Quantifying the Direct Economic Damage Caused by the Impact of Climate Change in Asia Pacific Region

By

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A thesis submitted to the Department of Economics And Social Science in partial fulfillment of the requirements for the degree of
MSc in Applied Economics

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Brac University
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Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
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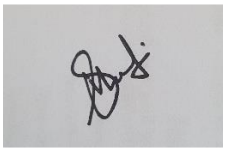

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Approval

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of Spring, 2022 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of MSc in Applied Economics on 10th January 2022.

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Abstract

Global warming or climate change has amplified the number of natural disasters around the world. Natural disasters include floods, various forms of storms, cyclones, heat waves, drought, wildfires etc. Two important indicators of global warming or climate change are rise in average global temperatures and variability in global rainfall. This paper examines the anthropogenic link between global GHG emissions and climate change indicators (temperature and precipitation levels) and natural disasters.

The Asia Pacific region has experienced the brunt of these natural disasters in recent decades and is counting billions of dollars in direct economic damage. Could there be a relationship between the aforementioned changes in climate and the rise in natural disasters in the Asia Pacific region? This paper looks at two important climate change indicators (temperature and precipitation) and tries to quantify the value of economic damage caused by the disasters annually.

In cointegration analysis under ARDL framework, there is a long-run association between the increase in direct economic damages in USD and climate change indicators. Global average temperature shows a positive and significant impact on economic damages. Furthermore, inspection of the short run relationship in an ECM model also displays a positive and significant relationship between one lag period of global average temperature and economic damage values. Granger causality examination corroborates the findings and reports a uni-directional causality running from global average temperature and economic damage value.

In conjunction with evidence from the literature that it is “very likely” that increases in global temperature, caused by increasing release of GHG in the atmosphere, is altering the climate system suggests a connection between economic damage caused by the natural disasters observed in the region and global warming.

Keywords: Global Warming; Climate Change; Natural Disaster; Economic Damage; ARDL; Granger Causality

Dedication

I dedicate my hard work to my family, my mentors and my well-wishers.

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First of all, I would like to express my gratitude to the almighty Allah for enabling me to complete this thesis.

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Author

Safwan Mahmood Safi

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List of Acronyms

GHG	Green House Gas
ARDL	Autoregressive Distributed Lag
ECM	Error Correction Model
UNESCAP	United Nations Economic and Social Commission for Asia and the Pacific
ADB	Asian Development Bank
IPCC	Intergovernmental Panel on Climate Change
GDP	Gross Domestic Product
WHO	World Health Organization
CRED	Center for Research on the Epidemiology of Disasters
NOAA	National Oceanic and Atmospheric Administration
NCAR	National Center for Atmospheric Research
OLS	Ordinary Least Squares
ACF	Autocorrelation Function
ADF	Augmented Dickey Fuller
VAR	Vector Autoregressive
AIC	Akaike Information Criterion
RESET	Regression Equation Specification Error Test
CUSUM	Cumulative Sum Control Chart

DW	Durban Watson
DRR	Disaster Risk Reduction

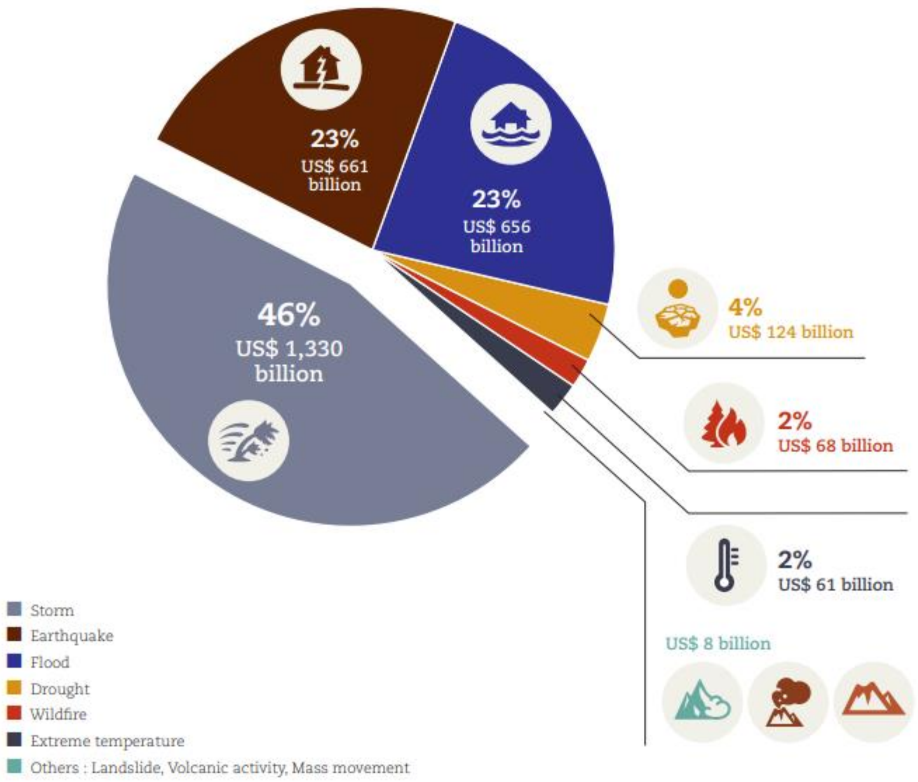
Chapter 1

Introduction

1.1 Impact of global warming on natural hazards

The worldwide phenomenon of climate change or global warming is amplifying the number of natural disasters around the world. Disasters naturally occur within weather cycles and hurricanes, typhoons, flooding, droughts, wildfires etc have always existed. But now we are observing an unprecedented level of destruction caused by the same events. Global Disaster Data from 1998 to 2017 reports that storms have emerged as the costliest form of disaster followed by floods globally as depicted in figure 1. Storms and Floods occupy top spots in disaster events among all forms of natural disasters.

Figure 1: Recorded economic losses in USD per disaster type (1998-2017)



Note. Adapted From "Economic Losses, Poverty & Disasters: 1998 – 2017" by P. Wallemacq, 2018, *Centre for Research on the Epidemiology of Disasters CRED*, p. 6. Copyright 2018 by CRED, United Nations Office for Disaster Risk Reduction.

Extreme weather has plagued several corners of the globe. Deadly heat waves and intense cold spells have increased fatality and deteriorated productivity and economic growth. It hampers agricultural production and raises energy use which further induces climate problems (Lemoine, 2021). According to Srivastava (2019), the years 2010 to 2019 were the warmest recorded decade. According to Wood (2018), natural disasters led to 870 million people from 160 countries losing their lives or livelihoods and being displaced from their homes. He also reported that floods, severe storms, droughts and various other climate induced extremes caused more than 90% of global disasters. Furthermore, the cost of damage from natural disasters around the world showed tremendous growth, from approximately $47 billion to $340 billion between 2009 and 2017. Guha-Sapir, Below and Hoyois (2015) informed that natural disasters have cost $1.7 trillion in damage since 2000.

What explains the seriousness of these weather events? Oxfam (2021) explains that climate hazards are worsened and the risk of extreme weather disasters are heightened by changes in global climate. Elevated air and water temperatures result in sea level rise, heavier storms and wind, more intense and longer drought spells, more frequent wildfires, heavier rainfall and flooding. The evidence is strong and the outcome is concerning. Oxfam also informs us that, between 2006-2016, the rate of sea level rise increased two and half times and in the last 30 years the number of disasters attributed to climate change increased three-fold. In the years 2019 and 2020 alone the world saw a number of climate disasters that ravaged various parts of the globe such as Australian wildfires, flooding in Afghanistan and Southeast Asia, Hurricane Eta in Central America, Cyclone Idai in Africa, plus deadly heat-waves in India, Pakistan and

Europe. From Africa to South Asia, millions of people lost shelter, livelihoods and lives as a result of the aforementioned weather events (Oxfam, 2021).

1.2 Asia and the Pacific faces a heavy burden

The vast Asia Pacific region suffers the most from climate change. The impact of climate change will be felt through climate extremes and multiple weather events (UNESCAP, 2017). In the year 2020, wildfires burned 18 million hectares of forest land and human habitat in Australia (Srivastava, 2020). In 2019, monsoon flooding in India killed approximately 1,900 people. Typhoon Hagibis ravaged parts of Japan and monsoon floods in China cost $15 billion in damages (Srivastava, 2020). In 2018, Asia and the Pacific was the location of almost half of the total 281 natural disaster events occurring worldwide (UNESCAP, 2019). Between 2014 and 2017, Asia witnessed 217 storms and cyclones, 236 cases of severe flooding and 55 earthquakes that shook 650 million people and caused the deaths of 33,000 people (Wood, 2018).

The Asia pacific region holds 60% of global population and suffers more from natural disasters than all other nations. Since 1970, people in Asia are 5 times more likely to be hit by natural disasters than any other region in the world (ADB, 2013). Between 1970 and 2018, 87% of its people were affected by Natural disasters (UNESCAP, 2019). Over the same period 142 million people were affected in Asia compared with 38 million in the rest of the world. Moreover, the region lost over $1.5 trillion between 1970 and 2018 (UNESCAP, 2019).

Wood (2018) said that Asian nations are vulnerable to extreme weather events. This is largely because many nations in Asia have a large and growing population who suffer from poverty. Poor, coastal, villages and farms do not have adequate defenses which leaves them vulnerable to monsoon rain and flooding. Heavy winds and floods destroy homes, crops and livestock. They also pollute fresh water supplies and cut routes of medicine and food supply. For example, a deadly tropical cyclone which hit the Chittagong region of south east Bangladesh in 1991, killed more than 135,000 people and made over 10 million people homeless (Wood, 2018).

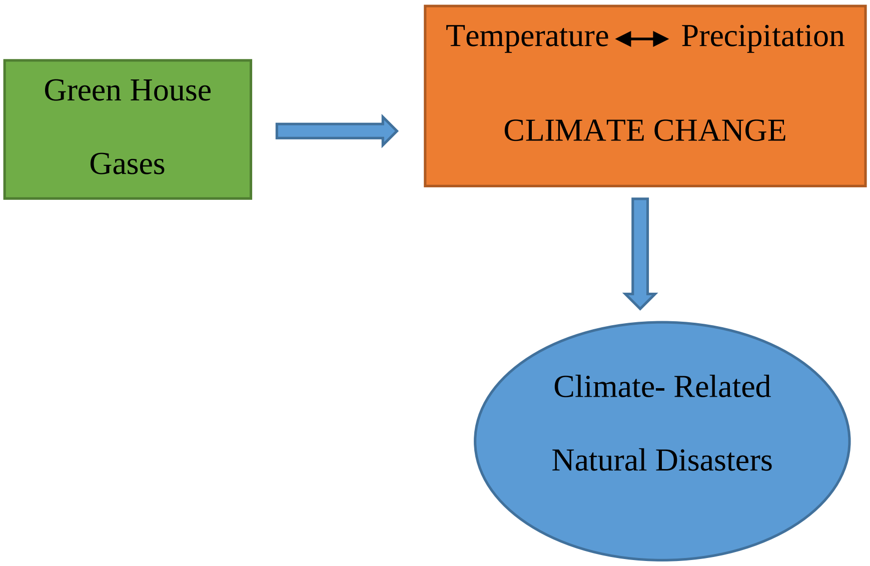
Environmental degradation and loss in tree cover due to logging and land clearance for farming depleted natural protection and increased risk of landslides (Wood, 2018).

Industrialization triggered rapid urbanization in many Asian nations. Many people were forced to live in poorly constructed and over-crowded cities near coastal regions and large rivers. ADB (2013) states that population growth in Asia has compelled millions of people to migrate to marginal lands and coastal areas, away from economically active and developed areas. This has exposed many people to storm surges from cyclones, drought, floods, landslides etc. Over the past century, the Asia Pacific region has undergone warming trends and greater temperature extremes. A warming world has resulted in heat waves, storms, rains and droughts becoming more extreme. Additionally, sea levels are rising, while landslides, floods and fires are occurring more frequently (ADB, 2013).

Climate change not only magnifies risk of disaster but also brings huge economic losses. In 2017, UNESCAP estimated that South-East Asia may witness a reduction in their GDP by up to 11% by 2100 due to surge in weather related disasters. Moreover, rise in droughts and floods will affect crop productivity and increase price of food. It is estimated that by 2030, more than 100 million people will be forced into acute poverty by climate change in the South East Asia region alone (UNESCAP, 2017).

1.3 Anthropogenic link to climate-related hazards

Figure 2: Linkages involving climate-related natural disasters



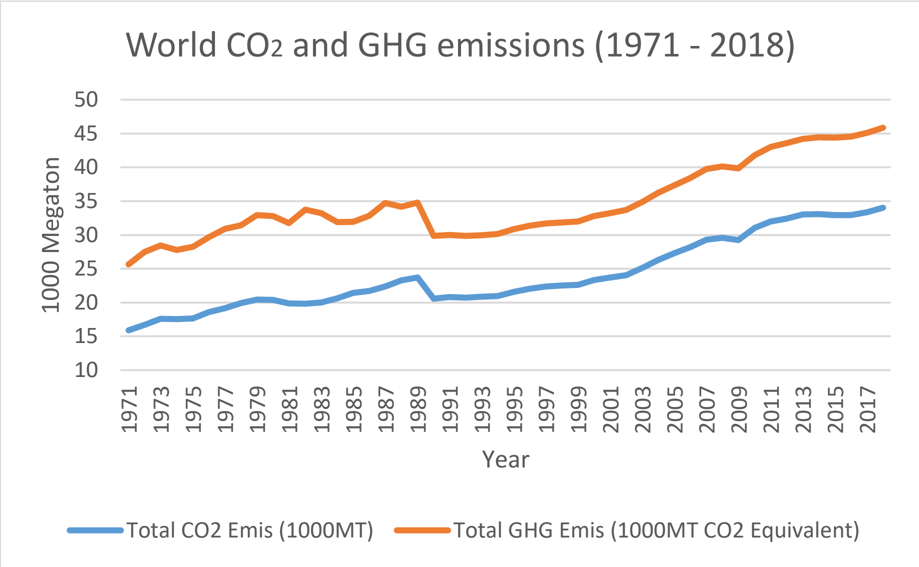
Note. This figure displays the causal chain of events starting from GHG emissions to climate related disasters. From "Climate-Related Disasters in Asia and the Pacific," By V. Thomas., J. Albert and R. Perez, 2013, *ADB Economics Working Paper Series No. 358*, p. 3. Copyright 2013 by Asian Development Bank.

Figure 2 illustrates the three linkages responsible for climate-related disasters as outlined by Lopez, Thomas and Tronsoco in 2015. Firstly, atmospheric GHG concentrations are altered by increasing emissions of GHG. These added emissions eventually affect global temperature and precipitation, two important global climate indicators (IPCC, 2007). Secondly, as the intensity of the climate variables rises in the atmosphere it modifies the frequency of climate-related hazards (IPCC, 2012). Climate related hazards include extreme temperatures (like drought, wildfires, or heat waves) and extreme precipitation (causing storms, floods etc). According to Thomas, Ramon and Perez (2013) there is a connection between the two climate hazards. An increase in temperature will raise the moisture-retaining capacity of the atmosphere which can lead to an increase in its water content which, in turn, may lead to greater rainfall. Finally, the risk of natural disasters is affected by the frequency of climate-related hazards (IPCC, 2012)

IPCC 2013 describes that the rise in global surface temperature from 1951 to 2010 was due to increase in anthropogenic increase in GHG concentrations in the atmosphere. IPCC (2014) stated that the warming of Earth's atmosphere and oceans, disappearing ice and elevation in sea level are prominent changes that have occurred. In the last 1400 years, the northern hemisphere has undergone increase in temperature starting from 1983. Worldwide, glaciers are disappearing and the Greenland and Antarctic ice sheets are melting (IPCC 2013)

As GHG concentration in the atmosphere is rising so is the warming of the air and the ocean. Reductions in ice, rising of the sea level, changes in global water cycle and climate extremes are already being observed. Humans are responsible for emitting GHGs at an alarming rate. Over 30 billion tons of carbon dioxide are being released every year along with other contributors of GHG namely methane (CH_4) and nitrous oxide (NO_2) (Lopez et al, 2015). Figure 3 depicts the rising trend in GHG and carbon dioxide emissions globally. Increase in GHG concentrations will trap more heat on earth and fuel the rise in global surface temperature. Land and ocean surface temperatures depicts a $0.85^{o}C$ increase over 1880 – 2012 level. The 10 hottest years on record after 1880 all took place after 1997 (Lopez et al, 2015) Figure 2 shows the level of CO_2 emissions and GHG emissions in 1000 Megaton per year.

Figure 3: World CO2 and GHG emissions (1971-2018)



Note. The graph shows the increasing trend in GHG and CO_2 emissions in the world from 1971 – 2018. World Development Indicators, Copyright 2021 by World Bank

Additionally, as average temperatures rise with GHG concentrations, average rainfall is also expected to increase. According to IPCC 2007, precipitation patterns are highly variable both spatially and temporally. Some regions will observe rise in heavy precipitation events while others will show no discernible change. However, a report by Westra, Alexander and Zwiers (2012) concludes that heavy rainfalls are increasing on average globally and that the rise is related with rising global average temperature. Other research have deducted that increased occurrences of heavy precipitation is casually linked with anthropogenic GHG emissions (O'Gorman and Schneider 2009; Min et al. 2011). Lenderink and Meijgaard (2010) and Trenberth (2011) have also established a causal link between extreme rainfalls with changes in global temperature.

Scientists consider that Carbon dioxide concentrations of 450 parts per million (ppm) to be the threshold beyond which the effort to limit global temperature rise of 2^{o}C relative to 1850 – 1900 levels will be difficult. Already carbon dioxide concentrations have surpassed 400 ppm in 2015 and if it continues at existing pace it will cross 450 ppm within 25 years (Lopez et al, 2015). In such instances the effort to curb temperature rise above 2°C will collapse and the world will fall into peril like the destruction of Amazon ecology or melting of permafrost (Stern 2013). The global increase in intense floods, storms, drought and intense temperatures are imminent due to their ominous link to climate change.

1.4 How climate related hazards affect nations

Lopez et al 2015 iterates that people as well as physical and economic infrastructure, including social and cultural assets, in various locations can be adversely affected by natural disasters. Such infrastructures are exposed to extreme adverse natural events (UNESCAP, 2019). For instance, because of economic opportunities, communities and industries tend to be built around coastal areas in order to take advantage of services provided by harbors and ports, employment opportunities and transportation. As more people are settling in these hazard-prone areas and as coastal areas are vulnerable to flooding, storms and cyclones, increasing numbers are exposing themselves to harm.

Climate change has created anomalies in weather and give rise to extreme temperatures. Global warming gave rise to periods of extreme heat waves especially in South Asia. Extreme heat waves reduce productivity and agricultural yield. Exposure to extended durations of heat has led to thousands of deaths in Asia (Dong et al, 2021). McKinsey Global Institute in 2021 reports that "by 2050 between 500 million to 700 million people in South Asia will live in regions which will have an annual probability of lethal heat waves of about 20%". Extreme cold spells have also gripped parts of Asia notably North Asia. Extreme cold not only causes death and disrupts transportation infrastructure but also destroys crops and reduce agricultural yield (Freychet et al, 2021). Climate change may also affect the intensity and frequency of rainfall. Asia Pacific region is one of the most densely populated areas and are highly vulnerable to environmental conditions. Intense precipitation leads to flooding and eventually to landslides, building collapse and casualties. Flooding also destroys houses, crops and livestock. Millions of people directly suffers loss due to intense precipitation and typhoons in Asia (Freychet, Hsu & Wu, 2016, chap. 5). The high mountainous regions of Asia is home to the largest number of glaciers outside of the polar areas. The surrounding glaciers are rapidly melting due to atmospheric warming which led to the expansion and formation of more glacial lakes. If water is suddenly released from these lakes, an outburst of floods will occur and ruin the lives and livelihoods of people living far away downstream, crossing international borders and creating trans-boundary threats (Université de Genève, 2021). The Hindu-Kush region, Tibetan plateau and surrounding mountainous regions, also known as the third pole, have become the hotspots for this risk

Drought is a significant hazard that highly impacts countries with large agricultural sector which contributes significantly to GDP. These countries are exposed as they depend on agriculture heavily. Notable countries in Asia who have substantial agricultural presence are India. Pakistan, Vietnam and China. Drought directly impacts rural people's livelihoods and cascades to food insecurity and famine in future. According to UNESCAP 2019, the average annual economic loss convened by agriculture would be $404,479 million or 1.4% of the region's GDP. Extreme heat waves and prolonged droughts also causes wildfires that occurs regularly in Australia and to some extent in Southeast Asia. Hot and dry conditions dries out ecosystems and increases the risk of wildfires. Wildfires releases vast quantities of carbon dioxide in the atmosphere which further aggravates global warming. Besides fatalities and destruction of vegetation, ecosystem and human habitats they emit fumes containing poisonous gas and fine particles into the atmosphere that causes health issues (WHO, 2021). Arid and semi-arid regions are open to attacks by high intensity sand and dust storms. Asia Pacific is the second largest dust emitter about half a billion tones (UNESCAP, 2019). These storms are a consequence of land degradation, deforestation, desertification, unsustainable land and water use and climate change factors (UNESCAP, 2019). Dust particles are carried thousands of kilometers by high winds which exacerbates desertification, drought and soil salinity. These conditions destroy crops, livestock and soil fertility (UNESCAP, 2018).

Natural hazards affect both developed and developing nations. But poorer countries pay a higher price. IPCC 2012 (Lopez et al. 2015) reports that fatality rates, number of people affected and economic losses are higher in developing nations. This is because developing nations have a higher percentage of people living in vulnerable urban and rural zones with weak infrastructure, absence of basic facilities and limited government capacity. Poor people have fewer resources to tackle disaster risk and as a result their effect on livelihood and losses are amplified, leaving them more exposed (Lopez et al. 2015)

1.5 Different impacts across sub-regions across Asia Pacific

The Asia Pacific region encompasses a vast geographical area – from China & Mongolia in the North, Australia and New Zealand in the South, Japan in the East and Turkey in the West. The impact of climate change differ by sub-region in Asia. The temperature increase is likely to raise the "number and duration of heat waves and droughts in semi-arid and arid areas in North and Central Asia" (UNESCAP, 2019). Sand and dust storms regularly hit arid and semi-arid regions comprising of Central Asia, Middle - East and North-East Asia and South-West Asia (UNESCAP, 2018). Extreme cold sometimes grips North Asia. Storm surges, Cyclones, Typhoons and floods affects mostly the coastal regions such as South-East Asia, South Asia and the Pacific. Higher rainfall with associated flooding and landslides are a danger to countries with major river basins in South and South-West Asia. Landslides also threaten North and Central Asia (UNESCAP, 2019). South-West and Central Asia is prone to a damaging sequence of adverse weather events such as drought, sand and dust storms, desertification and sometimes floods. The central Asia mountainous region and the third pole consists of thousands of glacial lakes and fear threats from glacial lake outburst. Australia and forests in South East Asia have seen frequent wildfires burning vegetation and ecosystem.

Overall South and South-East Asia are the most affected region in Asia they have high population densities in vulnerable settings. These regions face persistent poverty and incapacity to co-exist with risks of flood and drought (UNESCAP, 2019). This region accommodates the highest number of coastal cities, has many trans boundary river basins and significantly dependent on agriculture. They greatly suffer from storms, floods and drought due to uncertain climate, monsoon variability, the occurrence of El Nino and La Nina and other extreme weather events (UNESCAP, 2019).

Chapter 2

Study and Research Question

There is a great deal of study which depicts the science of climate change and the ominous link of climate change and natural disaster. Some studies have focused on specific natural disasters and their impact on people and economy. Furthermore, several research work illustrated strategies and policies to tackle natural disasters such as mitigation and capacity building techniques. However this study firstly examines the history and science of climate change and introduces the theoretical link between climate change and natural disasters in Asia Pacific region. Afterwards the study will try to quantify the direct economic damage caused by such natural disasters in Asia Pacific region. We have demonstrated that Asia Pacific region is a vast continent and is affected by various forms of natural disasters. Some regions have unique climate and geographic characteristics which makes them susceptible to specific climate disasters more intensely. However, the present study will accumulate the direct damage value of all kinds of climate influenced natural disasters which are frequently ravaging the continent and examine its co-integration with global climate change indicators: mean temperature and mean precipitation levels. The study will determine the long run and short run impact on direct economic damage value of natural disasters in Asia Pacific region. Finally it will investigate the causal effect and direction of causality between global climate change indicators and direct economic damage value of natural disasters in the Asia Pacific region.

The study is broken down into several sections. Section I covers the introduction of the study along with research question. Section II looks at the past literature of studies examining the science and relationship of climate change with natural disasters. Section III elaborates on the data utilized for the study and the methodology implemented for empirical analysis to investigate the relationship. Section IV reports the outcome of the empirical analysis. Finally section V presents the ending with conclusion and policy recommendations.

Chapter 3

Literature Review

This paper does not examine the link between GHG emissions and changes in climate variables such as temperature and precipitation. There are numerous research papers on the science of climate change (IPCC 2012; IPCC 2013; Hansen and Sato 2012; Huber and Knutti 2012; Trenberth 2011). In the past there were researches which estimated the impact of climate change on the probability and occurrences of specific hazards. For example, Stott, Stone and Allen (2004) and Rahmstorf and Coumou (2011) found that it is very likely that humans are responsible for altering climate and magnifying the risk of heat waves in Europe and Russia. Hoerlinget et al. (2012) and Nuccitelli (2014) discovered that human induced climate change is responsible for magnifying droughts in the Mediterranean and USA respectively. There are studies which indicate that climate change is responsible for increased risk of flooding occurring in England and Wales (Pall et al. 2011) and in Southeastern Australia with significant building damage (Schreider, Smith and Jakeman, 2000). Global warming leads to melting of ice and precipitation extremes which increase the risk of flooding (Tenberth, 2011). Studies predict that rising temperature will increase the intensity of hurricanes and cyclones (Grinsted, Moore and Jevrejeva 2013; Knutson et al. 2010). In fact climate change will double the economic losses from hurricanes globally (Hallegatte 2012). Abram et al. 2021 and Zong, Tian & Yin (2020) reported that climate change is responsible for rise and increased risk of wild fires in Australia and Central Asia respectively. Several past studies have established that rise in sea surface temperature or warm waters are elevating the strength of storms and hurricanes (Trenberth 2005; Sturgis, Smythe and Tucci 2014). The devastating typhoon Haiyan which hit the Philippines in 2013 was fuelled by rising seas surface temperature in the Pacific (Comiso, Perez and Stock 2015).

A great number of research papers focused on disaster management, mitigation and adaptation strategies to combat man made and climate induced natural disasters (Ikeda & Palakhamran 2020; Rentschler 2013). Some also considered the determinants of disaster cost (Rentchler 2013; Bakkensen, Shi & Zurita 2013). However this study builds on existing literature and assesses the significance of climate change indicators contributing to the direct economic losses caused by increase of natural disasters over time in Asia and the Pacific. This paper will actually investigate the observed changes in climate change indicators in Asia Pacific and then decipher whether there is any long run association between these changes in variables and the increase in direct economic damages caused by natural disasters. The paper will primarily build on past work by Thomas, Ramos and Perez (2013) and Lopez et al. (2015) who tried to explore the statistical relationship between changes in climate variables and the frequency of intense natural disasters.

Thomas et al. (2013) tried to investigate the relationship between changes in climate and the frequency of natural disasters in Asia Pacific region. Their paper segregated natural disasters into two categories: hydrometeorological disasters and climatological disasters. The dataset were sourced from the Emergency Event Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters (CRED). Their paper selected rising population exposure, greater population vulnerability and increasing climate-related hazards as determinants and independent variables responsible for the increased frequency of intense natural disasters in Asia Pacific region. The independent variable population exposure was represented by population densities. Population vulnerability was represented by real income per capita and real income per capita square. Two variables for indicating climate hazards were average precipitation deviation and average surface temperature anomaly. In the regression analysis within a model of disaster risk determination for 1971 - 2010, the team of researchers found a significant and positive association between average precipitation deviation and hydrometeorological disasters but a negative and significant relationship with climatological disasters. However, average temperature anomaly illustrated a positive and significant association with climatological disasters in Asia Pacific region. In this relationship greater precipitation were considered to be floods and storms and higher temperature were linked to droughts and heat waves. Additionally the research reported that population exposure also increases natural disasters significantly.

In 2015, Lopez et al expanded the work of Thomas et al (2013) and examined the same relationship but this time on a global scale. Their paper utilized the same dependent variables namely hydrometeorological and climatological disasters sourced from CRED. As climate-related hazards they selected annual surface temperature and precipitation anomaly. Population exposure represented by population density. However, this research considered GDP per capital and GDP per capita square as population vulnerability and additionally the research introduced two global climate indicators: Atmospheric CO_2 levels and annual sea surface temperature anomaly. Finally they have included an additional control variable total population. After regression analysis within a model of disaster risk determination for 1971 – 2013, the results displayed that global climate change indicators were positive and significantly impacts the frequency of the intense natural disasters. Moreover, regression analysis displayed that precipitation deviation were positively and significantly related to hydrometeorological events. For climatological events, precipitation deviation showed a negative but significant relationship, whereas temperature deviation had a negative and insignificant relationship. Additionally, both population exposure and vulnerability were positively linked to the frequency of intense natural disasters.

Along with the scientific association between GHG and changes in climate, the findings in the above two papers also suggested a relationship between the rising number of natural disasters and human induced emissions of GHG in the atmosphere.

In previous works by Thomas et al (2013) and Lopez et al (2015) the two dependent variables were the frequency of intense hydro meteorological disaster and climatological disaster. The intense natural disaster included disasters which comprised of those that killed 100 or more and affected 1000 or more (people who required immediate assistance such as food, water, shelter, sanitation and medical assistance). The dependent variable for this study will combine natural disaster of all intensities and consider the direct economic damage, instead of frequency, caused by natural disasters. The direct economic damages are recorded on basis of damage values incurred as a result of the natural disaster. The objective of this research paper is different because it will examine the long run association between climate change indicators and the damage impact by natural disasters induced by global warming. This research paper has also combined the two categories of natural disasters: hydro-meteorological and climatological into one variable. The number of people affected by natural disasters directly is a determinant of natural disaster and is incorporated as an independent variable. The study will integrate annual mean temperature and annual mean precipitation as global climate change indicators and our primary set of independent variables. More details of the data are elaborated in the next section

Chapter 4

Methodology

4.1 Data description

The research employed time-series data over the period 1979 – 2019. The data sets include:

Global Annual Mean temperature in ^{o}C (GATemp - Explanatory Variable 1)

Global Annual Mean Precipitation in mm (Glb_prcp - Explanatory Variable 2)

Total number of people affected (TotAPop - Explanatory Variable 3) – Consists of the sum of people in ('000000)/ million who were injured, made homeless and/or directly affected by the natural disasters in Asia Pacific. These are people who also requires immediate assistance and relief.

Total direct economic damage (TotEcDm - Dependent Variable) – The total value in US$ in ('0000000)/ million of all damages to property, crops and livestock directly or indirectly caused by respective natural disasters in Asia Pacific region. The damage value obtained for each disaster incurred at the moment of the event or true to the year of the event[1].

Our dependent variable and explanatory variable 3 were extracted from EM-DAT - the Emergency Event Database owned by the Centre for Research on the Epidemiology of Disasters (CRED). EM-DAT is a well known publicly available database on natural disasters and widely considered the most comprehensive. The total number of people affected by natural disasters is a determinant variable and a means to quantify the scale of natural disaster every

[1] It is to be noted that the direct economic damage value does not entail the opportunity cost whose calculation are beyond the scope of this research study

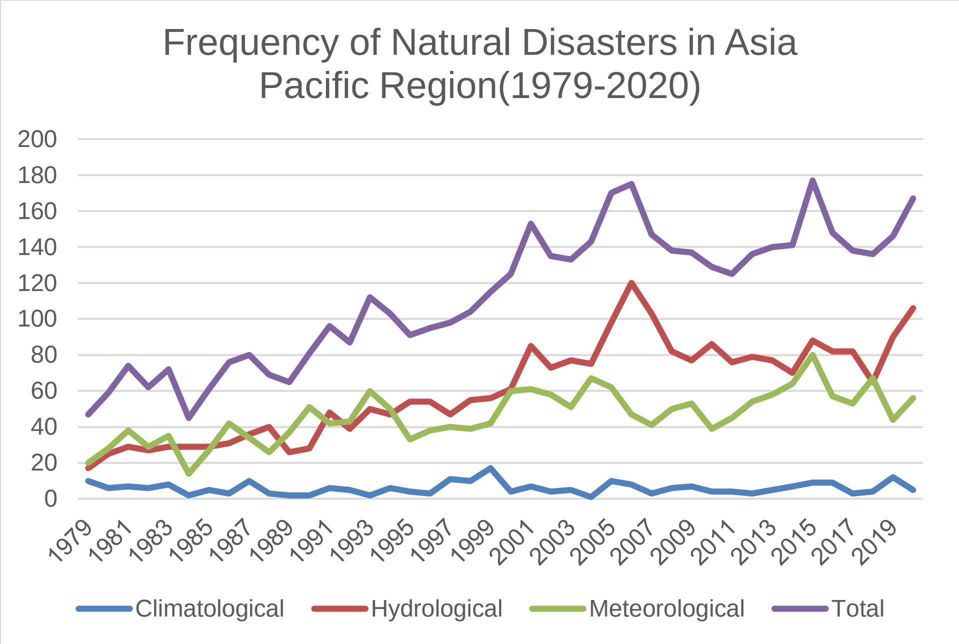
year. The recorded disaster selected as time series dataset have satisfied at least one of the following mentioned criteria: Total 10 deaths, Total 100 people affected and/or Declared by the country and/or made an appeal for international assistance. The explanatory variable 1 Global annual mean temperature was obtained from Kaggle, an online community for data scientists. The actual data is a part of The Berkley Earth Surface Temperature study published by Berkley Earth. The explanatory variable 2 Global Annual Mean Precipitation data was collected from National Oceanic and Atmospheric Administration (NOAA) of USA. This data is produced by the Global Precipitation Climatology Project of National Centre for Atmospheric Research (NCAR). The data estimates annual average rainfall on a 2.5 degree global grid from 1979 – 2019.

Among EM-DAT, the natural disaster category is divided into 5 groups; Biological, hydrological, meteorological, climatological and geological. Among them the climate influences the following three natural disaster groups out of five which are: climatological, meteorological and hydrological. CRED (2021) explains the chosen disasters as following:

- Climatological disasters are caused due to changes in “long-lived meso to macro scale atmospheric process ranging from intra-seasonal to multi-decadal variations in climate”. Such disasters include drought, heat-waves, glacial lake outburst and wildfire.
- Meteorological disasters occurs due to “short-lived, micro-meso scale extreme weather conditions” comprising of extreme temperature, fog and storm.
- Hydrological disasters happens because of the “occurrence, movement and distribution of surface water” which includes flood, landslide and wave action.

The following figure 4 illustrates the frequency of climate related natural disasters from 1979 – 2020 in Asia Pacific region. The total figures shows a general rising trend which is largely contributed by hydrological and meteorological disasters.

Figure 4: Frequency of natural disasters by type in Asia Pacific region (1979 - 2020)



Note: The graph shows the frequency of climate related disaster events occurring in Asia Pacific region from 1979 – 2020. EM-DAT, Copyright 2021 by Centre for Research on the Epidemiology of Disasters (CRED).

The direct economic damage in US$ and total number of people affected by the aforementioned category of natural disasters were recorded and examined for this study. Earth's average temperature and precipitation levels are indicators of global warming or climate change. Thomas et al. (2013), Lopez et al. (2015) and Asia Pacific Disaster Report (2017) identified an ominous link between climate change (caused by exacerbation of climate hazards) and resulting disaster events which have plagued our planet for several decades. Numerous past literatures have theorized and quantified impact of climate change on weather which is the root cause of natural disasters, or so which we are trying to investigate through empirical analysis in this study.

4.2 Methodology

This paper attempts to quantify the direct economic damage caused by recurring natural disasters in Asia Pacific from 1979 to 2019. The empirical framework for this study is specified and the implicit form is as follows:

Total Direct Economic Damage = f(Total Affected Population by Natural Disaster in Asia Pacific, Global Annual Precipitation in mm and Global Average Temperature in ^{o}C)

The functional form of the model is:

$TotEcDm = \beta_0 + \beta_1 TotAPop_t + \beta_2 Glb\_prcp_t + \beta_3 GATemp_t + \varepsilon_t$ ……………………….(1)

Here TotEcDm is the total direct economic damage caused by natural disaster in Asia Pacific region in million USD, TotAPop is the total number of people affected by natural disaster in million in Asia Pacific, Glb_prcp in the global annual precipitation mean in mm and GATemp is the global average temperature mean of the world measured in degree Celsius. Finally ε is the white noise error term.

Autoregressive distributed lag (ARDL) model encompasses a bound testing approach will be used in our analysis to ascertain the long-run relationship between Total economic damage in Asia Pacific, Total affected population in Asia Pacific and climate change indicators (Global average temperature & Global Annual Mean Precipitation). The ARDL model looks at conintegration and generates short-run and long-run coefficients simultaneously by using OLS estimation procedure. This cointegration approach was developed by Pesaran (1997) and Pesaran and Shin (1999). This method uses Wald testing (F-stat) to conclude the presence of long-term relationship among the selected variables. It is especially targeted for models whose chosen variables for the study are integrated of different orders. In fact it is applicable for variables who are I(1), I(0) or a combination of both. The ARDL approach, in such settings, gives realistic and efficient estimates. This model have several other advantages in comparison to other cointegration techniques such as Engle and Granger (1987) and Johansen and Juselius (1990) procedures.

- ❖ The ARDL approach gives a more efficient result for small sample data sizes unlike johansen cointegration technique which requires a great number data samples for validity.
- ❖ The ARDL test can produce valid estimates and t-statistics even if there are autocorrelation and endogeneity present (Harris and Sollis, 2003)
- ❖ In the presence of a single long-run relationship, the ARDL procedure can distinguish between endogenous and exogenous variables. It assumes that the response and explanatory variables have only a single reduced form equation relationship (Pesaran, Smith and Shin, 2001)
- ❖ Using error correction model (ECM) short-run adjustments can be integrated with the long-run equilibrium in the model without losing valid long-run coefficients (Dumrul & Kilicarsalan, 2017).
- ❖ Lastly, the ARDL model can have equal or different order of lag lengths for all variables and does not affect the asymptotic distribution of the test statistic (Pesaran et al., 2001)

The mathematical representation of ARDL(p, q_1, q_2, q_3) model is as follows:

$$\Delta Y_t = \alpha_{01} + \sum_{i=1}^{p} \beta_{1i} Y_{t-i} + \sum_{i=0}^{q1} \beta_{2i} X_{t-i} + \sum_{i=0}^{q2} \beta_{3i} Z_{t-i} + \sum_{i=0}^{q3} \beta_{4i} W_{t-i} + \delta_{1i} Y_{t-i} + \delta_{2i} X_{t-i} + \delta_{3i} Z_{t-i} + \delta_{4i} W_{t-i} + \varepsilon_{1t} \ldots\ldots\ldots\ldots\ldots(2)$$

Here Δ represents change or first difference operator. p, q_1 q_2 and q_3 are the lag lengths of the Y_t, X_t, Z_t and W_t respectively. The βs are the short-run coefficients and δs are the long-run coefficients. The error term ε_t is assumed to be independently and identically distributed.

In our model, Y_t = Total Direct Economic Damage in million USD (TotEcDm)

X_t = Number of people affected by Natural disaster in million (TotAPop)

Z_t = Global Annual Mean Precipitation in mm (Glb_prcp_mm)

W_t = Global Average Temperature of Earth in ^{0}C (GATemp)

Initially, we test for the existence of unit root in our variables and determine their order of integration. Past studies proposes numerous methods of unit-root test and since there may not be consistency in their results, we selected to view ACF in correlogram and perform Augmented Dickey Fuller (ADF) Test. In ADF test, the null hypothesis dictates that the variable series has a unit root or it is not stationary. The optimal number of lags for the unit root test may be obtained by estimating VAR and subsequent determination of lag length criteria, however in our case we opted to let Eviews automatically select lag length based on Akaike Information Criterion (AIC). The ARDL bound test is based on the assumption that the variables are either I(0) or I(1). If any series are found to be I(2) then the computed F-statistic provided by Pesaran et al. (2001) will become invalid. Therefore, the primary objective of unit root test is to ensure whether ARDL bound test is the appropriate measure and the result in not spurious.

In the second stage, the model/ theory tests the existence of a long-run relationship among the variables. As per our chosen format and expected direction of long-run relationship, we treat the TotEcDm (Y_t) as the dependent variable. The long-run relationship is tested by computing the Wald-coefficient test or F-statistics. The F-statistic is carried out on TotEcDm as the dependent variable while taking others to be the exogenous variables. The appropriate values for the maximum lags for each of the variable is chosen automatically by Eviews 10 based on AIC. The test is carried out on the joint null hypothesis that the long-run coefficients of the lagged variables are zero against the alternative that it is not.

The joint null hypothesis of no long-run relationship is defined by

$H_0 = \delta_{1i} = \delta_{2i} = \delta_{3i} = \delta_{4i} = 0$ (Long-run relationship/ cointegration does not exist)

$H_1 = \delta_{1i} \neq \delta_{2i} \neq \delta_{3i} \neq \delta_{4i}$ 0 (Long-run relationship/ cointegration exists)

In the bounds test, the F-statistics obtained is compared with the critical values stated by Pesaran et al. (2001). The F-test has a non-standard distribution. It depends on the number or regressors, and whether the variables in the model are I(0) or I(1). It also relies on the existence of a trend and/or intercept. Pesaran reports two sets of critical values. One set assuming that all the variables are I(0) which is known as the lower bound. Another set assuming that all variables are I(1) also known as the upper bound. If the computed F-statistic falls below the lower bound we would conclude that there is no cointegration among the variables. If the F-statistic falls above the upper bound then we can reject H_0 and understand that there is cointegration present. However, any values within the two bounds would render the inference inconclusive.

As Pesaran et al. (2001) stated, if the bounds test results shows no cointegration then accordingly there is no long-run relationship. In this case, short-run relationship is present and the short-run ARDL model will be specified. However, if the test confirms that a long run relationship exists, we can estimate an equation for the long-run relationships between the variables as below:

$$Y_t = \alpha_{01} + \sum_{i=1}^{p} \beta_{1i} Y_{t-i} + \sum_{i=1}^{q1} \beta_{2i} X_{t-i} + \sum_{i=1}^{q2} \beta_{3i} Z_{t-i} + \sum_{i=1}^{q3} \beta_{4i} W_{t-i} + \varepsilon_{1t} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

The next step, assuming that there is conintegration among the variables, involves the estimation of the short run coefficients and the associated long-run dynamic error correction models (ECM). In this stage a two-step procedure is carried out. In the first step the optimal lag number in the model are selected based on AIC. This is carried out by estimating unrestricted VAR model. Afterwards, the selected model is estimated through ordinary least-squares technique. The model is given below.

$$\Delta Y_t = \alpha_{01} + \sum_{i=1}^{p} \Delta\beta_{1i} Y_{t-i} + \sum_{i=1}^{q1} \Delta\beta_{2i} X_{t-i} + \sum_{i=1}^{q2} \Delta\beta_{3i} Z_{t-i} + \sum_{i=1}^{q3} \Delta\beta_{4i} W_{t-i} + \lambda\, ECT_{t-1} + \varepsilon_{1t} \ldots\ldots(4)$$

Here the ECT_{t-1} is the error correction term (ECT). The ECT is the lagged value of the residual and shows the long-term relationship in the model. It should be negative and statistically significant because it expresses the speed of adjustment. In other words it tells us how quickly the variables reverts back to the long-run equilibrium. The Beta's in this model represent short run coefficients and can also infer short run causality among the variables.

Diagnostic tests for the model

The ARDL Testing methodology bears a critical assumption. It is that the errors of Equation 2 must be serially independent and normally distributed. Hence 'Breusch-Godfrey Serial Correlation LM Test' will be used for examining serial independence or autocorrelation. 'Jarque-Bera' test will be used for examining whether the errors follow normal distribution in the model. Presence of heteroscedasticity will be checked using 'Breusch-Pagan-Godfrey' Test. Finally, The Ramsey RESET Test will be conducted to check for misspecification in the model. Other typical diagnostic indicators are the X^2 F-statistic and R^2 value

Stability test of the model

In order to measure the parameter stability of the model Recursive CUSUM and CUSUM of squares will be examined. These tests were suggested by Pesaran and pesaran (1997).

Granger Causality test

After discovering the long-run relationship between dependent and independent variables through the application of the ARDL bounds test, the Granger causality test can be applied to determine the direction of causality among the variables. This test invented by Professor

Granger in the 1960s states that if two or more time series shows cointegration, then there is granger causality between them. The causality may be unidirectional of bi-directional. According to Odhiambo (2009) and Narayan and Smyth (2008) a significant lagged error correction term, represented by the t-statistic or p-value, indicates that long run causal relationship exists between explanatory variables and response variable. This confirms that there is Granger-Causality atleast in one direction. Moreover F-statistic of the explanatory variable identifies the short-run causal effect in ECM. Significant short-run coefficients prove the existence of short-run relationship.

Under the ARDL-ECM framework, Granger-Causality test can be performed in few methods. The short-run causality may be checked using the regressor's statistical significance of t-statistics and Wald coefficient test. Pairwise Granger Causality test can also be used to test on direction of causality. The long-run causality will be examined by verifying the coefficient and statistical significance of the error correction term.

Chapter 5

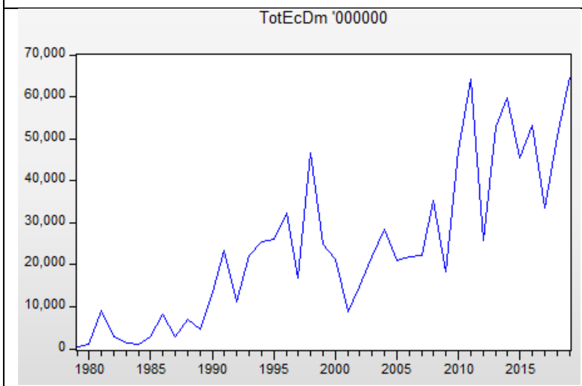
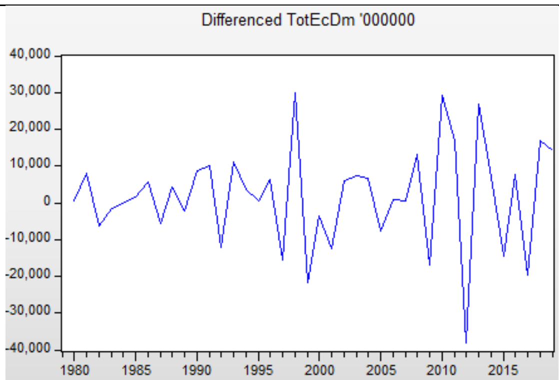
Estimation, results and analysis

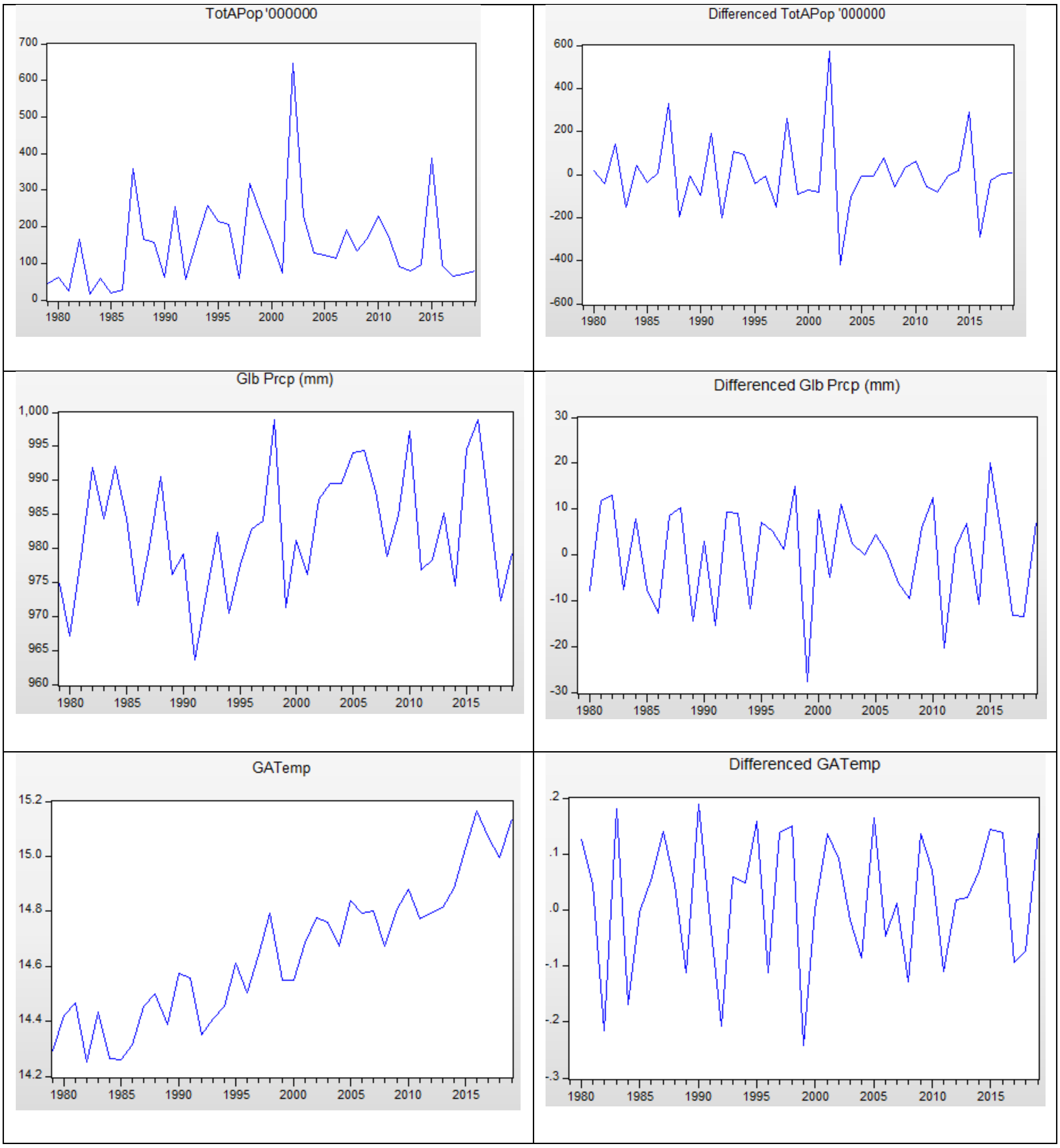
5.1 Unit root analysis

Before incorporating the ARDL bound testing approach we need to test the stationarity of each variable. The objective for this test is to ensure and examine that all the variables are I(0) or I(1) or of both nature for the computation of F-statistic. It is imperative that none of the variables can be I(2) because this would yield spurious results.

To check for unit root we are investigating the graph of the series at levels and at 1st difference represented in Figure 5. Additionally we will generate correlogram and examine the ACF pattern the output of which are presented in Figure 6. Finally we will estimate results generated using the conventional Augmented Dickey Fuller (ADF) test. The result of the tests are presented in Table 1.

Figure 5: Graphs of data series

Graph At Levels	Graph at 1st Difference
	



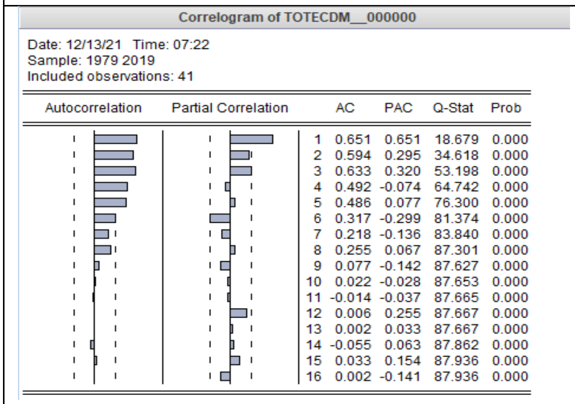
Note: The graphs shows the trend in study variables in level form and then the first differenced form to understand stationarity. Eviews 10. Copyright 2021 by Author

Figure 6: Correlogram of data series

Correlogram at Levels

Correlogram at 1st Difference

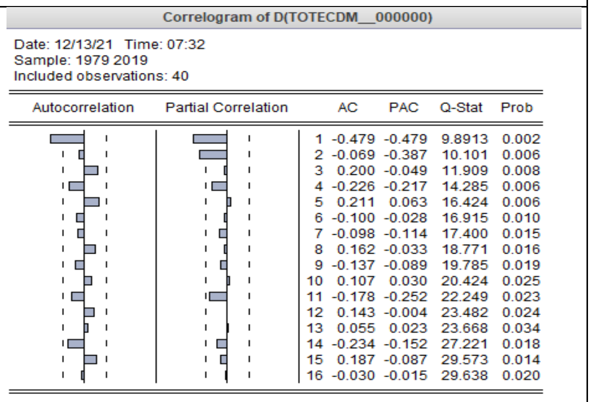
Correlogram of TotEcDm ('000000)



Correlogram of TOTECDM__000000

Date: 12/13/21 Time: 07:22
Sample: 1979 2019
Included observations: 41

	AC	PAC	Q-Stat	Prob
1	0.651	0.651	18.679	0.000
2	0.594	0.295	34.618	0.000
3	0.633	0.320	53.198	0.000
4	0.492	-0.074	64.742	0.000
5	0.486	0.077	76.300	0.000
6	0.317	-0.299	81.374	0.000
7	0.218	-0.136	83.840	0.000
8	0.255	0.067	87.301	0.000
9	0.077	-0.142	87.627	0.000
10	0.022	-0.028	87.653	0.000
11	-0.014	-0.037	87.665	0.000
12	0.006	0.255	87.667	0.000
13	0.002	0.033	87.667	0.000
14	-0.055	0.063	87.862	0.000
15	0.033	0.154	87.936	0.000
16	0.002	-0.141	87.936	0.000

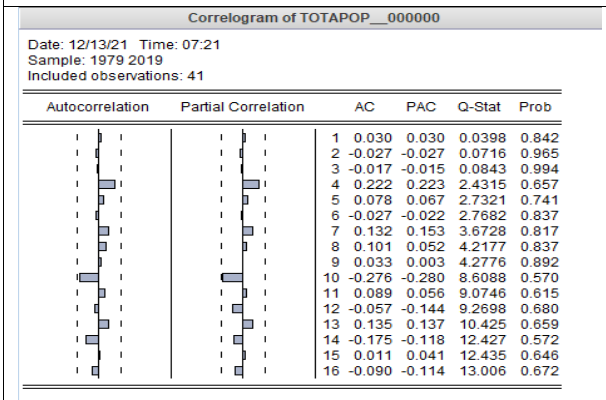


Correlogram of D(TOTECDM__000000)

Date: 12/13/21 Time: 07:32
Sample: 1979 2019
Included observations: 40

	AC	PAC	Q-Stat	Prob
1	-0.479	-0.479	9.8913	0.002
2	-0.069	-0.387	10.101	0.006
3	0.200	-0.049	11.909	0.008
4	-0.226	-0.217	14.285	0.006
5	0.211	0.063	16.424	0.006
6	-0.100	-0.028	16.915	0.010
7	-0.098	-0.114	17.400	0.015
8	0.162	-0.033	18.771	0.016
9	-0.137	-0.089	19.785	0.019
10	0.107	0.030	20.424	0.025
11	-0.178	-0.252	22.249	0.023
12	0.143	-0.004	23.482	0.024
13	0.055	0.023	23.668	0.034
14	-0.234	-0.152	27.221	0.018
15	0.187	-0.087	29.573	0.014
16	-0.030	-0.015	29.638	0.020

Correlogram of TotAPopAs ('000000)

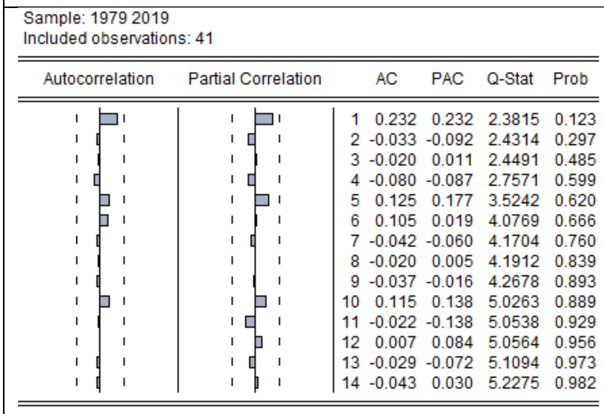


Correlogram of TOTAPOP__000000

Date: 12/13/21 Time: 07:21
Sample: 1979 2019
Included observations: 41

	AC	PAC	Q-Stat	Prob
1	0.030	0.030	0.0398	0.842
2	-0.027	-0.027	0.0716	0.965
3	-0.017	-0.015	0.0843	0.994
4	0.222	0.223	2.4315	0.657
5	0.078	0.067	2.7321	0.741
6	-0.027	-0.022	2.7682	0.837
7	0.132	0.153	3.6728	0.817
8	0.101	0.052	4.2177	0.837
9	0.033	0.003	4.2776	0.892
10	-0.276	-0.280	8.6088	0.570
11	0.089	0.056	9.0746	0.615
12	-0.057	-0.144	9.2698	0.680
13	0.135	0.137	10.425	0.659
14	-0.175	-0.118	12.427	0.572
15	0.011	0.041	12.435	0.646
16	-0.090	-0.114	13.006	0.672

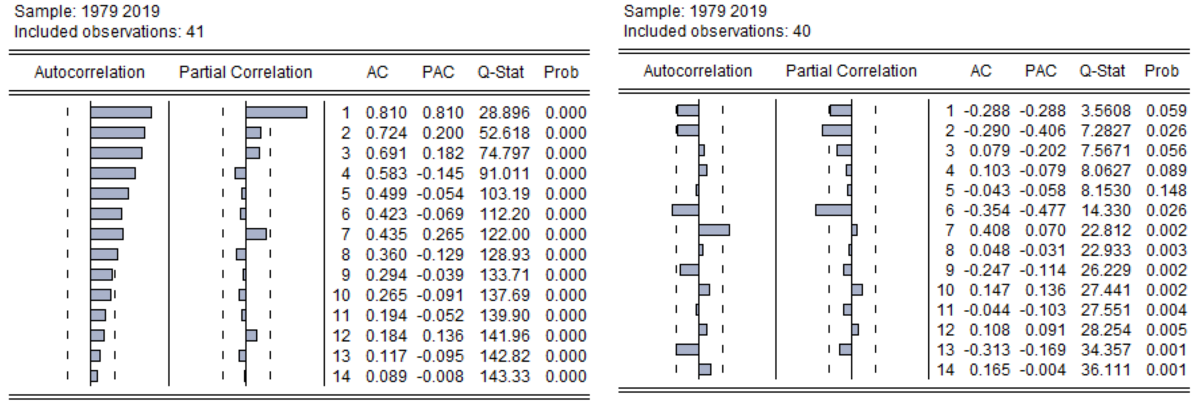
Correlogram of Glb_prcp_mm



Sample: 1979 2019
Included observations: 41

	AC	PAC	Q-Stat	Prob
1	0.232	0.232	2.3815	0.123
2	-0.033	-0.092	2.4314	0.297
3	-0.020	0.011	2.4491	0.485
4	-0.080	-0.087	2.7571	0.599
5	0.125	0.177	3.5242	0.620
6	0.105	0.019	4.0769	0.666
7	-0.042	-0.060	4.1704	0.760
8	-0.020	0.005	4.1912	0.839
9	-0.037	-0.016	4.2678	0.893
10	0.115	0.138	5.0263	0.889
11	-0.022	-0.138	5.0538	0.929
12	0.007	0.084	5.0564	0.956
13	-0.029	-0.072	5.1094	0.973
14	-0.043	0.030	5.2275	0.982

Correlogram of GATemp



Sample: 1979 2019
Included observations: 41

	AC	PAC	Q-Stat	Prob
1	0.810	0.810	28.896	0.000
2	0.724	0.200	52.618	0.000
3	0.691	0.182	74.797	0.000
4	0.583	-0.145	91.011	0.000
5	0.499	-0.054	103.19	0.000
6	0.423	-0.069	112.20	0.000
7	0.435	0.265	122.00	0.000
8	0.360	-0.129	128.93	0.000
9	0.294	-0.039	133.71	0.000
10	0.265	-0.091	137.69	0.000
11	0.194	-0.052	139.90	0.000
12	0.184	0.136	141.96	0.000
13	0.117	-0.095	142.82	0.000
14	0.089	-0.008	143.33	0.000

Sample: 1979 2019
Included observations: 40

	AC	PAC	Q-Stat	Prob
1	-0.288	-0.288	3.5608	0.059
2	-0.290	-0.406	7.2827	0.026
3	0.079	-0.202	7.5671	0.056
4	0.103	-0.079	8.0627	0.089
5	-0.043	-0.058	8.1530	0.148
6	-0.354	-0.477	14.330	0.026
7	0.408	0.070	22.812	0.002
8	0.048	-0.031	22.933	0.003
9	-0.247	-0.114	26.229	0.002
10	0.147	0.136	27.441	0.002
11	-0.044	-0.103	27.551	0.004
12	0.108	0.091	28.254	0.005
13	-0.313	-0.169	34.357	0.001
14	0.165	-0.004	36.111	0.001

Note: The figure displays the corellogram of all four study variables. Eviews 10. Copyright 2021 by Author

Table 1: ADF Test results

Total Economic Damage in USD (TotEcDm_000000)			
	ADF Equation	***P-Value (ADF)***	***Outcome***
Level	None	0.9996	Non-Stationary
	Intercept	0.9938	Non-Stationary
	Trend & Intercept	0.0001	Stationary
First Difference	None	0	Stationary
	Intercept	0.0001	Stationary
	Trend & Intercept	0.0008	Stationary

Total Affected Population in Asia (TotAPop_000000)			
Level	None	0.3343	Non-Stationary
	Intercept	0	Stationary
	Trend & Intercept	0	Stationary
First Difference	None	0	Stationary
	Intercept	0	Stationary
	Trend & Intercept	0.0025	Stationary
Global Annual Mean Precipitation (Glb_prcp_mm)			
Level	None	0.7063	Non-Stationary
	Intercept	0.0003	Stationary
	Trend & Intercept	0.0011	Stationary
First Difference	None	0	Stationary
	Intercept	0.0001	Stationary
	Trend & Intercept	0.0008	Stationary

Global Average Temp (GATemp)			
Level	None	0.9999	Non-Stationary
	Intercept	0.9932	Non-Stationary
	Trend & Intercept	0.7097	Non-Stationary

First Difference	None	0.6712	Non-Stationary
	Intercept	0	Stationary
	Trend & Intercept	0.0003	Stationary

Note: The table reports the ADF test results of all four study variables. Eviews 10. Copyright 2021 by Author

The graphs of the time series variables in Figure 5 illustrates that Total Direct Economic damage in USD and Global Average Temperature have a general upward trend at levels but a constant mean at differenced form. This suggests that they are not stationary at level. However, the graph of variable Total affected population and Global annual mean precipitation displays insignificant trend and constant mean which indicates that series is stationary at level. The correlograms of the data sets in Figure 6 depicts that only GATemp are non-stationary whereas TotEcDm, TotAPop and Glb-prcp are stationary at levels.

The study applied the ADF test on the variables[2] in level and first difference form under three versions: No trend & no intercept, only intercept and with trend & intercept. The dependent variable Total Direct Economic Damage in USD are I(1) under no trend & intercept and only intercept form. But considering trend & intercept the two series are stationary at I(0). The explanatory variable Total affected population in Asia Pacific is I(0). Similarly, explanatory variable Glb-prcp is also stationary at I(0). However, GATemp displays that it is stationary at first difference.

Although the ADF test illustrates contradictory results from graphical analysis for dependent variable TotEcDm but we can safely say that the variable is not I(2). Overall our findings indicate that only GATemp is I(1) whereas the rest of the variables are all I(0). Finally we can

[2]ADF Test on the log form of the variables were also conducted and the results are published in Appendix A. It is to be noted that one of the independent variable shows I(2) properties

conclude that the time series variables are I(0) and I(1). The absence of I(2) corroborates the application of ARDL bound testing technique.

5.2 Bound testing approach for cointegration

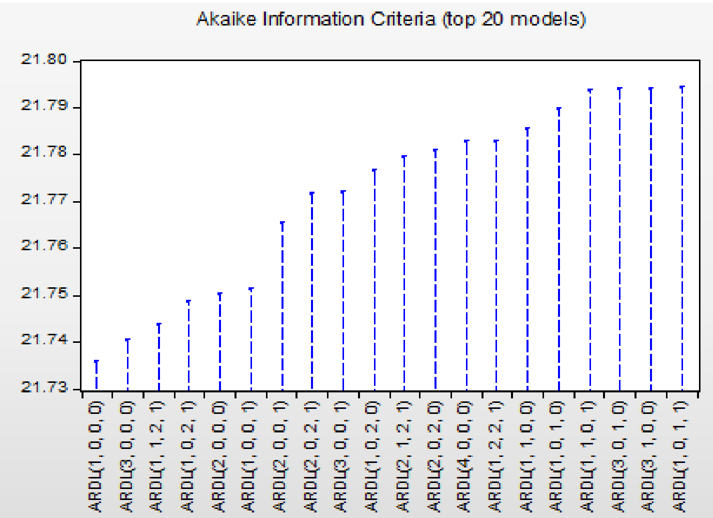
To check for long-run relationship among the variables bound testing approach is applied. The specific form of ARDL model for our study incorporating long-run and short-run coefficients are as follows:

$$\Delta TotEcDm_t = \alpha_{01} + \sum_{i=1}^{p} \Delta\beta_{1i} TotEcDm_{t-1} + \sum_{i=0}^{q1} \Delta\beta_{2i} TotAfPop_{t-i} + \sum_{i=0}^{q2} \Delta\beta_{3i} Glb\_prcp_{t-i} + \sum_{i=0}^{q3} \Delta\beta_{4i} GATemp_{t-i} + \delta_{1i} TotEcDm_{t-i} + \delta_{2i} TotAfPop_{t-i} + \delta_{3i} Glb\_prcp_{t-i} + \delta_{4i} GATemp_{t-i} + \varepsilon_{it} \quad \text{..............................} (5)$$

ARDL model estimation

The optimal lag length is selected automatically based on AIC. Figure 7 displays the optimal lag length for our ARDL (p, q_1, q_2, q_3) model:

Figure 7: Optimal lag length based on AIC



Note: The figure shows the AIC values of various combinations of ARDL model. EViews 10. Copyright 2021 by Author

Figure 7 demonstrates that ARDL (1,0,0,0) model will give the most efficient outcome for bound testing approach. Therefore, the optimum lag lengths of the variables TotEcDm, TotAPop, Glb-prcp and GATemp are p=1, $q_1 = 0$, $q_2 = 0$ and $q_3 = 0$ respectively.

ARDL Bounds Test

The eviews output of cointegration test results for the ARDL (1,0,0,0) and k=3 (number of independent variables) the relevant critical values with unrestricted constant and no trend are displayed in Table 2[3].

Table 2: Results of cointegration test

Critical Values	**Lower Bound I(0)**	**Upper Bound I(1)**
1%	4.29	5.61
5%	3.23	4.35
10%	2.72	3.77
F-Stat	***5.34***	
K	***3***	

Note: The table displays the F-Statistics of upper and lower bound for each level of significance. EViews 10. Copyright 2021 by Author

The F-stat result 5.34 of ARDL Bounds Testing implies that cointegration exists among the variables at 5% level of significance. The F-Stat > F_{UB} deduce that there is a long-run relationship among the variables.

[3]The results of the bounds test with unrestricted constant and trend are reported in Appendix B. The F-Stat is 7.32

Long-run relationship

The ARDL (1,0,0,0) model also explains the long run model. The long-run equilibrium relationship among the variables are estimated using the following equation.

$TotEcDm_t = \alpha_{01} + \delta_{11}\ TotEcDm_{t-1} + \delta_{2i}TotAfPop_{t-i} + \delta_{3i}Glb\_prcp_{t-i} + \delta_{4i}GATemp_{t-i} + \varepsilon_{1t}$ ………………… (6)

The long-run coefficients obtained from ARDL(1,0,0,0) model are reported in the following table[4]:

Table 3: Estimated long-run coefficients

Variables	Coefficients	T-stat	Probability (p-value)
TotAPop_000000	2.4237	0.1104	0.9127
Glb_prcp_mm	-221.97	-0.6971	0.4903
GAtemp	63839.91	5.6642	0.0000*

Note: The table reports the long-run coefficients of independent variables from ARDL model. EViews 10. Copyright 2021 by Author

The results shows only explanatory variable GAtemp has a positive impact on response variable and is significant at 5%. This indicates that a 1^0C increase in global average temperature will increase the total direct economic damage due to natural disasters by 63,839,910,000 USD in Asia Pacific. This is indicative that climate change is responsible for economic damage caused by natural disasters in Asis and the Pacific.

[4]The long run coefficients of the bounds test with unrestricted constant and trend are displayed in Appendix B

The result shows consistency with past papers where Lopez et al. (2015) who conducted Engle Granger co-integration test between global climate variables (CO_2 emissions and average sea surface temperature) and frequency of intense natural disasters (Hydrometeorological and climatological), found a long run relationship also.

Diagnostic tests of the ARDL (1, 0, 0, 0) model

The chosen model is a good fit and passes all the relevant diagnostic tests. The R^2 and Adj-R^2 value implies that 65.4% and 61.5% variation in the dependent variable are explained by the model and the rest by error term. The DW statistics is 2.26 which echoes that the model is not spurious. Additionally, the computed F-statistic = 16.55 and P-Value = 0.00 clearly rejects the null hypothesis that the repressor's have zero coefficients. The model also passes other diagnostics tests such as the serial correlation test (Breusch-Godfrey Serial LM Test), Normality (Jarque-Bera Test) and Heteroscedasticity (Breuch-Pagan-Godfrey Test).

Table 4: Model diagnostics test results

Diagnostic Test	F-statistic	Probability
Breusch-Godfrey Serial LM Test	1.5611	0.2250
Jarque-Bera Test	1.0028	0.6057
Breuch-Pagan-Godfrey Test	1.8989	0.1325

Note: The table depicts the various diagnostic test output. EViews 10. Copyright 2021 by Author

5.3 Short run dynamics and Error correction model

The equation below is used to estimate the short-run coefficients and error correction term. The error correction term is the representation of the long-run form.

$\Delta TotEcDm_t = \alpha_{01} + \sum_{i=1}^{p} \Delta\beta_{1i} TotEcDm_{t-i} + \sum_{i=1}^{q1} \Delta\beta_{2i} TotAfPop_{t-i} + \sum_{i=1}^{q2} \Delta\beta_{3i} Glb\_prcp_{t-I} + \sum_{i=1}^{q4} GATemp_{t-i} + \lambda ECT_{t-1} + \varepsilon_{1t}$ ……………………… (7)

Firstly the variables were estimated at level in the unrestricted VAR framework. The AIC was used for the lag length selection. The results of the ARDL-OLS regression of Error Correction Model with optimal lag structure 1 is reported in the next table[5].

Table 5: Error correction model results

Variables	**Coefficients**	**T-Statistic**	**Probability**
C	744.232	0.3905	0.6987
D(TotEcDm_000000(-1))	-0.0247	-0.1065	0.9159
D(TotAPop_000000(-1))	-3.7477	-0.3331	0.7412
D(Glb_prcp_mm_(-1))	70.968	0.3818	0.7051
D(GAtemp(-1))	38365.4	2.1941	0.0354*
Coint. Eq(-1)	-0.7845	-2.6269	0.0130*

Note: The table reports the short-run coefficients of independent variables from ARDL-OLS regression model. EViews 10. Copyright 2021 by Author

The ECM model results indicate that there are short run dynamics in conjunction with long-run relationship. The value and sign of lagged error correction term as [Coint. Eq(-1)] is negative and significant. This represents that there exists a long-term relationship between the dependent variable and independent variables. A high value of ECM shows speedy adjustment process. According to the results the value of ECM terms suggests that the change in total direct

[5]Error Correction Model output with unrestricted constant and trend are presented in Appendix C

economic damage from short run to long run is corrected by 78.5% every year significantly. Thus the disequilibrium occurring due to a shock will take only few years to reach equilibrium.

A significant ECT also means that the total affected population by natural disasters, global mean precipitation and global mean temperatures Granger cause total economic damage due to natural hazards in Asia Pacific region. This implies that that there is Granger causality in at least one direction that runs interactively through the error correction term.

The results also highlighted that only the 1 lag period of global average temperature is positive and significant and has a short run causal impact on the dependent variable. In other words, a 1^0C increase in global average temperature will cause \$38,365,400,000 worth total direct economic damage by natural disasters in Asia Pacific the following year. Climate indicator global average precipitation also shows a positive influence on dependent variable but results are insignificant at 5% level. Therefore, we may conclude that the overall impact of rise in global average temperature is time invariant, i.e., having similar long-run and short-run impact on natural disasters and associated economic damage caused by them.

Diagnostic tests of the ECM model

The R^2 and adjusted R^2 value of 43.1% and 34.5% shows that total affected population in Asia Pacific and global affected temperature jointly explains a moderate part of the variation in total direct economic damage due to natural hazards in Asia Pacific region. A significant F-stat deduces that the model is a good fit. The DW statistic of 1.94 shows that the model is not spurious. Additionally serial correlation LM test, normality, heteroscedasticity test and Ramsey RESET tests were performed whose results confirm that overall the model is a good fit and there is a linear relationship between the dependent and independent variables.

Table 6: ECM diagnostics test results

Diagnostic Test	F-statistic	Probability
Breusch-Godfrey Serial LM Test	1.1186	0.3396
Jarque-Bera Test	1.4743	0.4785
Breuch-Pagan-Godfrey Test	2.0266	0.1005
Ramsey RESET Test (Fitted Value)	-0.2994	0.7666

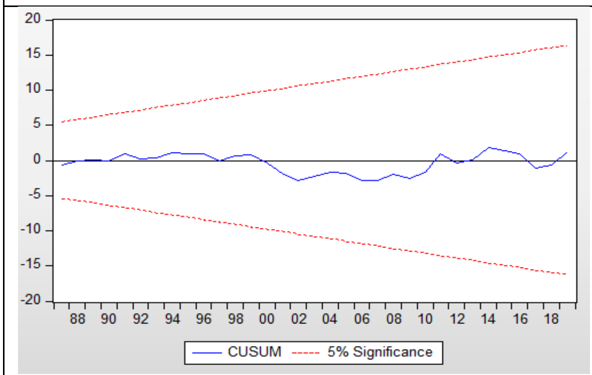
Note: The table depicts the various diagnostic test output. EViews 10. Copyright 2021 by Author

Stability tests of the ECM Model

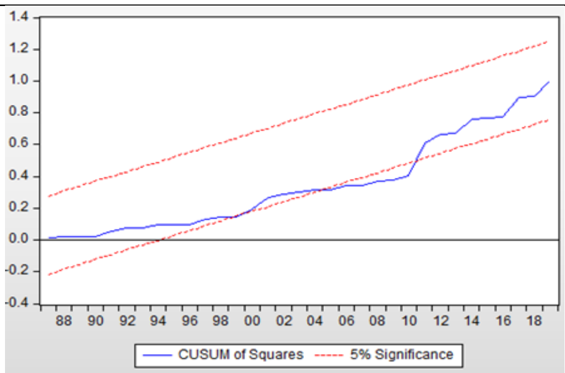
By using the short run dynamics the stability of the long-run coefficient is tested. After the ECM model given by equation (7) is estimated, the cumulative sum of recursive residuals (CUSUM) and the CUSUM of Square (CUSUMSQ) tests were applied to validate the parameter stability (Pesaran and Pesaran, 1997). Figure 8 plots the results for CUSUM and CUSUMSQ. The results display that the plots of the statistic falls within the critical band of 5% confidence interval of parameter stability. This corroborates that the coefficients are stable.

Figure 8: Plot of CUSUM test and CUSUMSQ test

CUSUM Test Output



CUCUMSQ Test Output



Note: The figure shows the CUSUM and CUSUMSQ test plots. EViews 10. Copyright 2021 by Author

5.4 Granger causality test

After examining the long-run and short-run relationship between the variables, we have used the Wald Test and Pairwise Granger causality test to determine and asses the causality between the variables. Since we observed cointegration and long-run Granger causality among the variables, it is likely to expected that there may be an uni or bidirectional causality between the series. The Wald Test results are reported below

Table 7: Results of Wald test on coefficients of independent variables

Variable	F-Statistics	Probability (Short-run)
D(TotAPop_000000)	0.0122	0.9126
D(Glb_prcp_mm)	0.4503	0.5066
D(GATemp)	13.549	0.0008*

Note: The figure shows the f- statistics values of Wald coefficients. EViews 10. Copyright 2021 by Author

The Wald-Test on coefficients of independent variables displays that only GATemp or Global average temperature is significant and Granger causes direct economic damages due to natural hazard in Asia Pacific region. This finding validates our outcome of short run causal impact derived from ECM. The direction of short run causal impact is investigated using Pairwise Granger Causality test. The results are shown below.

Table 8: Results of Pairwise Granger causality test

Variable	Probability Values				Direction of Causality
	TotEcDm_000000	TotAPop_000000	Glb-prcp_mm	GATemp	
TotEcDm_000000		0.8972	0.8882	0.2560	
TotAPop_000000	0.8671		0.5301	0.6598	
Glb_prcp_mm	0.6423	0.3621		0.2075	
GATemp	0.0009	0.5613	0.2603		GATemp→TotEcDm

Note: The figure shows the probability values derived from Pairwise Granger Causality test. EViews 10. Copyright 2021 by Author

From the reported results we have found only the uni-directional causality running from global average temperature to total direct economic damage due to natural disasters in Asia Pacific region. Therefore, we may conclude from granger causality test that the rise in global average temperatures annually is the reason for the increase in the direct economic damage caused by the rise in natural disasters in Asia Pacific region.

Chapter 6

Conclusion

We have seen that natural disasters featured heavily in the media in recent years. South and Southeast Asia tops the list of the regions affected. Heavy storms, typhoons and cyclones have caused significant damages in various parts of Asia and the Pacific. Wildfires and storms have devastated Australian economy. Peoples Republic of China, India, Indonesia, The Republic of Korea, Japan, Thailand, Vietnam etc are worst affected by floods and storms (Lopez et al. 2015). Droughts and extreme temperature have curtailed food production and productivity. Asia and the Pacific is among the most vulnerable in terms of people affected by climate change and its resulting disasters (Wallemacq, 2018).

Climate change is an integral finding in this paper. Human emissions of greenhouse gases are affecting the climate and scientists have examined this to a great extent for over 150 years (Thomas et al. 2013). Atmospheric carbon dioxide concentrations have exceeded 400 ppm and is likely to reach 450 ppm within a couple of decades (Kemp, 2019). Many scientists believe that 450 ppm to be a dangerous level which will raise the mean surface temperature by 2^0C and its related impacts on climate related disasters.

Past literature and recent observations reports that high GHG emissions are responsible for its increased concentrations in the atmosphere. Higher concentrations of GHG catalyzes changes in global temperature and precipitation levels. Based on this scientific association, the findings in this paper lead us to formulate a connection between increasing climate induced natural disasters in Asia Pacific region and global emissions of GHG. However, the main purpose of this study is to quantify the direct economic damages caused by natural disasters in Asia Pacific region and establish a long run association of it with global warming or climate change indicators over recent decades. Taken together the econometric analysis suggest that global mean annual temperature play a significant part in instigating natural disasters in Asia Pacific region by incurring billions of dollars in damages. Although precipitation also has links to GHG emissions and influences heavy rainfalls and storms and resulting floods but this paper could not find any significant consequences to natural disasters.

Climate change is considered by many to be bigger threat than all global economic setbacks. There is a worldwide increase in natural disasters. Asia Pacific region bearing more densely populated, poorer and environmentally degraded regions are taking a heavy toll. High population exposure and exacerbating weather disasters in this area weigh heavily over the region's economic success and global strategic importance (Thomas et al. 2013). The region's population continues to rise fast and drive global economic growth. Yet, global manufacturing zones are being built in hazard prone and ill-prepared areas. The recent trends in disasters suggest that if they continue they are likely to fundamentally alter the regional development paradigm.

According to Lopez et al. (2015) some argue that there appears to be a false dilemma of balancing growth with the environment. A long-term strategy which focuses on economic growth at the expense of environmental destruction will actually worsen climate change, mostly to the detriment of the poor. If sustained growth is the objective then the climate challenge must be met. In order to do so, we specially need to strengthen ***disaster resilience***, prioritize ***urban management*** and adopt ***climate action*** as part of an optimal growth strategy.

Disaster resilience needs to be incorporated into national growth strategies. Two important component of ***disaster resilience*** are *disaster prevention* and *disaster risk reduction DRR*. Disaster prevention does not receive the same emphasis as disaster response – reaction in relief and reconstruction. Disaster prevention has a higher payoff over disaster response (Hallgate, 2021; World Bank, 2010). Important steps in disaster prevention strategies are to reduce vulnerability, increase capacity to withstand and stronger response to recovery. Actions like relocation, investment in infrastructure and services and recovery insurance are good examples of policy actions. DRR involves measures to avoid or curtail casualties and economic damage from disasters. Now cross-cutting tools like regional early warning systems, innovation in space applications and improved forecasting ability have evolved to counter disaster impacts. Japan and Philippines have greatly benefited by implementing DRR measures as described by Lopez et al. (2015). Yet, not enough investments are directed towards improving DRR over disaster response. It is recommended that governments spend 1% to 2% of their national budgets on DRR and focus on promoting their effective use to reap full benefits (Lopez et al, 2015).

Secondly, planners need to focus on ***urban management*** as a strategic thrust. According to Lopez et al. (2015) the five cities considered most vulnerable to climate hazards are all in Asia: Dhaka, Manila, Bangkok, Yangon and Jakarta. These cities are overcrowded and located in fragile settings making them prone to disaster impacts. The vulnerable cities have withstood massive agglomeration and unplanned settlements sprung up outside city limits. They have inadequate infrastructure and safety standards. It is imperative that the settlements are rebuild with appropriate infrastructure and services, good governance and meeting all safety standards and environmental care.

Thirdly, ***climate action*** need to play a central role in national plans. Dealing with climate change has become a precedent to economic growth. Adapting to climate change through proper planning and judicious management of the location decisions of people and businesses, shielding the natural ecosystem occupies higher urgency (Thomas et al. 2013). The underprivileged community are hit hardest which is why *climate adaptation* and *climate mitigation* needs to be highlighted. Policies need to be targeted to influence location decisions and build resilient communities. Resilience intrinsically connects DRR and sustainable development. Switching to a low-carbon path and adopting green technology is essential to reduce GHG emission and confront rising trend in climate related disasters. Phasing out fossil fuel subsidies, encourage renewable energy and expanding climate finance are possible policy actions that could be directed to fight climate change. If not global, decisions may be taken unilaterally to cut back on carbon emissions to curb pollution, opening way for cleaner air.

Global warming is central to climate change. By far it is the most pressing concern for governments, the development community and all societies. With the rise in GHG emissions and the resulting economic impact from increasing trends in natural disasters, implementing effective strategies to fight and mitigate impacts of climate change need to become the integral approach to sustainable development and economic growth.

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Appendix A.

ADF Test Result (Log Form)

Variable	**Specification**	**ADF Test Output**
LtotEcDm	Intercept	I(1)
	Intercept & Trend	I(0)
LtotAPop	Intercept	I(2)
	Intercept & Trend	I(2)
LGlb_prcp	Intercept	I(0)
	Intercept & Trend	I(0)
LGatemp	Intercept	I(1)
	Intercept & Trend	I(1)

Appendix B.

Results of Cointegration Bounds Test with unrestricted constant and trend

	With Time Trend	
Critical Values	**Lower Bound I(0)**	**Upper Bound I(1)**
1%	5.17	6.36
5%	4.01	5.07
10%	3.47	4.45
F-Stat	***7.32***	
K	***3***	

Estimated Long-run coefficients with unrestricted constant and trend

	With Time Trend		
Variables	**Coefficients**	**T-stat**	**Probability (p-value)**
TotAPop_000000	-3.1981	-0.2031	0.8404

Appendix C.

Error Correction Model results for unrestricted constant and trend

Variables	Coefficients	T-statistics	Probability
C	473.797	0.1292	0.8980
D(TotEcDm_000000(-1))	-0.0192	-0.0998	0.7850
D(TotAPop_000000(-1))	-2.9183	-0.2751	0.7850
D(Glb_prcp_mm_(-1))	79.770	0.4575	0.6504
D(GAtemp(-1))	22844.10	1.4734	0.1504
Coint. Eq(-1)	-0.9067	-3.4864	0.0014*
@Trend	24.910	0.1606	0.8734