. Carbon Dioxide in the Atmosphere

Greenhouse gases absorb the thermal infrared energy radiated by land and ocean surfaces (warmed by sunlight) and with time release it. Carbon dioxide is one of the gases to absorb that heat. In absence of the greenhouse effect, the average temperature of earth would be below freezing, making the living conditions extremely harsh. In the recent years, the increases in greenhouse gases has disrupted the balance of earth's energy budget, therefore increasing the earth's average temperature. A single CO_2 molecules have a short residence time of approximately 5 years in the atmosphere. The additional CO_2 in the atmosphere stays there on a time scale of centuries (Lindsey, 2018).

The Global Warming Potential (GWP) of CO_2 is less than other greenhouse gases; methane and nitrous oxide but is more potent as its residence time and concentration in the atmosphere is more. In comparison to water vapors, its GWP and concentration is less but it absorbs those thermal energy wavelengths that water vapor does not, thus making it a distinctive GHG. It has been observed that increase in CO_2 concentration in the atmosphere is responsible for more than half of the imbalance in the energy budget and has led to overall temperature increase. (Lindsey, 2018).

CO_2 is released in the atmosphere, primarily due to anthropogenic activities. CO_2 contributes approximately 63% to the greenhouse effect, therefore it a chief contributor of the climate change (Sun et al., 2017). Carbon dioxide concentration is on a steady rise because of the burning of fossil fuels. Fossil fuels includes natural gas, coal and petroleum that contains carbon, which plants took from the atmosphere through photosynthesis over the span of millions of years. By burning the fossil fuels the carbon is being returned to the atmosphere. The CO_2 emissions from energy consumption are different in different countries. This difference is due to diverse domestic energy conformations (Olabemiwo *et al.,* 2017).

2.2. The Carbon Cycle

For many decades now, anthropogenic activities have been a huge part of a biogeochemical cycle; the carbon cycle. The carbon exchange takes place between atmosphere, lithosphere, biosphere, oceans and organic matter in soil. This carbon takes different formations during the exchange (Rice *et al.,* 2004).

The basic carbon cycle is has following steps (Ophardt & Emeritus, 2013):

1. Photosynthesis:

Photosynthesis is complex reaction series that helps plants to convert the atmospheric CO_2 to carbohydrates (glucose).

$$\mathbf{6CO_2 + 6H_2O \text{ ------> } C_6H_{12}O_6 + 6O_2}$$

2. Respiration/Metabolism:

When organic matter reacts with oxygen to give carbon dioxide, water and energy, it is combustion. Metabolism takes place when animals digest the organic matter consumed as food. In their cells chain reactions occur in the presence of oxygen. It converts carbohydrates into CO_2, water and energy. Bacteria also decompose waste materials (organic) and similar reaction takes place.

$$\mathbf{C_6H_{12}O_6 + 6O_2 \text{ ------> } 6CO_2 + 6H_2O + Energy}$$

3. Sedimentation:

Globally, the carbon cycle utilizes the carbon existing in fossil fuels, rocks, soils, atmosphere and oceans. Carbon dioxide is water soluble therefore it is absorbed into water bodies. In marine ecosystems, the shelled organisms make calcium carbonate from this absorbed CO_2. When they die, they drop to the bottom and the calcium carbonate accumulate as sediments. Figure 2.1 shows the steps of carbon cycle in all the spheres.

$$\mathbf{H_2O + CO_2 \text{ ----> } H_2CO_3 \text{ ----> } H^+ + HCO_3^-}$$

$$\mathbf{HCO_3^- \text{ ----> } H^+ + CO_3^{-2}}$$

$$\mathbf{CO_3^{-2} + Ca^{+2} \text{----> } CaCO_3}$$

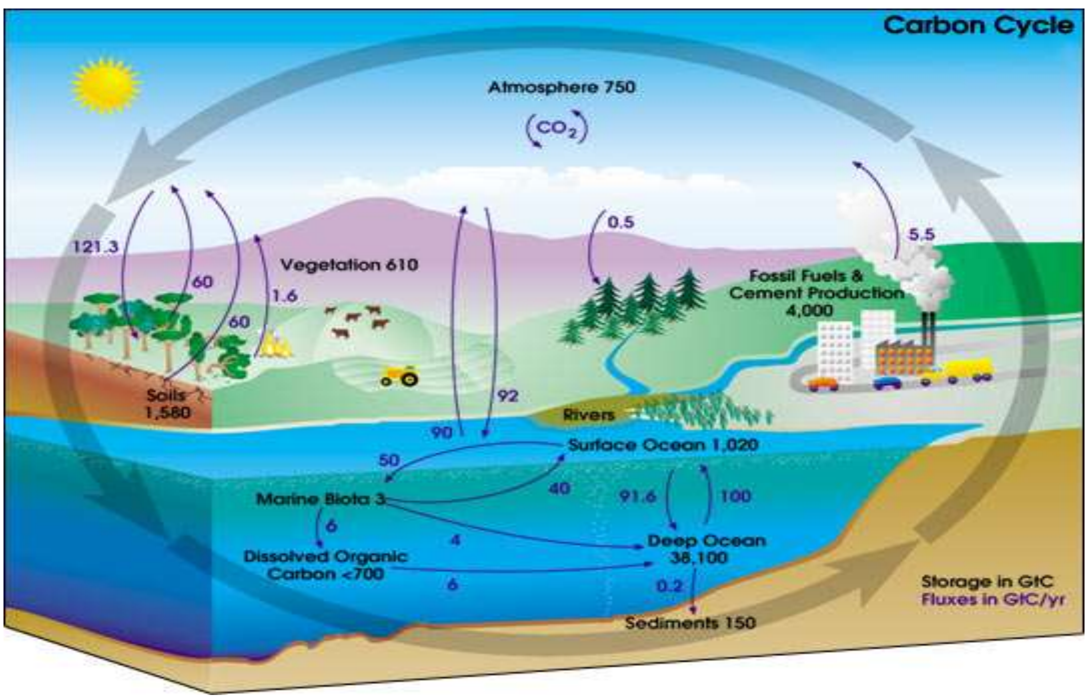


Figure 2.1. The Carbon Cycle (Source: Ophardt & Emeritus, 2013)

2.3. Sources and Sinks of Carbon Dioxide

Natural sinks and sources also contribute in the net CO_2 emissions. For CO_2 the sources are natural and anthropogenic. As discussed above natural sources include oceans, respiration, decomposition, volcanic activities and forest fires. The anthropogenic activities that directly release CO_2 in the atmosphere are; fossil fuel, biomass fuel consumption in vehicles, residential and public sector, manufacturing and industry sectors (majorly from cement production) and urban areas. Land use change and deforestation is also responsible for CO_2 release in the atmosphere. (Velasco *et al.*, 2014).

Similarly the sinks are categorized as natural sinks and artificial sinks. Terrestrial sinks include vegetation and soils. During the day photosynthesis takes place and scoops CO_2 from the atmosphere. Respiration release CO_2 in the atmosphere in small amount. Soils and underground activities also release CO_2 in the atmosphere (Prairie and Duarte, 2007). Oceans also act as CO_2 sinks and help to sequester carbon from the atmosphere.

The artificial carbon sequestration involves efforts to enhance natural sinks. It also include many other techniques such as geological sequestration which includes inserting CO_2 into the concealed geological formations such as old fuel reservoirs, coal seams and aquifers that are unable to be mined. Regenerative agriculture is a method to enhance the sequestering potential of soils. Another technique is mineral sequestration, where CO_2 is injected into magnesium or calcium rich areas. The CO_2 reacts with magnesium or calcium and form carbonate salts. Currently, CO_2 capture is being done mostly by absorption it onto numerous amine-based solvents (Carbon sequestration-artificial vs. natural). The current research is not enough on the above mentioned artificial processes and need further testing and improvement. Table 2.1 shows the carbon balance in the atmosphere.

Table 2.1. Carbon Balance in Atmosphere (Source: Rice *et al.*, 2004)

Factor	Carbon emissions flux into atmosphere (gigatons C/year)	Movement of C out of atmosphere (gigatons C/year)
Fossil fuel burning	4 – 5	
Soil organic matter oxidation / erosion	61 - 62	
Respiration from organisms in biosphere	50	
Deforestation	2	
Incorporation into biosphere through photosynthesis		110
Diffusion into oceans		2.5
Net	117 - 119	112.5
Overall Annual Net Increase in Atmospheric Carbon	+ 4.5 - 6.5	

2.4. Increase in Atmospheric CO_2

The global atmospheric CO_2 is on a steady increase from the start of industrial revolution. The emissions have been on a steady increase ever since. In 1850s when industrial revolution started the CO_2 concentration was 280 ppm and it went up to 381 ppm in 2006. The concentration of CO_2 has not been this high in the last 20 million years as it is today. The recorded rate in the recent years is highest from the time official monitoring began in 1959 (Canadell *et al.*, 2007).

Three factors majorly determine the growth rate of atmospheric CO_2. These factors include: economic activity on a global level, the carbon demanding economy, and lastly the performance of sinks and sources of carbon. It has been observed that from 2000 onwards, the economy of the world has been on a steady increase. Therefore the carbon emissions for every unit of economic activity has been increasing, and the effectiveness of carbon sinks has been decreasing. These changes collectively are leading towards an increased atmospheric CO_2 emissions worldwide. (Canadell *et al.,* 2007).

The global growth rate from 2000 to 2006 has been recorded to be 1.93 ppm y^{-1}. Net atmospheric CO_2 emissions from 1959 to 2006 along with the sinks and sources are shown in figure 2.2

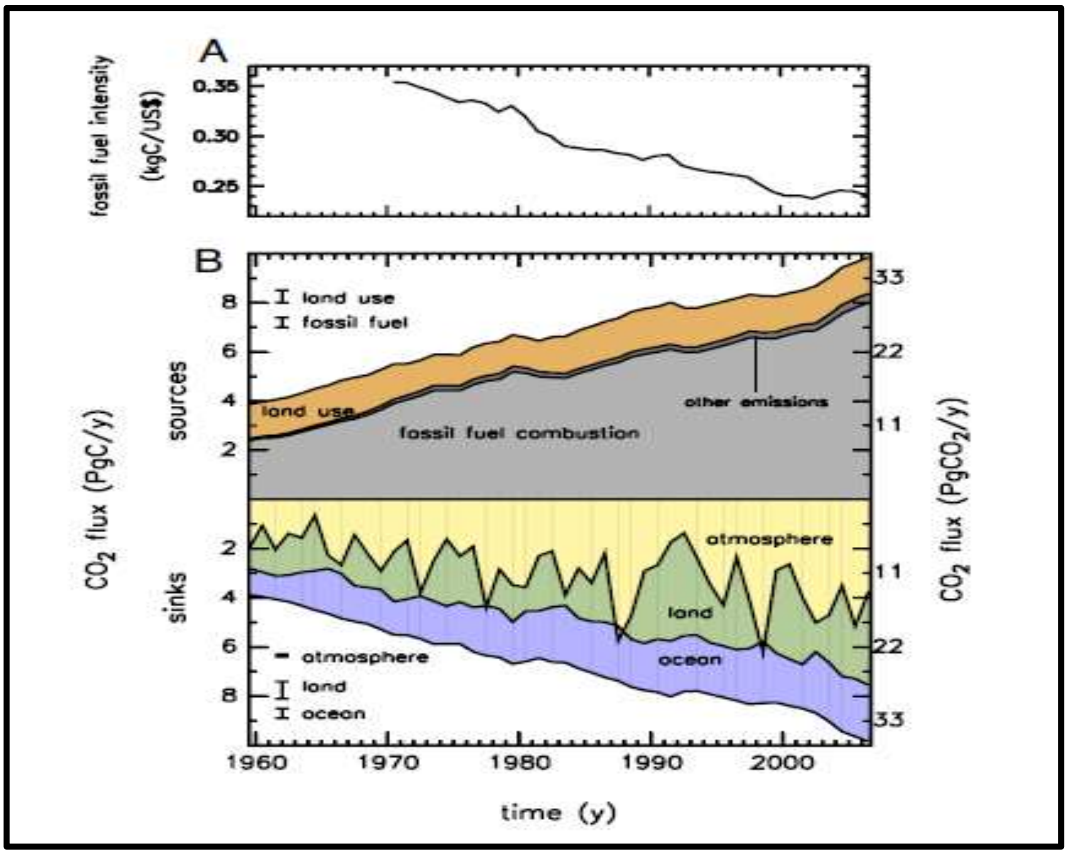


Figure 2.2. Global Warming Potential (Fossil Fuel), 1970-2006 (A). Net CO_2 1959-2006 (B). Global Warming Potential (Fossil Fuel), based on market exchange rates (USD) (B1). Sources of CO_2 emissions in atmosphere (B2) situation of atmospheric CO_2 and sinks. (Source: Canadell *et al.*, 2007)

2.5. Emissions Inventories

The emission inventories developed for CO_2 only considers the CO_2 emissions from fossil fuel combustion. The emissions data from humans, soils and the potential offset by vegetation in urban areas are not taken into account, despite being important sources and sinks (Velasco *et al.,* 2014). These emissions are calculated on the basis of energy economics and statistics. They are calculated for a long period and are usually available as annual datasets. These calculations do not include the diurnal fluctuations in the associated activities and also the spatial distribution of CO_2 emissions generation points. A common method to quantify the concentration of air pollutants is the bottom-up aggregation approach. It includes emission factors and the activity log as well as respective technologies. It also includes their spatiotemporal distribution (Velasco *et al.*, 2014).

The accuracy of these emission inventories is a key for the efficient and effective design of policies and strategies for GHG mitigation (Smit *et al.*, 2010). If correct activity log is employed then the data from the existing emission factors can be used to correctly predict the emissions (Andres et al., 2012). Small errors can cause huge uncertainties during analytical processes (Marland, 2008), (Velasco *et al.*, 2014).

2.6. ARIMA Models for the Forecast

The accurate forecasting of CO_2 emissions would help the concerned policy makers in understanding the current scenario as well as the future trends in the CO_2 emission. It would help them in modifying their existing policies accordingly.

ARIMA models have been employed to forecast the CO_2 emissions. CO_2 emissions and energy consumption, due to their importance and impacts, has been modelled for many countries. ARIMA models are widely preferred forecasting models because the best fit model is selected according to the time series data available and its flexibility (Sen *et al.*, 2016). The ARIMA models were first employed by Box and Jenkins and are sometimes called Box-Jenkins models (Box & Tiao, 1975). After that a number of studies have been conducted where exclusively ARIMA models have been used for the forecasting, because of their efficiency (Sen *et al.*, 2016).

CO_2 emissions, due to severe impacts, has been modelled using ARIMA models. Pao and Tsai (2011) compare Grey Model (GM) and ARIMA for three different variables; energy consumption, CO_2 emissions and economic growth. The results indicate that all the best fit models of GM and ARIMA have mean absolute percent error (MAPE) of 3% making the forecasting performance of both models highly significant. Pao et al. (2012) employ the ARIMA linear model along with three other forecasting models; the nonlinear GM (1, 1), nonlinear grey Bernoulli model (NGBM) and NGBM-OP (optimized). All models forecasted CO_2 emissions, energy consumption and GDP for China. The study proposes that China should devise such policies and strategies that will not only improve energy efficacy but will also help to conserve energy. Liu et al. (2014) tries to check if China can achieve its reduced CO_2 emissions target set at the Copenhagen Conference from the perspective of the country's current thermal power scenario. The forecast results clearly indicate that if the thermal power plants of China continue to expand at the present rate then an increasing trend of CO_2 emissions is inevitable and set targets would be hard to achieve.

Tudor (2016) investigated CO_2 emissions in Bahrain by using seven different forecasting models including ARIMA. According to the forecast results Bahrain cannot meet its target of reduced carbon emissions set at Kyoto Protocol. Sen et al. (2016) investigates pig iron manufacturing organization in India and forecast energy consumption and GHG emissions by employing ARIMA model. The results were aimed to know the best fit model of ARIMA so that the forecast can help the managers to know the future trends of the chosen variables, in order to improve the environmental policy. Nawaz et al. (2018) used ARIMA models to forecast energy consumption and CO_2 emissions for the first time in Pakistan. The study finds the best fit model for both, energy consumption and CO_2 emissions. The findings will aid the policy makers to develop approaches which will help to minimize the negative impacts of CO_2 emissions in the country without compromising on its development.

The ARIMA model has some limitations as well. It works efficiently for long time series data (preferably 50 observations) whereas regression is efficient for small time series data (Abeysinghe *et al.,* 2003). Second limitation is that the ARIMA is appropriate if forecasting is done for small period of time (for example 10 years) but it is not deemed appropriate it forecasting is being done for long period of time (for example 20 years or more). It has also been observed that if the dataset is long and extensive then the ARIMA forecasting performance improves and is deemed accurate (Sen *et al.,* 2016).

2.7. Regression Analysis for CO_2 Emissions

Regression analysis has been successfully employed in many forecasting studies as well. Olabemiwo *et al.* (2016) conducted a study where they forecasted CO_2 emissions in Persian Gulf States which are world largest producers of crude oil and gas. They employed the least square technique and the result of these seven states showed that the CO_2 emission will increase at a rate of 7.7% per year. Similarly for forecasting the residential energy consumption, Fumo & Biswas (2015) used the regression analysis. Simple and multiple linear regression and quadratic regression analysis were performed.

In case of Pakistan several studies have been found where cointegration relationship was explored. The variables were CO_2 emissions, trade, consumption of energy and lastly economic growth in case of Pakistan (Shahzad *et al.*, 2017). Another study employed dynamic causality analysis for Carbon emissions, energy consumption and economic growth (Mirza & Kanwal, 2017). Kuznets curve has also been explored for Pakistan (Ahmed & Long, 2012). Hardly any study was found where multiple regression was done the with variables; CO_2 emissions, energy production, fossil fuel consumption and cement production. This study covers this aspect along with the univariate ARIMA models.

2.8. Rationale of the Study

Since energy sector is a huge contributor of the CO_2 emissions, and impacts have been severe, hence forecast of CO_2 emissions becomes pivotal. Previously many studies have been conducted in which CO_2 emissions have been forecasted for many countries, as reviewed above. In case of Pakistan, only one study has been found by Nawaz *et al.,* in 2018 in which both energy consumption and CO_2 emissions have been forecasted using ARIMA model. There was hardly any study found which included different CO_2 emission scenarios especially the CPEC scenario.

The study will help the concerned people to adopt certain measures, to curb the CO_2 emissions and lessen the adverse impacts because of it. Apart from energy, the major sectors to target are industry, transport, agriculture, forestry, land use change and planning (Lin & Ahmed, 2017).

Chapter 3

Materials and Methods

3.1. General Methodology

CO_2 emissions data was obtained from three global emission inventories database; Emissions of Atmospheric Compounds and Compilation of Ancillary Data (ECCAD) Database, Emission Database for Global Atmospheric Research (EDGAR) Database and Carbon Dioxide Information Analysis Centre (CDIAC) Database. The database has annual sector wise CO_2 emission and the total emissions over Pakistan. The units for REAS dataset were converted to make them uniform with other datasets. The Mann Kendall test was employed on the time series data to identify the significance of the trend. The datasets were then correlated with fossil fuel energy consumption, total energy production, thermal energy production and cement production data for Pakistan. The inventories datasets were also correlated with the Satellite CO_2 emissions (AIRS and OCO-2).

The CO_2 emissions datasets from inventories were then subjected to ARIMA model in R software (R Development Core Team, 2018) to forecast the CO_2 emissions till 2030. The accuracy of the model was calculated in percentage using Mean Absolute Error (MAE). Different scenarios were developed for CO_2 emissions and ARIMA was employed on them to get predictions till 2030. It will help to analyze the CO_2 emission level by 2030. Additionally multiple regression was employed on the inventories data along with the three variables; fossil fuel consumption, energy production and cement production. Regression analysis was performed in Stata (StataCorp., 2015) and the respective results were compiled.

3.2. Tools involved in the Study

Different tools were used to carry out the study and to perform the required statistical tests. Table 3.1 gives an account of the software involved in the present study along-with their respective purpose.

Table 3.1. Tools used to carry out the Study

No.	Tools	Purpose
1.	**R 3.5.0**	The software was used to make data stationary and run ARIMA model to get the emissions forecast till 2030.
2.	**Stata SE 14**	This datasets were subjected to multiple regression
3.	**Excel Stat**	It was used to employ Mann Kendall Test
4.	**MS Excel**	Correlations, graphs, tables and figures were made in MS Excel. Mean Absolute error was also calculated.
5	**ArcGIS 10.3.1**	Extracted satellite CO_2 emissions data over Pakistan

3.3. Detailed Methodology

3.3.1. Data Acquisition

The CO_2 emissions datasets were acquired from three different global emission inventories database; ECCAD, EDGAR and CDIAC. The CO_2 emission datasets are annual averages. REAS data download from ECCAD database is shown in figure 3.1. All inventories except REAS have data of sector wise CO_2 emissions and then total CO_2 emissions is given. The details of different datasets acquired are given in the table 3.2.

Satellite data for CO_2 emissions was taken from AIRS and OCO-2. This data was available in moles and was converted to parts per million (ppm), it is mean monthly data from 2002 to 2016. The satellite data was extracted over Pakistan using ArcMap (ESRI, 2015) as shown in figure 3.2 and the yearly means were calculated in Excel. As the three datasets were found to be highly correlated therefore we ran regression for one inventory dataset. The EDGAR dataset was analyzed with different variables. The variables selected for this study includes:

1. Fossil fuel Energy
2. Energy Production
3. Cement Production

The fossil fuel energy consumption data for Pakistan was retrieved from International Energy Agency; IEA (1970-2014), total energy production data for Pakistan was retrieved from Power System Statistics Report (1970-2014) and Cement production data for Pakistan was retrieved from All Pakistan Cement Manufacturer Association (1990-2015).

Table 3.2. CO_2 emission datasets specifications

No.	Inventory type	Inventory Database	Sectors	Time	Duration	Units
1.	CDIAC	CDIAC	Fuels (solid, liquid and gas), Bunker Fuels, Gas Flares and Production of Cement	Annual	1972-2014	Kt
2.	EDGAR	EDGAR	Manufacturing Industries and Construction, Residential and other sectors, Solid fuels,	Annual	1970-2015	Kt
3.	REAS	ECCAD	None	Annual	1980-2010	kg/m^2/s

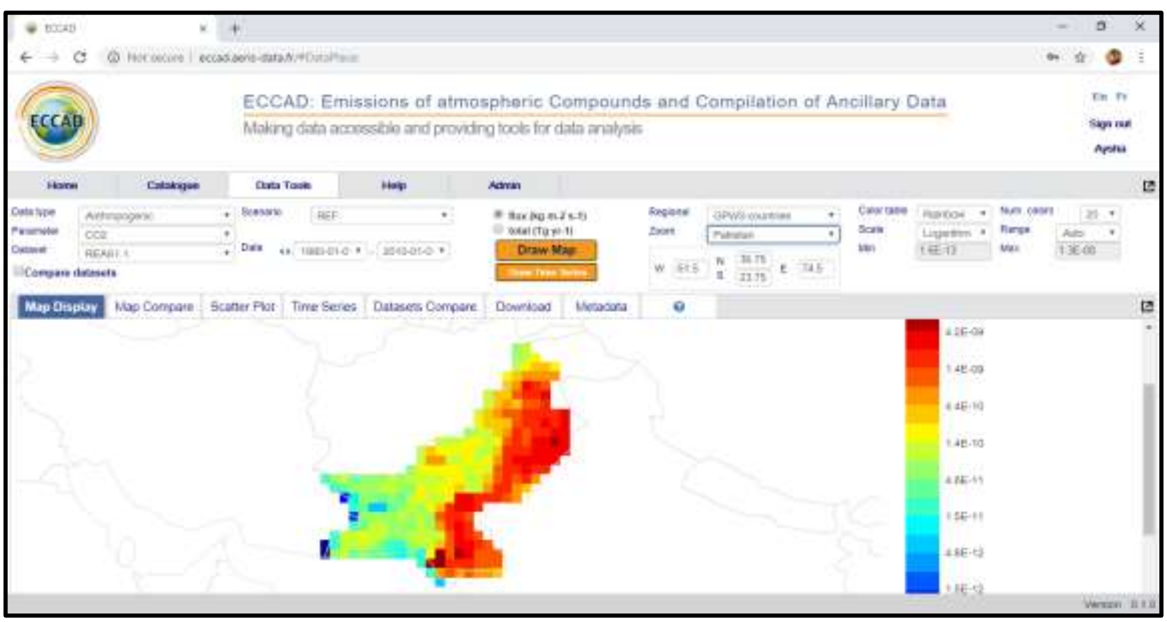


Figure 3.1. REAS data retrieval from ECCAD database

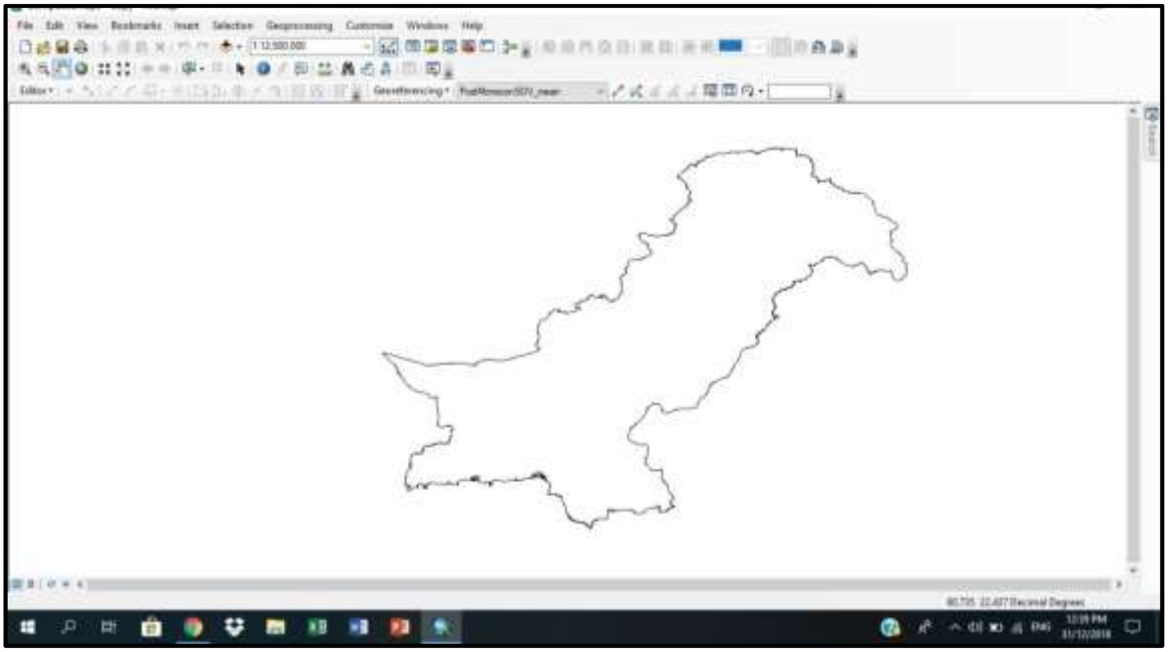


Figure 3.2. Satellite Observations for CO_2 emissions extraction over Pakistan in ArcGIS

3.3.2. Unit Conversions

First the units for REAS datasets were converted from kg/m^2/s to kilotons (kt), for every year, to make it align with the other inventories data. It was unit conversion where kilogram was converted to kilotons. Additionally the time was changed from second to year and the area (m^2) was taken that of Pakistan.

Satellite data for CO_2 emissions, available in moles, was converted to parts per million (ppm). The conversion was done by multiplying the moles with a million (10^6).

$$\textbf{Concentration in ppm} = \textbf{Concentration in moles x } \mathbf{10^6}$$

Then the satellite data (ppm) was converted from ppm to kiloton so that a proper comparison can be done of satellite data with the inventory data (which is in kilotons) after the correlation. The formula is given below:

$$\textbf{Concentration in mg/m}^3 = \frac{\textbf{Conc. in ppm x Molecular Weight}}{\textbf{Air at STP}}$$

(Source: http://www.aresok.org/npg/nioshdbs/calc.htm)

Concentration in mg/m^3 was converted to kt/m^3 and multiplied by volume to get the concentration in kton. Volume for Pakistan was taken as:

Area for Pakistan = 796096 km^2 or 7.9×10^{11} m^2

Height = 150m (Existing Stack Height) (Engconsult Ltd., 2012).

Volume = 1.185×10^{14} m^3

3.3.3. Correlation and Comparisons

The inventories and their respective sectors were compared and analyzed. The inventories were correlated with the independent variables selected for the study. The satellite data and inventories data were also correlated and the results were duly recorded. Microsoft Excel was used for correlation and comparisons.

Correlation is when we try to find statistical relation between two variables. It is used to measure the linear relationship as well as the direction between two continuous variables. By better understanding the relationships between variables we can carry out our data analysis and modeling. When the variables are increasing or decreasing together than the correlation is positive. When both variables are moving in opposite directions than the correlation is negative. Correlation can be neural or zero, when no relationship between the variables is found. (Correlation, 2006)

3.3.4. Trend Test

The trend test is widely used to identify if the trend is significant in time series data. Man-Kendall test was employed for identifying the significance of the trend of available datasets. It is a trend test that has been extensively used on climate data, hydrological data and environment data. The main purpose is to check if the values of a time series increase or decrease with the increase in time (Pohlert, 2016).

For the test we assume that:

The null hypothesis, H_0 = no significant trend is present

The alternative hypothesis, H_a = significant trend is present

H_a is accepted in the case when the p-value is less than the significance value; 0.05. In this study the Mann Kendall test was performed in Excel Stat as shown in figure 3.3 to check the significance of the trends of the datasets.

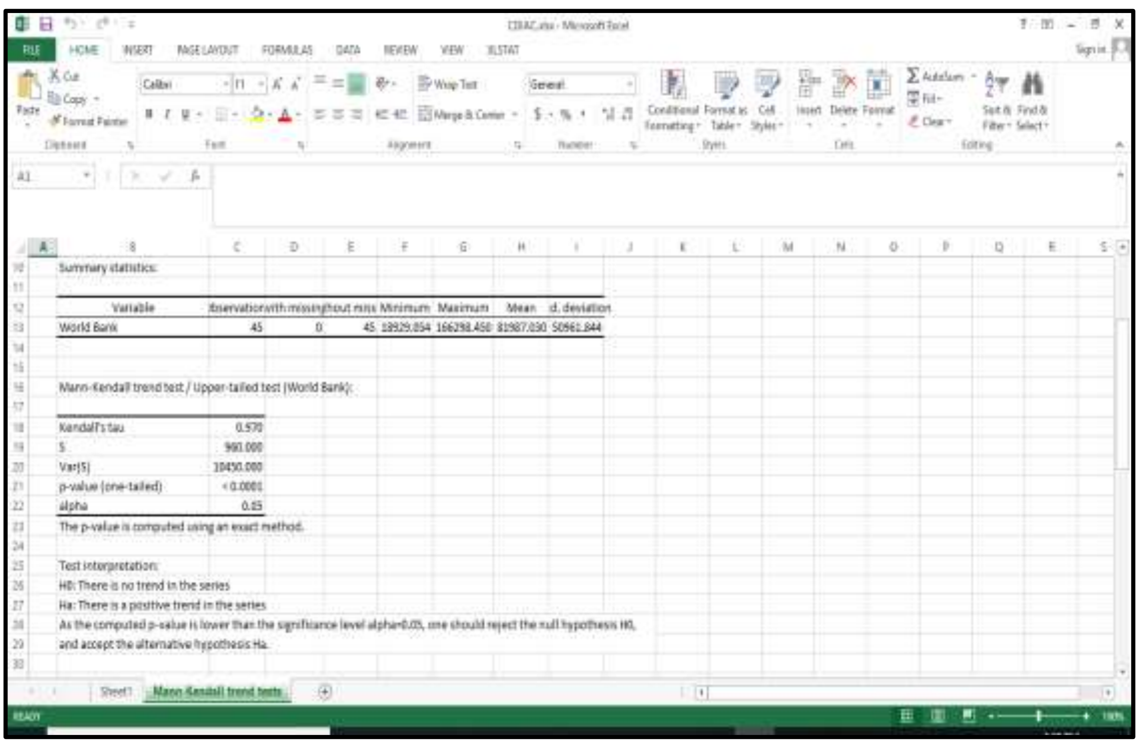


Figure 3.3. Mann Kendall Test employed in Excel Stat

3.3.5. ARIMA

ARIMA model was chosen because of its flexibility, worldwide applicability and acceptability. Though this model has not been commonly used for Pakistan CO_2 emissions, it is being widely used for the forecast of time series data for many other countries. According to ARIMA forecast technique the variable current values depend upon its own lags along with the current and previous lags of the white noise error term of that variable (Nawaz *et al*., 2018).

ARIMA are univariate time series models based on ARMA Model. The ARMA model is used in the case when the datasets are already stationary on the other hand ARIMA model is used when the datasets are not stationary. The ARIMA models were first employed by Box and Jenkins and are sometimes called Box-Jenkins models (Box & Tiao, 1975). The typical steps involved in ARIMA model are model selection, parameters calculation, and lastly the forecast (Mondal *et al*., 2014).

The AR(p) model means Auto-Regressive model of order p (Yuan *et al*., 2016). The equation is:

$$\mathbf{y_t = b + \varphi_1 b_{t-1} + \ldots + \varphi_p b_{t-p} + b_t} \qquad \textbf{(i)}$$

Where:

$\varphi_1 \ldots \varphi_p$ = Model parameters

b = Constant

b_t = Error/Noise

The MA(q) model means Moving Average model of order q. the equation is:

$$\mathbf{y_t = b + \theta_1 b_{t-1} + \ldots + \theta_q b_{t-q} + b_t} \qquad \textbf{(ii)}$$

Where:

$\theta_1 \ldots \theta_q$ = Model parameters

μ = Expectation of y_t (usually assumed as 0)

b_t, b_{t-1}, …, and b_{t-q} = Error/Noise

The ARMA (p, q) is a combination of both AR (p) and MA(q) models. The equation is as follows:

$$\mathbf{y_t = \mu + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots. + \varphi_p y_{t-p} + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \ldots. + \theta_q u_{t-q} + u_t} \qquad \textbf{(iii)}$$

If the variables are not stationary at the level then dataset is differenced, and the ARMA model is converted into ARIMA (Nawaz *et al.,* 2018). ARIMA model is a non-seasonal model which is employed on yearly data. It is also written as ARIMA (p,d,q) model where p,d,q are non-negative integers (Nau, 2018), where:

p = the autoregressive terms, the (AR) part

d = the differences needed to make data stationary, the (I) part

q = the errors present in the equation, the (MA) part.

R Studio was used for employing ARIMA in this study as shown in figure 3.4. First, the datasets were imported and made stationary as all our datasets were not stationary. Augmented Dickey Fuller test was employed, developed by Dickey and Fuller (Dickey & Fuller, 1979), to check the stationarity. The data is differenced to make it stationary and optimal parameters (p,d,q) are determined.

The ACF (autocorrelation function) and PACF (partial autocorrelation function) were checked whether the model selected by Akaike Information Criteria (AIC) technique is suitable. The AIC is an important measure of a statistical model. It checks the goodness of fit of the model. Usually a model with lowest AIC value is chosen because it is considered almost similar to the real data. AICc is the correction of AIC and for selecting best fit model AIC/AICc has been deemed more beneficial than using BIC (Bayesian Information Criterion) (Anderson, 2008). The best fit model was then employed for the forecast. After the forecast, the accuracy of the model was checked by Mean Absolute Percent Error (MAPE) and by calculating Mean Absolute Error (MAE) (Mondal *et al.*, 2014).

3.3.6. CO_2 Emissions Scenarios

This study not only forecasts the business as usual (BAU) CO_2 emissions scenario till 2030 but also forecast emissions in case of four other scenarios. These scenario have been developed for the first time in case of Pakistan. The CPEC scenario holds more significance as it is based on real case scenario. The scenarios used and developed for this study are listed:

a. CPEC scenario, when coal based energy projects under CPEC will be operational. The high priority energy projects which would be operational by 2020 were selected and the CO_2 emissions were calculated from their energy generating capacity (Amin, 2018). Theses emissions were added in the BAU scenario and then the forecast was done till 2030.

b. 40% increase in BAU scenario was developed to show what is likely to happen by 2030 if the country increase its investment in non-renewable energy projects such as coal based projects.

c. 20% increase in BAU scenario try to show what is likely to happen by 2030 if the country invest equally in renewable energy projects along with the coal based projects.

d. 20% decrease in BAU scenario try to show what is likely to happen if the country gives attention towards initiating mitigation projects and make an effort to curb its emissions as pledged in its submitted INDCs.

e. An ideal scenario was also developed where emissions were reduced by 40%, to show what can happen if the country decides to replace its major chunk of energy mix from coal based to renewable and green energy.

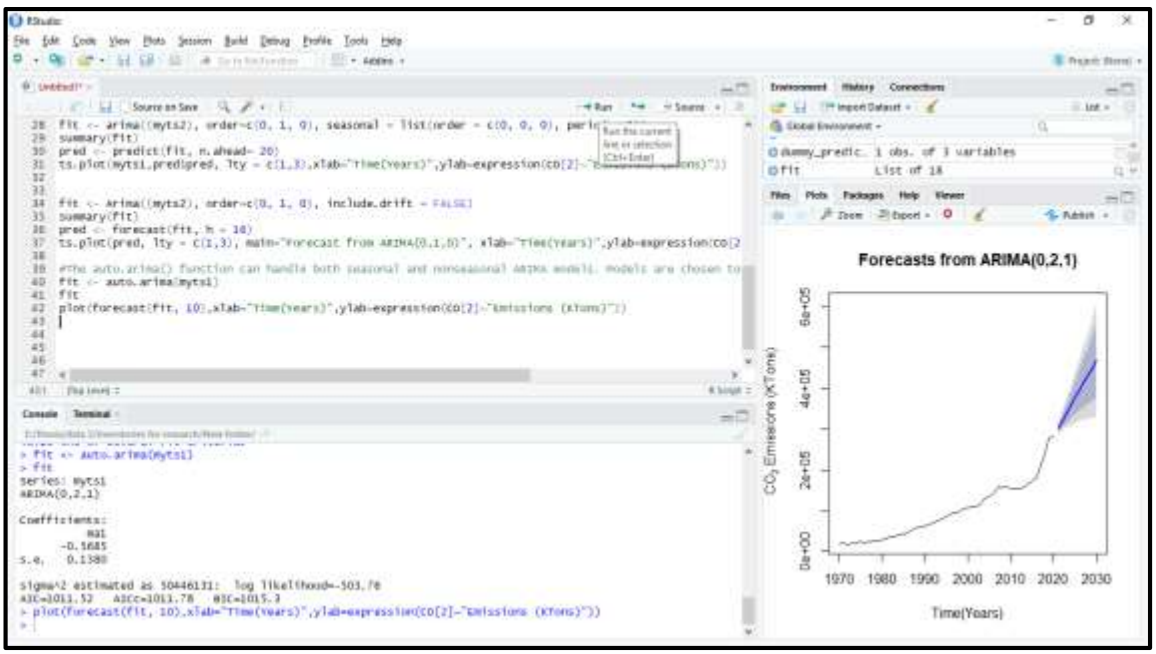


Figure 3.4. ARIMA models employed in R Studio

CPEC Scenario was developed, where the energy production data from the new coal Power energy projects were added in the business as usual scenario. The Coal Power Plants under the CPEC would contribute 6900 MW of the total 10,187 MW (68%). All the high priority projects would be operational by 2020 in Pakistan (Amin, 2018). The energy production data (MW) was converted to CO_2 equivalent as 1KWh = 1689g CO_2 equivalent (IPCC

Report, 2011). The additional CO_2 emissions were added in the current emissions and the data was extended till 2020. ARIMA model was then employed on the developed scenario and the emissions were forecasted till 2030. At the end percent relative change for all the forecasts was computed.

3.3.6. Regression Analysis

As the three inventories were highly correlated therefore the CO_2 dataset for EDGAR inventory was subjected to Regression analysis by using three independent variables as discussed above:

1. Fossil fuel Energy
2. Cement Production
3. Energy Production

First the unit root test was executed on the CO_2 datasets as well as the independent variables selected, to check the stationarity. After which the type of statistical model was chosen depending on the stationarity. The regression model varies with the number of differences taken to make the datasets stationary. All the datasets were stationary at order one i-e after the first difference I(1). This satisfies the condition for OLS regression. The ordinary least squares is a form of linear regression and the equation for multi linear regression is given (Fumo & Biswas, 2015):

$$\mathbf{y_i = b_o + b_1x_1 + b_2x_2 \ldots. + b_px_p + e}$$

Where, y_i = Response Variable

b_o = Estimate of regression intercept (constant)

b_1, b_2, b_p = Regression Coefficient

x_1, x_2, x_p = Predictor Variable

e = Error term (divergence between observed and predicted values)

After regression, unit root test was executed on the residuals to check if they were stationarity or not. Residual (r) is the error term which is computed by taking the difference between the observed value (x) and the predicted value (x_o) of the dependent variable. All the data points have their respective residuals.

Residual = Observation - Prediction

$$\mathbf{r = x - x_o}$$

Stationary residuals indicate that the ordinary least squares is the correct model chosen to carry out the regression. The unit root test employed for this study was augmented dickey fuller test (ADF). All these analysis were performed in Stata as shown in figure 3.5.

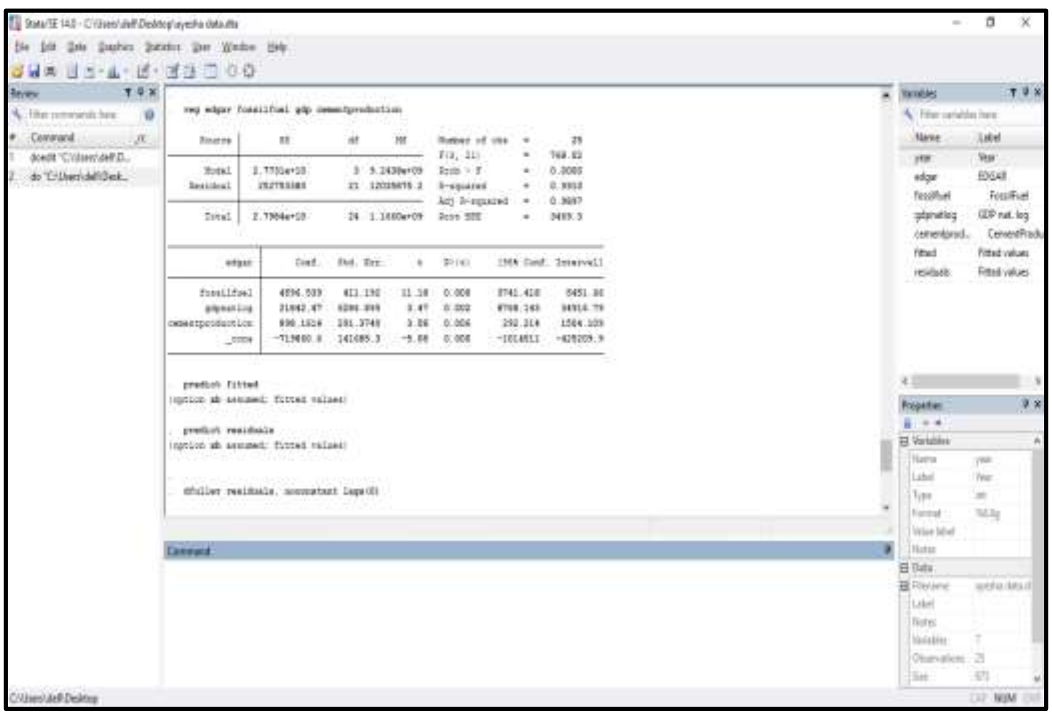


Figure 3.5. Regression Analysis employed in Stata

3.3. Methodology Flow Chart

The study was commenced in the manner explained by the flow chart given below.

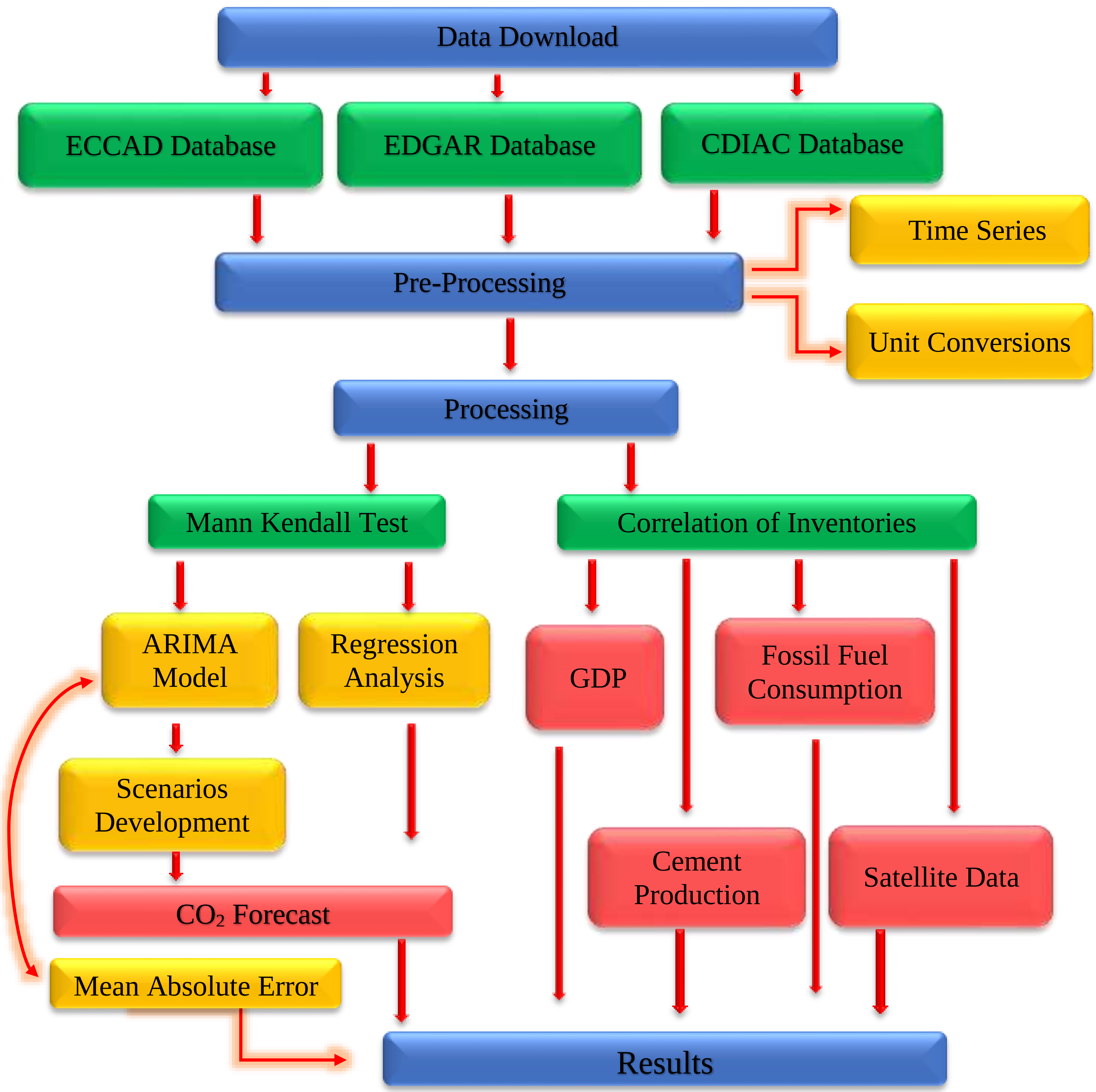


Figure 3.3. Flow chart of the study highlighting the methods and materials used to carry out the study

Chapter 4

Results and Discussion

4.1. CO_2 Emissions trend for Pakistan

The total CO_2 emission of the global emission inventories for Pakistan can be seen in figure 4.1. The datasets from all inventories clearly indicate that the CO_2 emissions have increased manifolds since 1970. The statistical summary of the datasets is given in the table 4.1.

Table 4.1. Statistical Summary of the Inventories Datasets

Variables	Observations	Minimum (kt)	Maximum (kt)	Mean	Std. deviation
CDIAC	43	18929.1	166298.5	84697.7	50512.4
EDGAR	46	18827.2	174843.4	81958.2	51585.7
REAS	31	25353.7	158397.8	77955.6	37804.7

The anthropogenic emission data, for different sectors and for different fuel types, was available for EDGAR and CDIAC respectively. CDIAC sector wise emission data clearly indicate that the liquid and gas fuels are the major sources of CO_2 emissions, followed by solid fuels. EDGAR sector wise data indicates that the energy, transport and residential sectors as well as manufacturing industries are the main CO_2 emissions sources. Figure 4.2

gives the assessment of sector wise emissions record for Pakistan whereas the pie charts given in figure 4.3 gives their relative percentage.

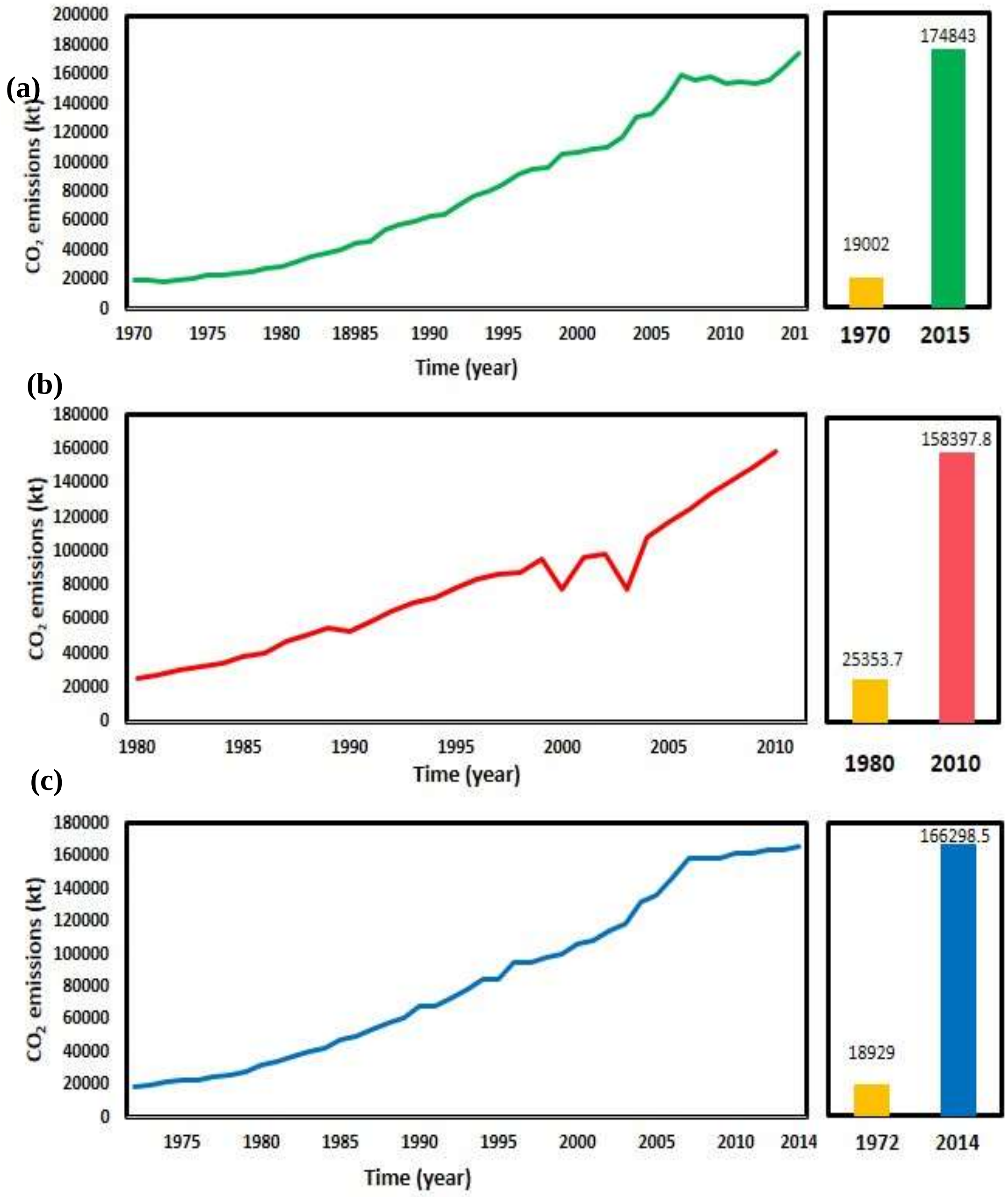
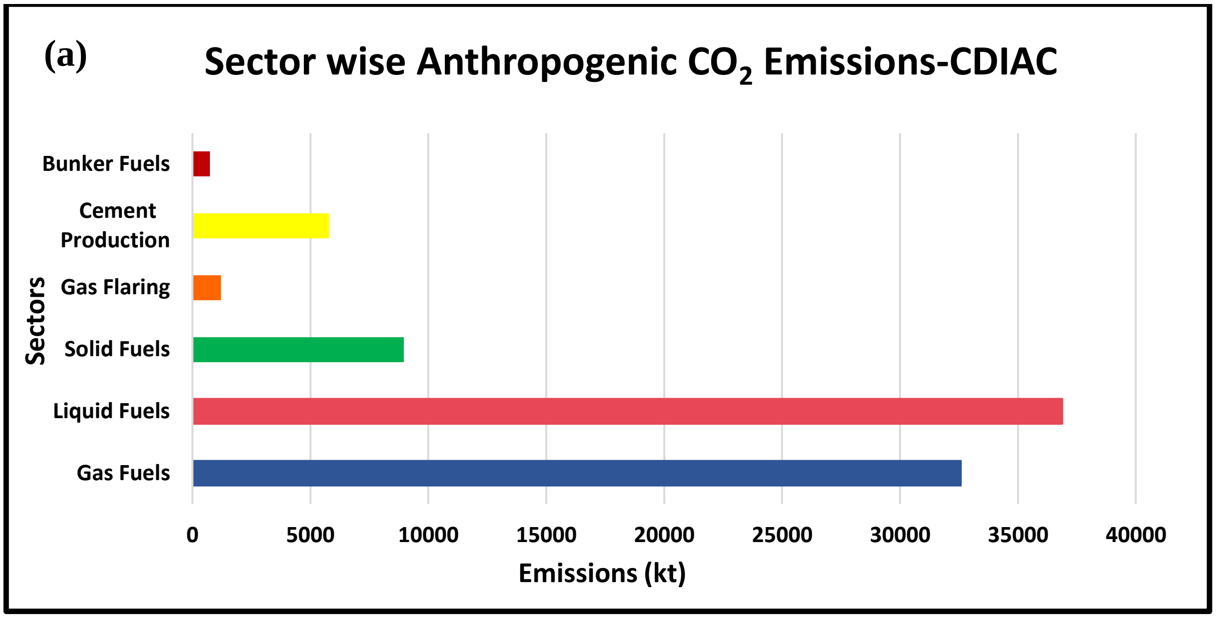


Figure 4.1. Time series of the inventories (a) CO_2 emissions for Pakistan from 1970 to 2015-EDGAR Inventory (b) CO_2 emissions for Pakistan from 1980 to 2010-REAS Inventory (c) CO_2 emissions for Pakistan from 1972 to 2014-CDIAC Inventory



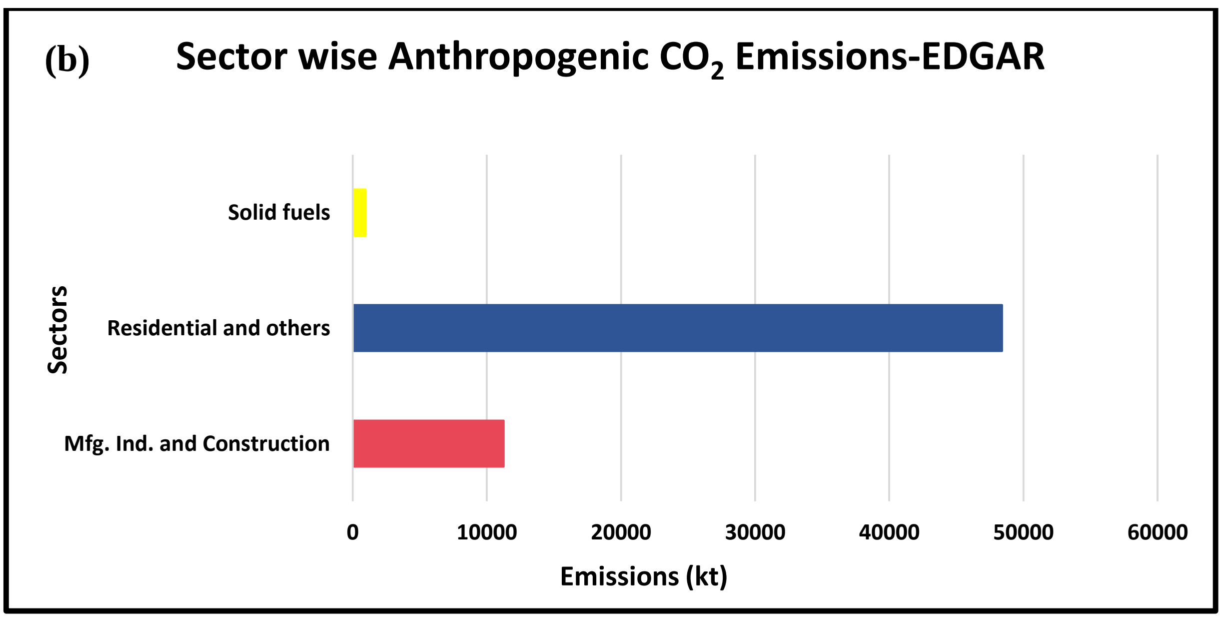


Figure 4.2. Sector wise emission data available for the inventories (a). Anthropogenic CO_2 emissions in Pakistan-CDIAC (b). Anthropogenic CO_2 emissions in Pakistan-EDGAR

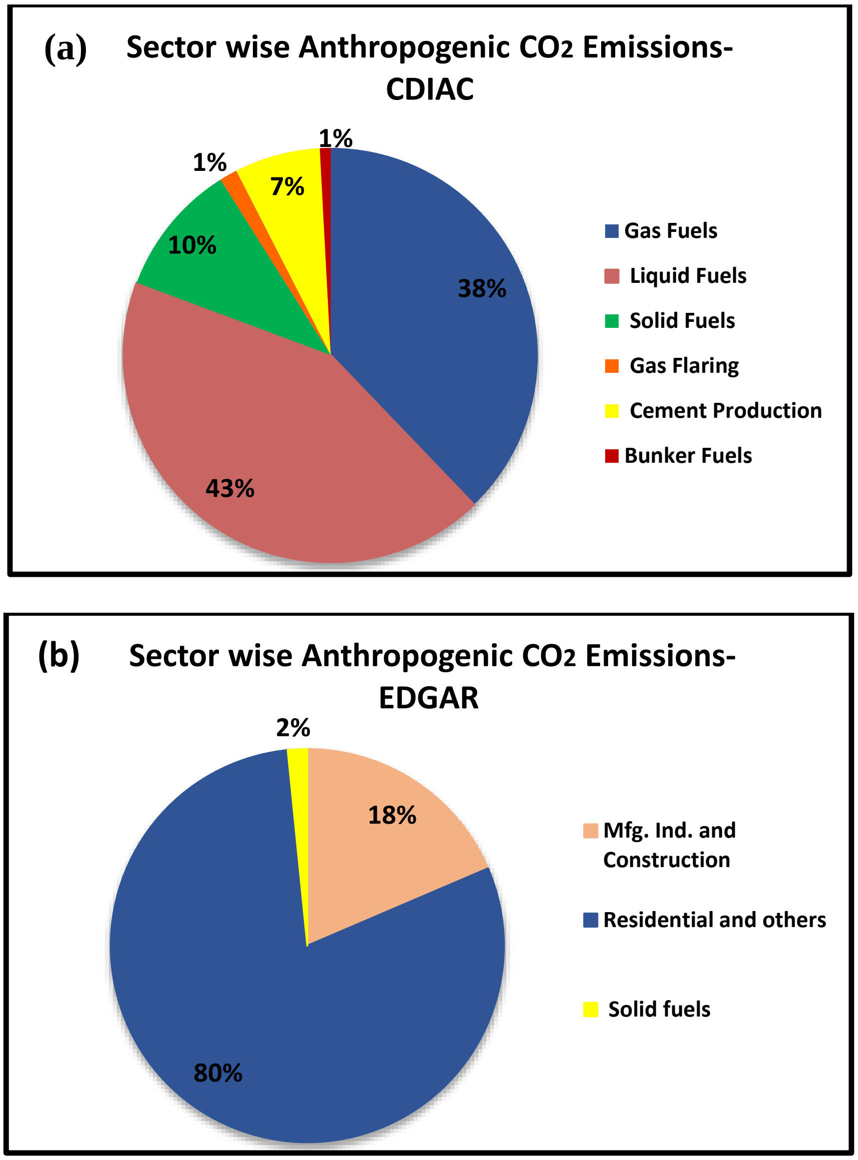


Figure 4.3. Pie Charts for anthropogenic sector wise CO_2 emissions in Pakistan (a). For CDIAC inventory (b). For EDGAR inventory

4.2. Correlations of Inventories Datasets with Satellite Observations and Independent Variables

The correlation of all the inventories with each other was calculated. As indicated by table 4.2(a) the inventories are highly correlated with each other. The correlations between inventory and satellite data and the inventories with the independent variables were also computed. The results indicate that all the datasets are highly correlated; with the satellite data as well as with the variables chosen for the study. The results of correlation of satellite data with inventory data are given in the table 4.2(b). The results of correlation of independent variables with inventory data are given in the Table 4.2(c).

Table 4.2(a). Correlation among the Inventories Datasets

Inventories	EDGAR-CDIAC	EDGAR-REAS	REAS-CDIAC
Correlation	0.99	0.98	0.98

Table 4.2(b). Correlation between Satellite Observations and Inventories Datasets

Inventories	CDIAC	EDGAR	REAS
Satellite Data	0.87	0.81	0.87

Figure 4.4 shows the comparison of the inventories datasets with the fossil fuel consumption for Pakistan whereas figure 4.5 shows the comparison of inventories datasets with total energy production of Pakistan and lastly figure 4.6 shows the comparison of the inventories datasets with the cement production for Pakistan.

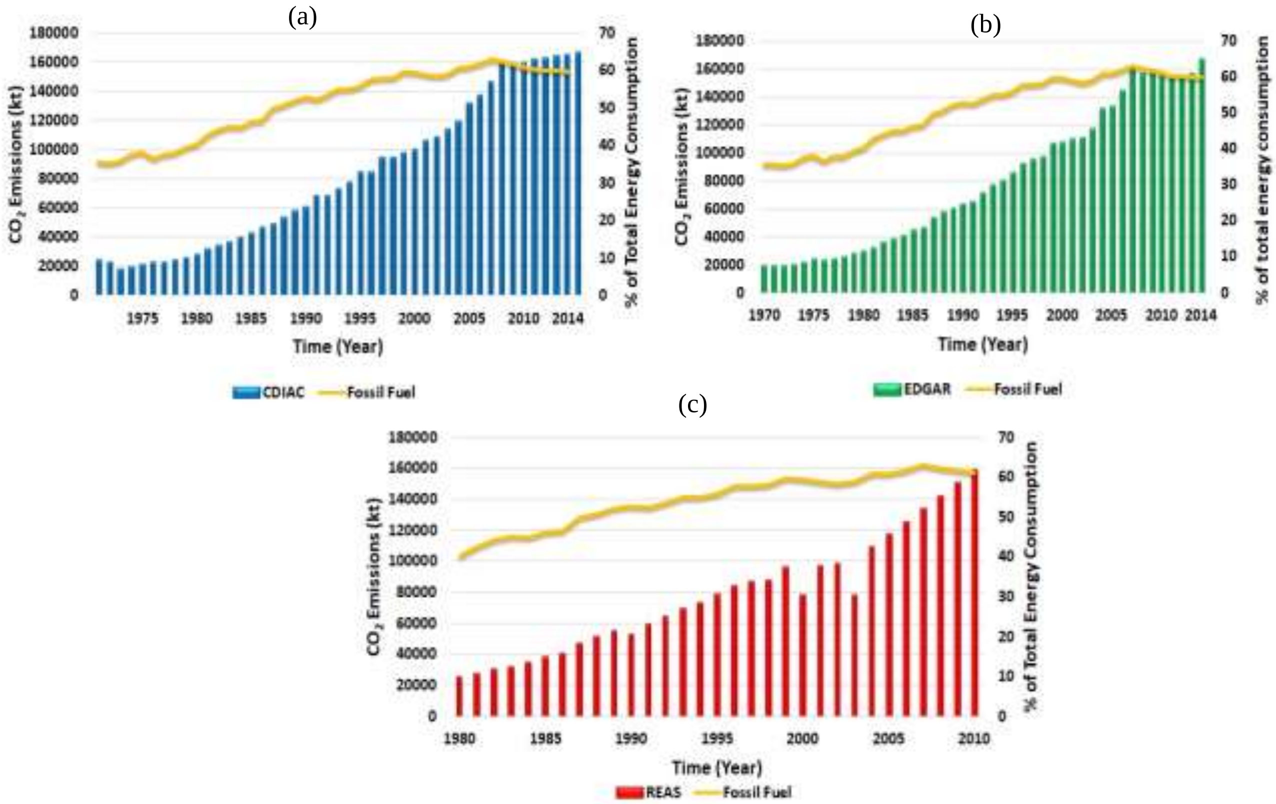


Figure 4.4. The graphs showing the relationship between the CO_2 Emission (kt) and fossil fuel consumption (% of total energy consumption) for Pakistan (a) for CDIAC (b) for EDGAR (c) for REAS

Table 4.2(c). Correlation of Predictor variables with the Inventories datasets

Variables	CDIAC	EDGAR	REAS
Fossil Fuel Consumption	0.92	0.93	0.91
Cement Production	0.95	0.94	0.94
Energy Production	0.98	0.98	0.95

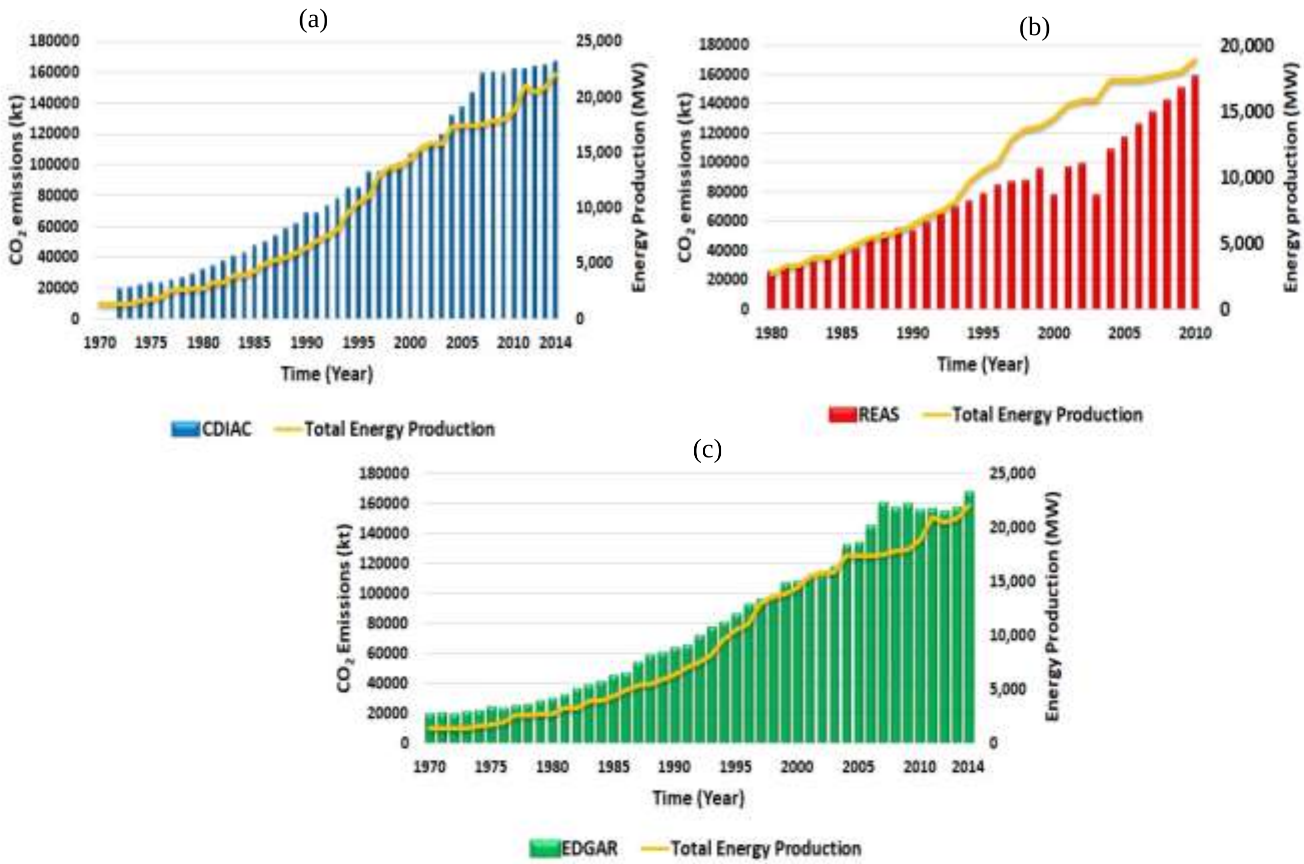


Figure 4.5. The graphs showing the relationship between the CO_2 Emission (kt) and total energy production (MW) for Pakistan (a) for CDIAC (b) for REAS (c) for EDGAR

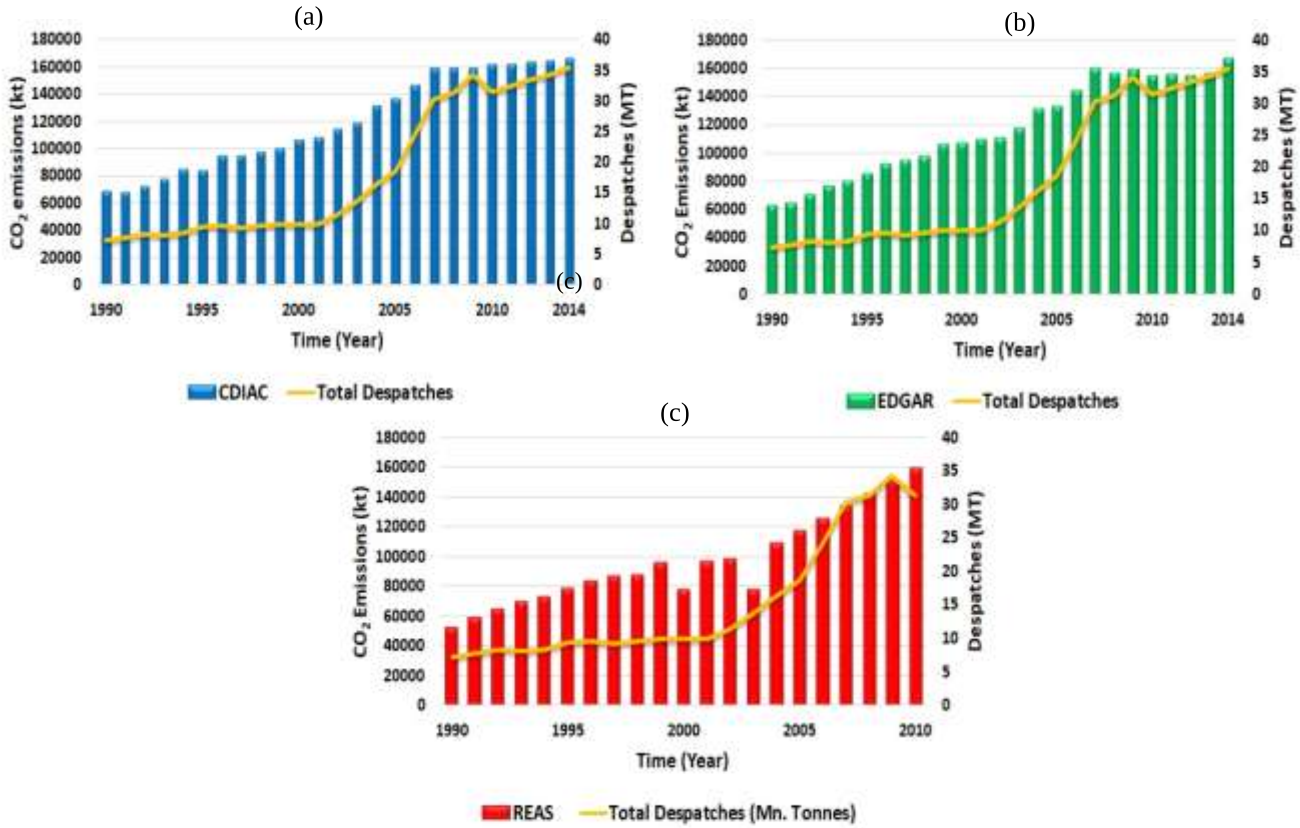


Figure 4.6. The graphs showing the relationship between the CO_2 Emission (kt) and cement production (Million tons) for Pakistan (a) for CDIAC (b) for EDGAR (c) for REAS

Satellite data units were converted from ppm to kilotons to make it more align with the inventories data. As satellite data was monthly therefore yearly averages were taken for the satellite and inventories data comparison. The comparison is given in figure 4.7 below. In principle the satellite emissions should be more than the inventory emissions. In this case all the inventories data shows higher CO_2 emissions in comparison with the satellite data. The reason is that for satellite data we have taken the height only 150 meters (existing stack height in Pakistan) therefore the emissions under this height is lower.

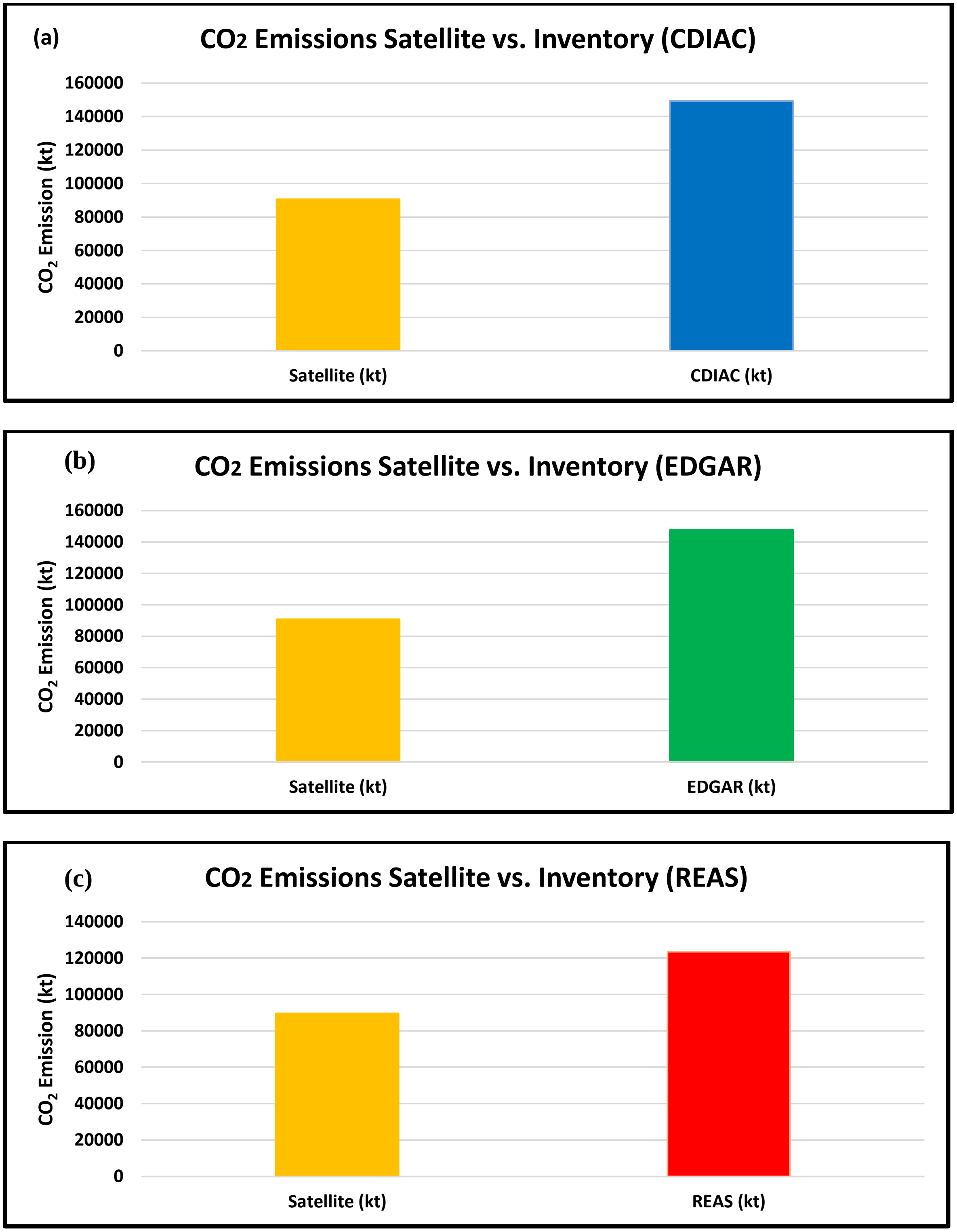


Figure 4.7. Comparison between Satellite observations and Inventory data (a) Satellite and CDIAC inventory comparison (b) Satellite and EDGAR inventory comparison (c) Satellite and REAS inventory comparison

4.3. Mann Kendall Test

The Mann Kendall test was employed on the datasets in Excel Stat and the results were recorded accordingly. The test results show that the observed trends are statistically significant for all the datasets. The p-value was less than 0.05, therefore alternative hypothesis (H_a) was acceptable, which was the existing temporal trends in the time series. The results for the test are given in the table 4.3. After checking the significance of the datasets, we applied the statistical tests on them.

Table 4.3. Mann-Kendall trend test / Upper-tailed test

Trend/Upper Tailed Test	**EDGAR**	**REAS**	**CDIAC**
Kendall's tau	0.965	0.943	0.97
p-value (one-tailed)	< 0.05	< 0.05	< 0.05
Alpha	0.05	0.05	0.05
H_0	Rejected	Rejected	Rejected

4.4. ARIMA Model

After checking the significance of the trend by using Mann Kendall test, ARIMA was applied on all the three inventories in R Studio. Augmented Dickey-Fuller test checked the stationarity of the datasets. All the datasets were not stationary therefore the data was made stationary by taking the required differences. For CDIAC the data was stationary after second difference whereas for EDGAR and REAS the data was stationary only after first difference. The best fit model was applied on the respective inventories datasets and forecast was done till the year 2030. Mean Absolute Percent Error was noted and Mean Absolute Error (MAE) was calculated as calculated by Mondal et al., 2014. The detail of the ARIMA model types of the datasets and their respective errors are shown in the table 4.4.

Table 4.4. ARIMA models for Inventories and the respective errors

Inventory	Model (p,d,q)	MAE	MAPE
EDGAR	(0,1,0)	3.3	4.6
CDIAC	(0,2,1)	8.2	3.8
REAS	(0,1,1)	21.3	6.3

The plots of differenced inventories datasets are shown in figure 4.5 and the plots of the forecast done by ARIMA models for respective inventories are shown in figure 4.8. The forecast plots of all inventories clearly show that the CO_2 emissions are steadily increasing till 2030.

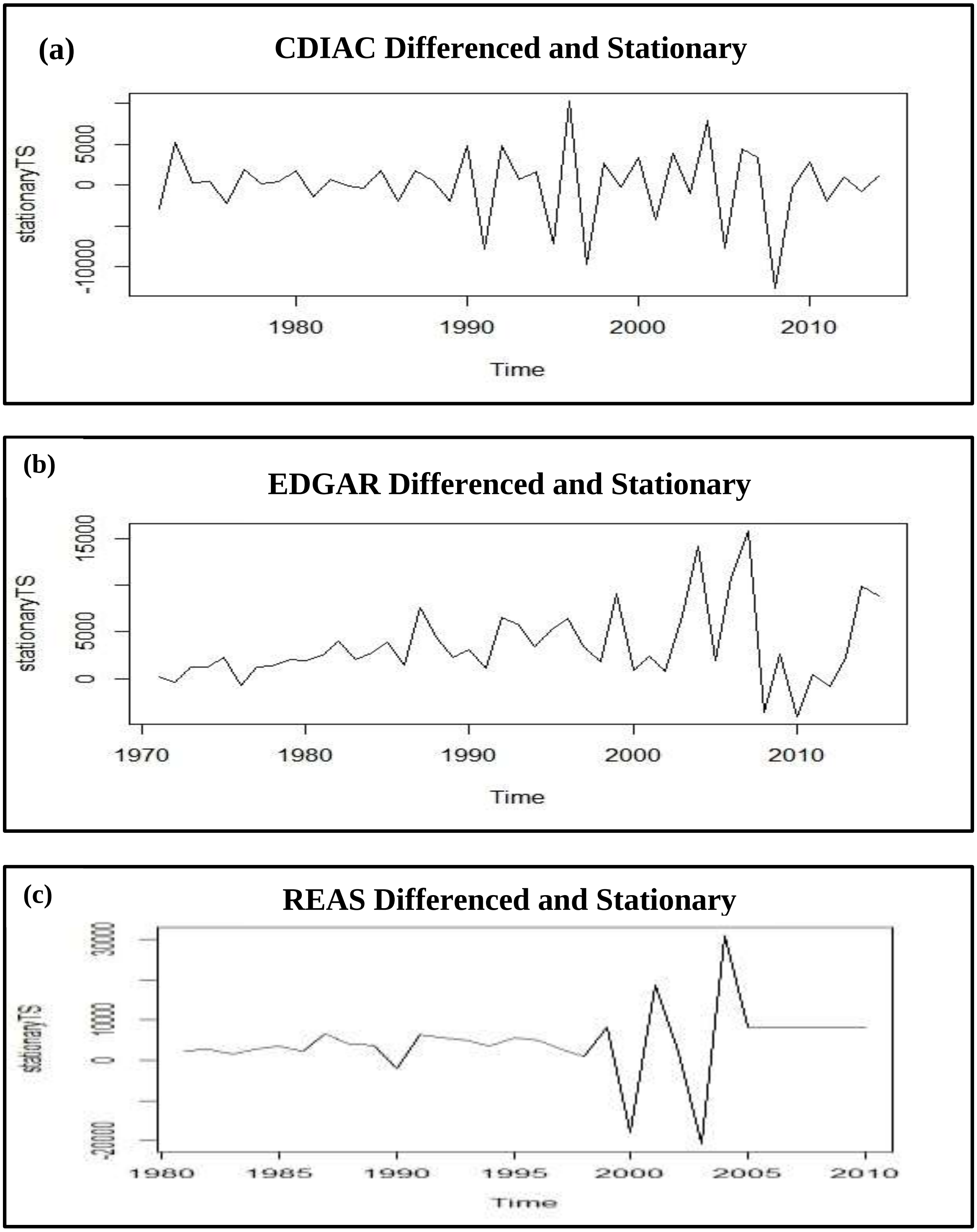
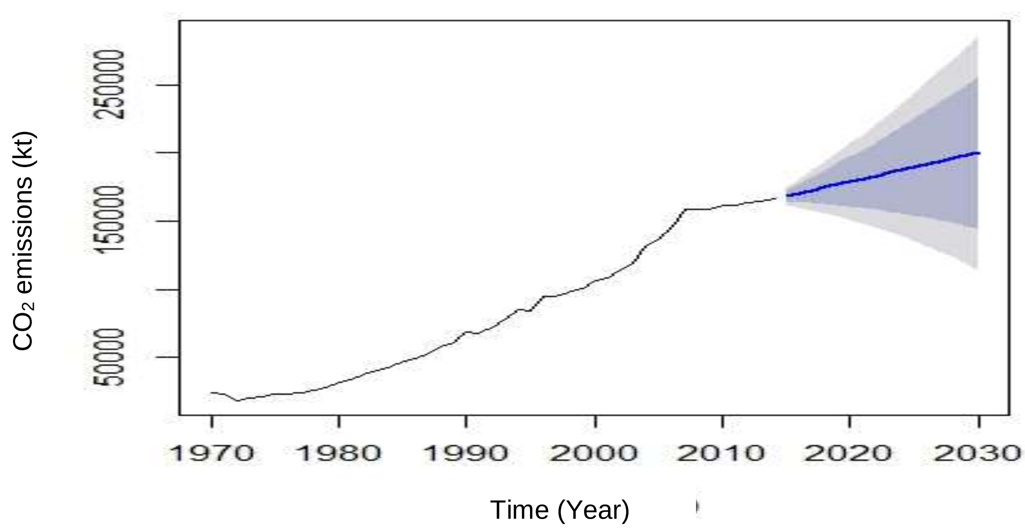
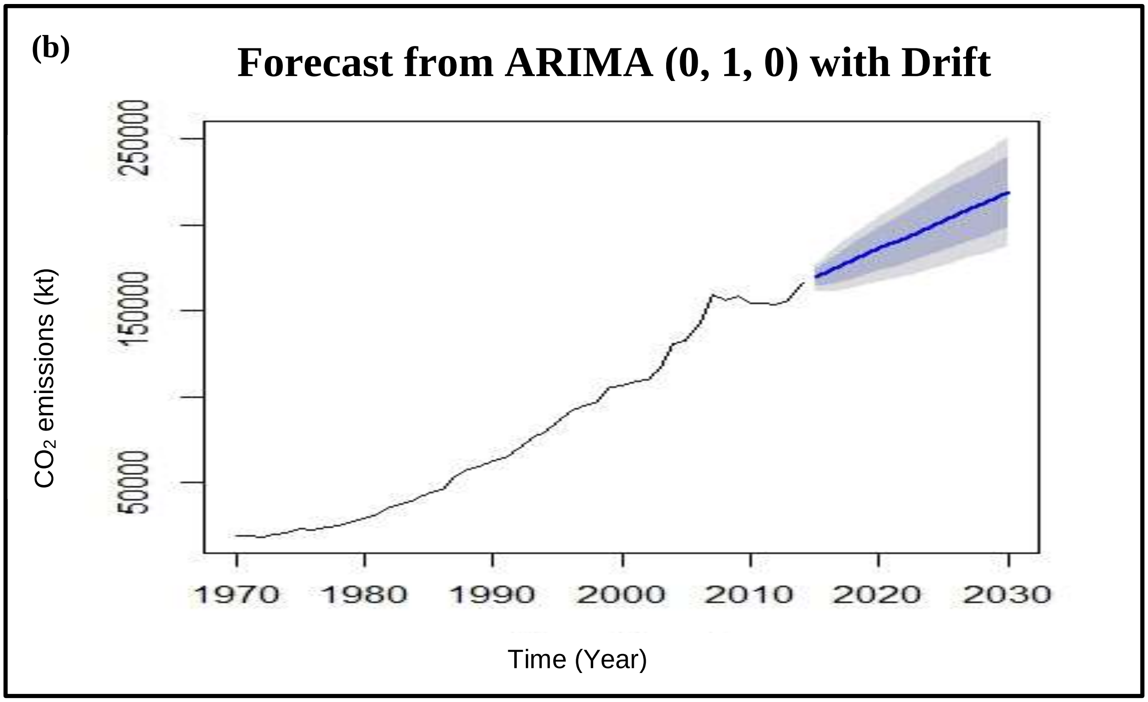


Figure 4.8. The plots of differenced inventories datasets (a) differenced dataset of CDIAC (b) differenced dataset of EDGAR (c) differenced dataset of REAS

As seen from figure 4.9 for EDGAR the baseline emissions were 174843 Kton and the projection shows that emissions will increase up to 226790 Kton by the year 2030. For REAS the baseline emissions were 158397.7 Kton and the projected emissions will increase up to 243893.6 by the year 2030. And lastly for CDIAC the baseline emissions were 166298.5 Kton and the projected emissions will increase up to 200288.6 Kton by 2030. These projections are for the business as usual scenario. The lines around the forecast shows the confidence interval of the forecast at 95% and 80%.

(a) **Forecast of CO_2 emissions from ARIMA (0, 2, 1)**





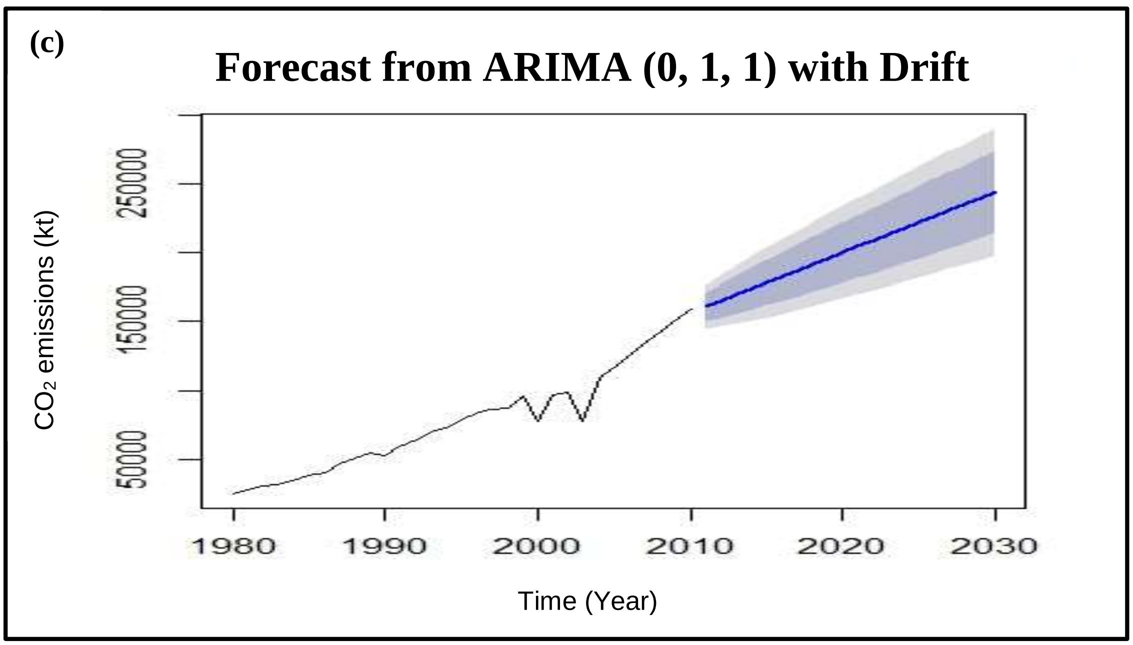


Figure 4.9. The forecast till 2030 by ARIMA models on the respective inventories (a) The forecast according to ARIMA (0, 2, 1), best selected model for CDIAC Inventory (b) The forecast according to ARIMA (0, 1, 0) with drift, best selected model for EDGAR Inventory (c) The forecast according to ARIMA (0, 1, 1) with drift, best selected model for REAS Inventory. The shaded area shows confidence interval at 95% and 80%.

4.5. CO_2 Emission Scenarios of Pakistan

Different scenarios were developed on the EDGAR inventory data. EDGAR was chosen for the scenarios development as the emission inventories were highly correlated. CPEC scenario was added to baseline emissions to give it a real case scenario as CPEC projects are currently underway. The new coal based energy projects will increase the 2015 CO_2 emissions by approximately 60%. Then ARIMA model was employed to the developed scenario.

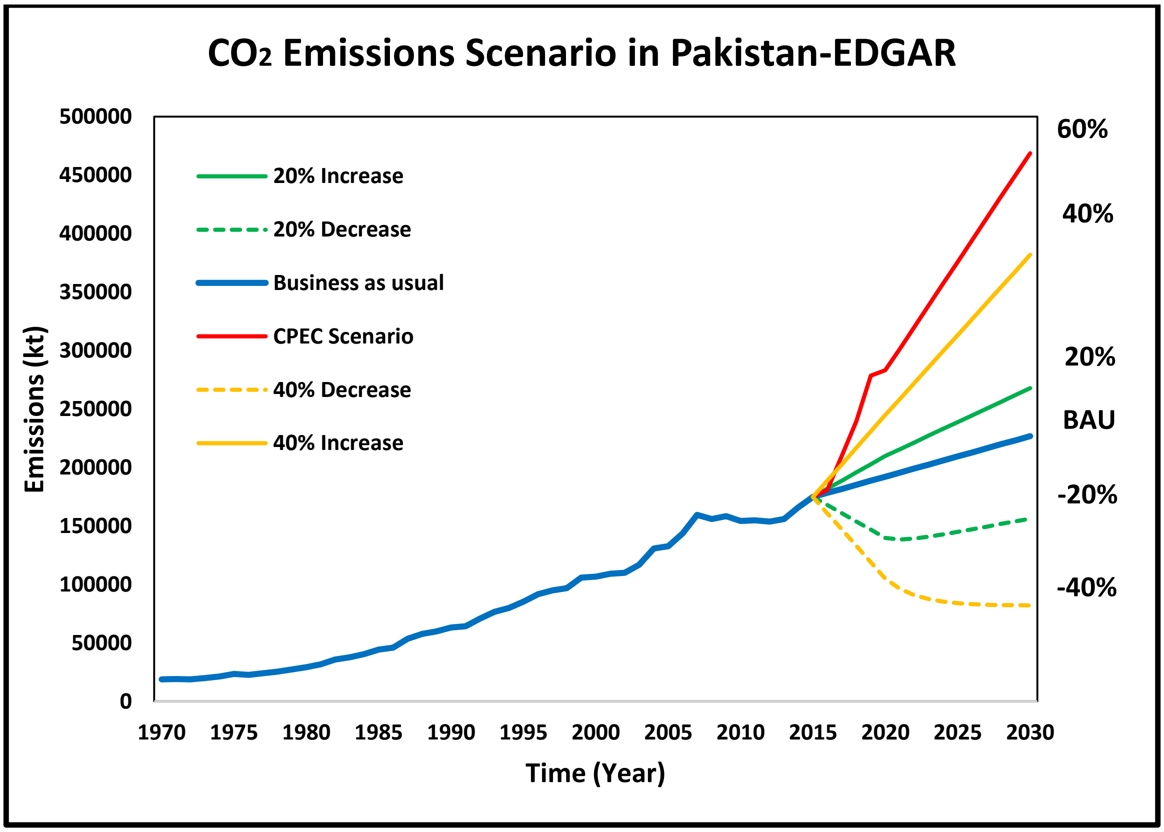


Figure 4.10. CO_2 emissions Scenarios developed for EDGAR inventory and their forecasts. The scenarios include Business as usual (BAU) scenario, CPEC scenario, 20% increase and decrease scenarios and 40% increase and decrease scenarios

Figure 4.10 shows that the CPEC and 40% increase in BAU scenarios will lead to a substantial increase in the CO_2 emissions by 2030. This indicates that the current policies and projects would not help us to curb our CO_2 emissions and immediate measures are required to avoid this situation in the near future. 20% increase in baseline emissions suggest that the emissions increase by 2030 would not be huge therefore coal power projects should be made green and more investments should be made in the renewable energy projects. 20% decrease in the baseline emissions show that the emissions first that the 20% decrease in the baseline emissions would not be enough and impactful in the overall emissions decrease. Therefore the implementation of mitigation strategies alone would not be enough and there is a need to invest in renewable and green technologies that would help to curb the emissions efficiently. 40% decrease in the baseline emissions shows that the predicted emissions are showing a significant decrease in the CO_2 emissions and then it is stationary by 2030. This suggests that the mitigatory efforts and renewable projects will prove to be efficient to help the country reduce its emissions. As evident from the graph the 40% reduced emissions will take the country's CO_2 emissions back to 1990s emissions level. If we want to achieve the carbon neutral mark in our energy sector then more than 40% decrease in the BAU is required. Therefore we can say that the country can make its energy sector carbon neutral in a matter of few years, if appropriate measures are taken.

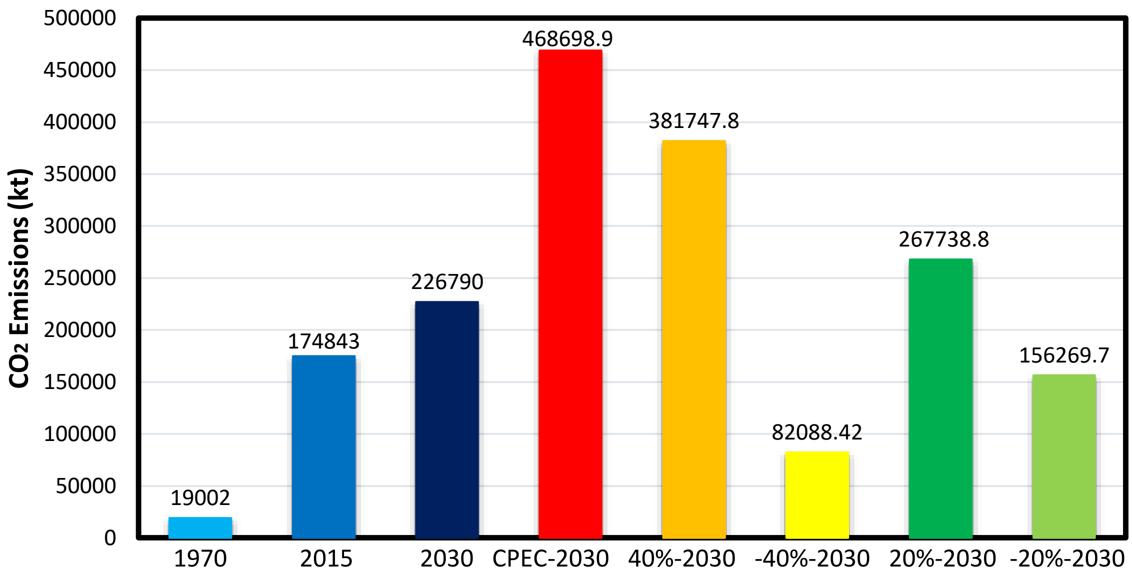


Figure 4.11. The graph shows the CO_2 emissions for BAU scenario for the years 1970, 2015 and projected emissions for 2030. Projected CO_2 emissions for other scenarios are shown for the year 2030.

As mentioned above the projected emissions for EDGAR-BAU will increase up to 226790kt by 2030. The forecast for CPEC scenario shows that the emission by the year 2030 would be 468699 kt. Similarly the 20% increased emissions scenario will increase the CO_2 emissions to 267739 kt by 2030 whereas 20% decrease will decrease the CO_2 emissions to 156270 kt. A 40% increased emissions till 2020 show that the emissions will further increase up to 381747.8 kt. An ideal scenario, where emissions were reduced to 40%, was developed and ARIMA model was employed and the forecast shows that the emissions were significantly reduced to 82088.4 kt. These changes over the years for all the scenarios is shown the figure 4.11.

Table 4.5 (a) show the relative change of the CO_2 emissions of the inventories (as downloaded from the databases) and their respective forecast (till 2030). The relative change of modelled CO_2 emissions for EDGAR and CDIAC are 27% and 19%

respectively. For REAS it is higher because long term forecast was done (20 years) for it. Table 4.5 (b) shows the percent relative change of the CO_2 emissions scenarios, developed for EDGAR inventory.

Table 4.5(a). Percent Relative Change for Actual and Modelled Inventory data

Actual Emissions	Percent relative change (%)	Modelled Emissions	Percent relative change (%)
CDIAC (1972-2014)	673	**CDIAC (2015-2030)**	19
EDGAR (1970-2015)	820	**EDGAR (2016-2030)**	27
REAS (1980-2010)	525	**REAS (2011-2030)**	52

Table 4.5(b). Percent Relative Change of the Forecasts for EDGAR Scenarios

Scenarios	BAU	CPEC	20% Increase	20% Decrease	40% Decrease	40% Increase
% Relative Change	27	159	47	-6	102	-48.9

4.5. Regression Analysis for CO_2 Emissions

Due to the high correlation of all inventories, EDGAR inventory was taken again for regression. The statistical summary of the predictor variables and response variable is given in the table 4.6. The stationarity of the independent variables chosen for this study along with the CO_2 emission data was checked by ADF test.

Table 4.6. Statistical Summary of the Dependent and Independent Variables

Variables	Observations	Mean	Std. Dev.
EDGAR (kt)	25	117494.2	34146.9
Fossil fuel consumption (%)	25	58.6	2.9
Energy Production (MW)	25	14848.48	4657
Cement Production (M. Tons)	25	18.2	10.9

The null hypothesis H_0 indicates that dataset is not stationary. The test results for all variables showed that the absolute value of the test statistics Z(t) was less than the critical values therefore we cannot reject the H_0. The results for the ADF test for all variables are given in table 4.7.

Difference was taken of all the datasets to check at what level they will get stationary. It was found that all the independent variables and the dependent variable was stationary at I(1); after the first difference. This condition indicate that the type of regression suitable for the datasets would be ordinary least squares regression also known as OLS Regression. Hence OLS regression was employed on the datasets. Table 4.8 shows the outcomes for the OLS regression.

Table 4.7. Results for Augmented Dickey Fuller test for the unit root for all the variables

Variables	Test Statistics Z(t)	1% Critical Value	5% Critical Value	10% Critical Value
EDGAR	-0.75	-3.75	-3	-2.63
Fossil fuel	-2.19	-3.75	-3	-2.63
Energy Production	-1.041	-3.75	-3	-2.63
Cement Production	0.556	-3.75	-3	-2.63

Table 4.8. Results for OLS Regression

EDGAR	Coefficient	P-value	[95% Conf. Interval]
Fossil Fuel	3625.365	< 0.05	2988.8 4261.9
Cement Production	1456.818	< 0.05	1297.5 1616.2
Energy Production	2.072814	< 0.05	1.5 2.6
Constant	-152095	< 0.05	-184089.2 -120101.3

The results as shown in table 4.8 clearly show that all the independent variables are responsible for the CO_2 emissions. The P-value is less than the significant value 0.05 for all variables; fossil fuel, energy production and cement production. It infers that the regression model can be used for forecasting CO_2 emissions for the datasets used.

The coefficients indicate that for one unit increase in the fossil fuel consumption the CO_2 emissions will increase by 3625.4 kt. Similarly one unit increase in energy production will increase the CO_2 emissions by 2.1 kt. Lastly for one unit increase in cement production, the CO_2 emissions will increase by 1456.8 kt. It can be seen that the increase in CO_2 emissions is more with the increase in fossil fuel consumption, followed by cement production and energy production. Therefore it is obvious from the positive coefficients and significant P value that the impact of all the independent variables is significant on CO_2 emissions. They all are responsible for the increase in CO_2 emissions in the country.

After OLS regression, predicted values and residual values were computed. To validate OLS regression for the datasets, the stationarity of the residuals was checked. If the residuals are stationary then we know for sure that OLS regression was the correct model chosen to carry out the regression. The stationarity of the residuals were checked with ADF test and the absolute value of test statistics Z(t) was found to be greater than the critical values. Hence the residuals are stationary and OLS regression was the correct model for the regression. The table 4.9 shows the outcomes of the result for ADF test for residuals.

Table 4.9. Results for Augmented Dickey Fuller test for unit root for the residuals

Residuals	Test Statistics	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	3.68	-2.66	-1.95	-1.6

A residual plot (residual vs. fitted) was made to check if the linear regression model was appropriate for the data. Residuals are kept on y-axis and predictions are on x-axis. If the residual points are dispersed randomly around x-axis it indicates that linear model is suitable. If the distribution is uniform then a non-linear model is suitable.

An rvf plot is shown in figure 4.12. It clearly shows random distribution of the residuals therefore the linear regression was appropriate.

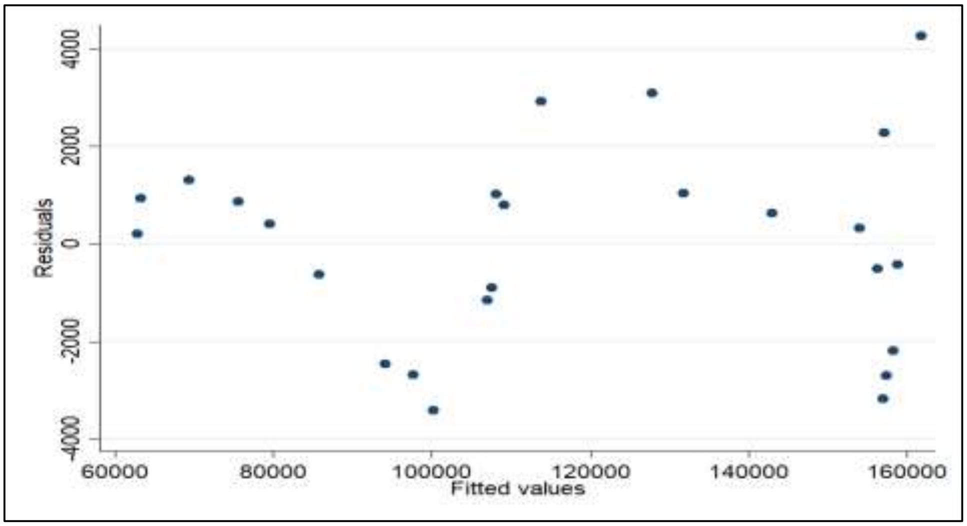


Figure 4.12. Residual vs. Fitted plot (rvf plot) showing random distribution of the residuals

The multicollinearity (correlation among predictor variables) was checked by VIF (Variance Inflation Factor) and it was found to be 5.14. VIF higher than 10 means that the variables are highly correlated and it affects the p-value and the model becomes unreliable. VIF closer to 1 means that the model is reliable, as the predictor variables are not affected by correlation among themselves. Table 4.10 shows the VIF values for the predictor variables.

Table 4.10. VIF showing the Multicollinearity among the predictor variables

Predictor Variables	VIF
Energy Production	7.45
Fossil Fuel Consumption	4.33
Cement Production	3.63
Mean VIF	5.14

Chapter 5

Conclusions and Recommendations

5.1. Conclusions

From the study conducted we come to the conclusion that the CO_2 emissions are bound to increase in Pakistan in the coming years. The results from both tests, a uni-variable and a multi-variable, confirm that the emissions will increase in the coming years. The accurateness of the models employed was checked and both were found highly fitting and showed minimum error.

The forecast of the different scenarios developed have indicated, what is likely to happen when we make an effort to curb the emissions and alternatively if we do not make an effort to curb the emissions

The increase was found to be huge in the wake of the recent coal power projects under the CPEC. Although the CPEC is beneficial for the country's development but the increased CO_2 emissions pose a severe threat to the environment and ultimately people's well-being, especially when the vulnerability of the country is already amongst the highest in the world. 20% decrease from BAU is not as impactful as 40% decrease, as evident from the forecasts. If we make an effort to curb our emissions by switching to greener and renewable technologies, the emissions can steadily go down.

The results for OLS regression shows that the increase in all three variables chosen; fossil fuel energy consumption, energy production and cement production will increase the CO_2 emissions. The p-value for all of them was less than 0.05 which means that this model can be used for projections as the results are statistically significant.

Therefore the increasing fossil fuel consumption and many industrial practices in the country are questionable. There is a dire need to go for environmentally safe options, if we want to pursue our pledge and more importantly if we want to negate the impacts of climate change in the country.

5.2. Recommendations

Keeping in view the results and the limitations of this work, following recommendations have been designed:

1. The results from both the models show increasing CO_2 emissions trend therefore the policy makers and the associated people should devise such policies and strategies that will make our energy sector greener. Renewable energy generating plants should be given priority instead of coal based power plants. Investments must be made to make the already installed technology green. Subsidies and incentives on green technologies and environmental friendly practices should be given. This will encourage the investors and the common people towards sustainability and these joint efforts can help to decrease the CO_2 emissions in the country.
2. Major sectors for the CO_2 emissions in Pakistan have been identified and discussed in the study. These sectors and their emissions should be kept in mind while formulating the policies and efforts should be made that will help to reduce the emissions for that sector.
3. This study does not include the forecast of all the GHGs emissions, therefore it is recommended to forecast the rest of the GHGs of the country. This will give a better and a refined picture of the current emissions situation in the coming years. It may help the policy makers to control GHGs emissions from the country.

4. Efforts should be made to devise accurate and updated GHGs emission inventories at national level because they are key for the efficient and effective design of policies and strategies for GHG mitigation.
5. The issue of climate change can be efficiently and effectively tackled and resolved if joint and sincere efforts are made by the concerned people. Public must be made aware and should be involved in this cause. This study is a small but a significant contribution that can help to reduce the CO_2 emissions in Pakistan.

References

Abeysinghe, T., Balasooriya, U., Tsui, A. (2003). Small-Sample forecasting: regression or ARIMA models? *J. Quant. Econ.* 1, 103-13. https://doi.org/10.1007/BF03404652.

Ahmed, K. & Long, W. (2012). Environmental Kuznets Curve and Pakistan: An Empirical Analysis. *Procedia Economics and Finance*, 1, 4-13. doi: 10.1016/S2212-5671(12)00003-2

Ali, G. (2018). Climate change and associated spatial heterogeneity of Pakistan: Empirical evidence using multidisciplinary approach. *Science of the Total Environment,* 634, 95-108. https://doi.org/10.1016/j.scitotenv.2018.03.170

Amin, S. (2018). February. *Energy Projects under the CPEC regulatory aspect. ICAP Conference: CPEC Myths and Realities*. 17 February 2018. https://www.icap.org.pk/cpecconference/pdf/SalmanAminCPECNEPRA.pdf (accessed 4 October 2018).

Anderson, D. R. (2008). *Model based inference in the life sciences: A primer on evidence*. New York: Springer.

Andres, R.K., Boden, T.A., Breon, F.-M., Ciais, P., Davis, S., Erickson, D., Gregg, J.S., Jacobson, A., Marland, G., Miller, J., Oda, T., Olivier, J.G.J., Raupach, M.R., Rayner, P., Treanton, K. (2012). A synthesis of carbon dioxide emissions from fossil-fuel combustion. *Biogeosciences* 9, 1845e1871.

Auffhammer, M., & Carson, R. T. (2008). Forecasting the path China's CO_2 emissions using provincial level information. *Journal of Environmental Economics and Management*, 55, 229–247.

Baber, N. (2008). World in Focus-Focus on Pakistan. World Almanac Library, Stamford, Ct.

Box, G. E. P., & Tiao, G. C. (1975). Intervention analysis with applications to economic and environmental problems. *Journal of the American Statistical Association,*. 70-79.

Carbon sequestration - artificial vs natural. (n.d.). Retrieved from http://www.carbonify.com/articles/carbon-sequestration.htm.

Canadell, J. G., Quere, C. L., Raupach, M. R., Field, C. B., Buitenhuis, E. T., Ciais, P., . . . Marland, G. (2007). Contributions to accelerating atmospheric CO2 growth from economic activity, carbon intensity, and efficiency of natural sinks. PNAS, 104(47). doi:www.pnas.org/cgi/doi/10.1073/pnas.0702737104.

CDIAC-Carbon Dioxide Information Analysis Centre. Berkeley Lab (ESS-DIVE). 5 March 2017. http://cdiac.ess-dive.lbl.gov/ftp/ndp030/nation.1751_2014.ems (accessed 2 November 2016).

Chaudhary, Q. Z., Rasul, G., Kamal, A., Mangrio, M. A., & Mahmood, S. (2015). *Technical Report on Karachi Heat wave June 2015* (Rep.).

China Pakistan Economic Corridor (CPEC)-Energy Priority Projects. http://cpec.gov.pk/energy (accessed 4 October 2018).

Conversion Calculator. Retrieved from http://www.aresok.org/npg/nioshdbs/calc.htm

Dickey, D. A., & Fuller, W. A. (1979) Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American statistical association,* 74, 427-431.

Ding, S., Dang. Y., Li, X., Wang, J., Zhao, K. (2017). Forecasting Chinese CO_2 emissions from fuel combustion using a novel grey multivariable model. *Journal of Cleaner Production*, 162, 1527-1538.

Ebrahim, T. Z. (2015). Pakistan offers nothing to Paris Climate Summit. https://www.thethirdpole.net/2015/11/18/pakistan-offers-nothingto-paris-climate-summit (accessed 24 December 2018).

ECCAD- Emissions of Atmospheric Compounds and Compilation of Ancillary Data. https://eccad.aeris-data.fr/#WelcomePlace: (accessed 26 December 2017).

Eckstein, D. Künzel, V. Schäfer, L. (2018). *Global climate risk index 2018.* Germanwatch. https://germanwatch.org/sites/germanwatch.org/files/publication/20432.pdf (accessed 9 December 2018).

EDGAR-Emission Database for Global Atmospheric Research. 30 October 2017. http://edgar.jrc.ec.europa.eu/overview.php?v=CO2ts1990-2015 (accessed 2 January 2018).

Edigar, V.S., & Akar, S. (2007). ARIMA forecasting of primary energy demand by fuel in Turkey. *Energy Policy*, 35, 1701-1708.

Engconsult Ltd. (2012). *Environmental Impact Assessment of Rehabilitation of Thermal Power Station Jamshoro* (Rep.). (Reference: D2JS1GRH).

Environmental Systems Research Institute (ESRI). (2015). ArcGIS Release 10.3.1. Redlands, CA.

Fang, D., Zhang, X., Yu, Q., Jin, T.C., & Tian, L. (2017). A novel method of carbon dioxide emission forecasting based on improved Gaussian processes regression. *Journal of Cleaner Production,* 1-8.

Farooqi, A. B., Khan, A. H., & Mir. H. (2005). Climate change perspective in Pakistan. *Pakistan J Meteorol*, 2(3), 11–21.

Fumo, N. & Biswas, M. A. R. (2015). Regression analysis for prediction of residential energy consumption. *Renewable and Sustainable Energy Reviews,* 47, 332-343. http://dx.doi.org/10.1016/j.rser.2015.03.035.

Future alternatives, and institutional infrastructure: An overview. *Renewable and Sustainable Energy Reviews*, 156-167. http://dx.doi.org/10.1016/j.rser.2016.11.057

IEA-Global Energy & CO_2 Status Report 2017 (Rep.). (2018).

INDC, (2015). Pakistan-Intended Nationally Determined Contribution, Submitted to COP21.http://www4.unfccc.int/submissions/indc/Submission%20Pages/submissions.aspx INDC.pdf (accessed 17 December 2018).

Khan, M. Z. A. (2012). Climate change: cause and effect. *Journal of Environment and Earth Science*, 2(4).

Lecture 13-Correlation (2006), Retrieved from http://archive.dimacs.rutgers.edu/dci/2006/Lecture13_Correlation.pdf

Lin, B., & Ahmed, I. (2017). Analysis of energy related carbon dioxide emission and reduction potential in Pakistan. *Journal of Cleaner Production*, 143, 278-287.

Lindsey, R. (2018, August 01). Retrieved from https://www.climate.gov/news-features/understanding-climate/climate-change-atmospheric-carbon-dioxide

Liu, L., Zong, H., Zhao, E., Chen, C., & Wang, J. (2014). Can China realize its carbon emission reduction goal in 2020: From the perspective of thermal power development. *Applied Energy*, 124, 199-212. http://dx.doi.org/10.1016/j.apenergy.2014.03.001

Madruga, R. P., Sokona, Y., Seyboth, K., Matschoss, P., Kadner, S., Zwickel, T., . . . Stechow, C. V. (2011). Intergovernmental Panel on Climate Change-Special Report on Renewable Energy Sources and Climate Change Mitigation (p. 1075, Rep.) (O. Edenhofer, Ed.). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Marland, G., (2008). Uncertainties in accounting for CO2 from fossil fuels. *J. Ind. Ecol*. 12, 136-139.

Mir, K. A., Purohit, P., & Mehmood, S. (2017). Sectoral assessment of greenhouse gas emissions in Pakistan. *Environ Sci Pollut Res*, 24, 27345-27355. http://dx.doi.org/10.1007/s11356-017-0354-y

Mirza, F. M. & Kanwal, A. (2017). Energy consumption, carbon emissions and economic growth in Pakistan: Dynamic causality analysis. *Renewable and Sustainable Energy Reviews,* 72, 1233-1240. http://dx.doi.org/10.1016/j.rser.2016.10.081

Mohiuddin, O., Sarkodie, S. A., & Obaidullah, M. (2016). The relationship between carbon dioxide emissions, energy consumption, and GDP: A recent evidence from Pakistan. *Cogent Engineering,* 3. http://dx.doi.org/10.1080/23311916.2016.1210491

Mondal, P., Shit, L., & Goswami, S. (2014). Study of effectiveness of time series modeling (ARIMA) in forecasting stock Prices. *International Journal of Computer Science, Engineering and Applications*, 4(2). http://dx.doi.org/10.5121/ijcsea.2014.4202

Moomaw, W., Burgherr, P., Heath, G., Lenzen, M., Nyboer, J., & Verbruggen, A. (2011) Annex II: Methodology. *IPCC Special Report on Renewable Energy Sources and*

Climate Change Mitigation (Publication). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. / (accessed 17 December 2018).

National Climate Change Policy-Ministry of Climate Change, Govt. of Pakistan (Rep.). (2012).

Nau, R. (2018, June 1). Statistical forecasting: notes on regression and time series analysis. Retrieved from https://people.duke.edu/~rnau/411home.htm

Nawaz, A. D., Ghumro, N. H., & Shaikh, G. M. (2018). Forecasting Energy Consumption and CO2 Emission Using ARIMA in Pakistan. Engineering Science and Technology International Research Journal, 1(4), 53-58.

Nordhaus, William, D., (2006). The "Stern Review" on the Economics of Climate Change. *National Bureau of Economic Research*, No. w12741.

Olabemiwo, F.A., Danmaliki, G.I., Oyehan, T.A., & Tawabini, B. S. (2017). Forecasting CO_2 emissions in Persian Gulf State. *Global J. Environ. Sci. Manage*, 3(1), 1-10.

Ophardt, C. & Emeritus,. (2013) *Carbon Cycle*. Retrieved from: https://chem.libretexts.org/Bookshelves/Environmental_Chemistry/Supplemental_Modules_(Environmental_Chemistry)/Biochemical_Cycles/Carbon_Cycle

Pao, H. T., Fu, H. C., & Tseng, C. L. (2012). Forecasting of CO2 emissions, energy consumption and economic growth in China using an improved grey model. *Energy*, 40, 400-409. http://dx.doi.org/10.1016/j.energy.2012.01.037

Pao, H. T., & Tsai, C. M. (2011). Modeling and forecasting the CO2 emissions, energy consumption, and economic growth in Brazil. *Energy*, 36, 2450-2458. doi:http://dx.doi.org/10.1016/j.energy.2011.01.032

Pohlert, T. (2016). Non-parametric trend tests and change-point detection. CC BY-ND, 4.

Prairie, Y.T., Duarte, C.M. (2007). Direct and indirect metabolic CO2 release by humanity. *Biogeosciences* 4, 215-217.

R Development Core Team (2018). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

Rafique, M., & Rehman, S. (2017). National energy scenario of Pakistan – Current status, future alternatives, and institutional infrastructure: An overview. *Renewable and Sustainable Energy Reviews*, 156-167. http://dx.doi.org/10.1016/j.rser.2016.11.057

Rasul, G., Afzal, M., Zahid, M., & Bukhari, S. A. (2012.). *Climate Change in Pakistan Focused on Sindh Province* (Tech. No. PMD-25/2012).

Residual Analysis in Regression. Retrieved from: https://stattrek.com/regression/residual-analysis.aspx

Rice, C. W., Nelson, R., & Jones, L. (2004). *What is Carbon and the Carbon Cycle?* (Publication).

Seinfeld JH, Pandis SN (2006) Atmospheric chemistry and physics: from air pollution to climate change, 2nd edn. John Wiley & Sons, New York

Sen, P., Roy, M., & Pal, P. (2016). Application of ARIMA for forecasting energy consumption and GHG emission: A case study of an Indian pig iron manufacturing organization. *Energy,* 116, 1031-1038. http://dx.doi.org/10.1016/j.energy.2016.10.068

Shahzad, S. J. H., Kumar, R.R., Zakariya, M., & Hurr, M. (2017). Carbon emissions, energy consumption, trade openness and financial development in Pakistan: a revisit. *Renewable and Sustainable Energy Review,* 70, 185–192.

Siew LY, Chin LY, Wee MJ. ARIMA and integrated ARFIMA models for forecasting air pollution index in Shah Alam, Selangor. Malays J Anal Sci 2008;12(1):257e63.

Smit, R., Ntziachristos, L., Boulter, P. (2010). Validation of road vehicle and traffic emission models e a review and meta-analysis. *Atmos. Environ*. 44, 2943e2953

StataCorp. (2015). Stata Statistical Software: Release 14. College Station, TX: StataCorp LP.

Stocker, T. F., Qin, D., Plattner, G. K., Tignor, M., Allen, S. K., Boschung, J., . . . Midgley, P. M. (Eds.). (n.d.). IPCC, 2013: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (Rep.). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.

Sun, W., Wang, C., & Zhang, C. (2017). Factor analysis and Forecasting of CO_2 emissions in Heibei, using extreme learning machine based on optical swarm optimization. *Journal of Cleaner Production,* 162, 1095-1101.

Tudon, C. (2016). Predicting the Evolution of CO2 Emissions in Bahrain with Automated Forecasting Methods. *Sustainability,* 8. doi:http://dx.doi.org/10.3390/su8090923

United Nations Population Fund. https://www.unfpa.org/data/transparency-portal/unfpa-pakistan (accessed 2 January 2019).

Velasco, E., Perrusquia, R., Jimenez, E., Hernandez, F., Camacho, P., Rodríguez, S., . . . Molina, L. T. (2014). Sources and sinks of carbon dioxide in a neighborhood of

Mexico City. *Atmospheric Environment*, 97, 226-238. http://dx.doi.org/10.1016/j.atmosenv.2014.08.018

Yang, Y. (2005). Can the strengths of AIC and BIC be shared? A conflict between model identification and regression estimation. *Biometrika,* 92(4), 937-950.

Yousuf, I., Ghumman, A. R., Hashmi, H. N., & Kamal, M. A. (2014). Carbon emissions from power sector in Pakistan and opportunities to mitigate those. *Renewable and Sustainable Energy Reviews*, 34, 71-77. http://dx.doi.org/10.1016/j.rser.2014.03.003

Yuan, C., Liu, S., & Fang, Z. (2016). Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM (1,1) model. *Energy*, 100, 384-390. doi: http://dx.doi.org/10.1016/j.energy.2016.02.001