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Examination of Intense Climate-Related Disasters in Asia-Pacific

by

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Abstract

The frequency of intense floods and storms is increasing globally, particularly in Asia-Pacific, amid the specter of climate change. Associated with these natural disasters are more variable and extreme rainfall and temperatures as recorded in publicly available databases for the world, Asia-Pacific, and the Philippines, the case examined in detail. The risks of these events are resulting from a confluence of three factors: rising exposure of populations, increasing vulnerabilities, and the changing nature of the hazards themselves. All three factors are contributing to increasingly turn hazards of nature into intense natural disasters. The economies along coastal areas in South, Southeast (for example the Philippines), and East Asia are at the greatest risk, with the heaviest toll on low- and lower-middle-income economies. These catastrophes threaten the otherwise dramatic progress on poverty reduction of the past three decades in Asia-Pacific. This outlook points to the urgent need for economies not only to adapt their exposure and capacity in relation to natural disasters, but also to mitigate climate change that seems to underlie the new trends.

Key Words: disasters, risk, climate-change, vulnerability

Key Points

- There is evidence that intense natural disasters are rising, particularly in Asia-Pacific, largely on account of rising climate-related disasters such as meteorological (storms), hydrological (floods) and extreme temperature events.
- Across the world, and in Asia-Pacific, the impact of these natural disasters is borne by low and lower-middle income countries.
- From 1971 to 2010, temperature anomalies during weather-related disasters have averages that are rising across the years, while total precipitation (during months when these intense disasters occurred) appears to be having slightly more variability.
- Evidence indicates that changes in the global climate conditions (such as temperature anomalies and precipitation deviations from normal) are linked with rising carbon dioxide concentration.
- Natural disasters result when hazards of nature, which are influenced by climate conditions, hit vulnerable areas: some sub-regions (South East Asia, Southern Asia and East Asia), particularly the following economies in Asia-Pacific: China, India, Bangladesh, Myanmar and Philippines are more vulnerable to weather-related disasters, i.e. hydrological and meteorological disasters, than other areas in the region.
- Major factors explaining vulnerability to intense climate-related disasters in Asia-Pacific include (i) the rising number of people exposed to hazards in low-lying cities near coasts (approximated by population growth); (ii) adaptive capacity (high population density) (iii) climatic factors (proportion of an economy that is tropical, amount of precipitation, average temperature).
- The strength of these factors depends on location: the amount of precipitation (deviations from normal) explains weather-disaster risk in South Asia and South East Asia while in East Asia temperature anomalies deviations, explain weather-related disaster risks.
- In the Philippines, there is no evidence of rising annual occurrence of tropical cyclones, even more extreme tropical cyclones, but typical paths of tropical cyclones are changing in the past sixty years.
- Damages and casualties from tropical cyclones are rising in the Philippines, with the huge damages in recent past coming from tropical cyclones of lower intensity (than typhoons), but with much heavier rains.
- In the Philippines, there is evidence of rising temperatures and increasing trends in the frequency of extreme daily rainfall, though these trends are not uniform throughout the country.
- In Luzon, one the three major islands of the Philippines located in the northernmost area of the archipelago, there is also evidence of more frequent rainfall greater than 350 millimeters in rather recent years, than the 275 millimeters rainfall events of the 1960s and 1970s.
- Using results of climate models, the mean temperature, the number of hot days, as well as the number of days with heavy precipitation in the Philippines are projected to rise in 2020 and 2050 from their baseline levels.
- Although the main effects of climate change may well be in the very near future, there is some evidence that the increasing severity of intense weather-related disasters are a confluence of changing nature of hazards, rising population exposure, and limited adaptive capacity, thus further and improved adaptation measures are needed.

1. Introduction

1.1. Recent floods, earthquakes and storms in some economies across Asia and the Pacific have brought attention to developing resilience to disasters[1], especially on account of their impact on lives and property. These events clearly erode on whatever gains have been made in human and economic development, particularly in Asia and the Pacific, where trends in poverty reduction have been phenomenal in recent times, and where these extreme incidents occur more frequently than other regions of the world. Damages can be further aggravated if people living in areas that are risk-prone to these disasters depend on livelihood that is easily affected by such hazards of nature (IEG, 2006).

1.2. There is growing concern that the number of floods, storms and other climate-related disasters may be on the rise resulting from environmental degradation, population pressure in coastal areas and mega-cities, and the possible effects of human-induced climate change. Since its establishment by the United Nations in 1988, the Intergovernmental Panel on Climate Change (IPCC) has thus far come up with four comprehensive assessments on data on human-induced climate change, the environmental and socio-economic impact, and the possible options for adaptation to these consequences as well as mitigation of their effects. The 2007 IPCC report builds on as well as expands the scope of previous assessments. This report indicated that global average surface temperature has increased 0.76°C over the past one and a half centuries. It also suggests that climate change is largely a result of human-induced greenhouse gas (GHG) emissions and that if business as usual continues, then by the end of this century, global temperatures could rise to more than 4°C above 1980–1999 levels (ranging from 2.4–6.4°C), under pessimistic climate scenarios. A recently release special report (IPCC, 2012) discusses the relationship between climate change as well as extreme weather and climate events, the impacts of such events, and the strategies to manage the associated risks. The Stern Review (2006), initiated by the UK government, made an even stronger argument in recommending urgent policy action to combat human-made climate change than previous assessments, including those of the IPCC, although the conclusions of the Stern Review have been subsequently contested (see, e.g., Nordhaus, 2007; Weitzman, 2007; Tol and Yohe 2006; Dasgupta, 2007). The Asian Development Bank (ADB) has efforts to examine the economics of climate change in various sub-regions of Asia-Pacific. The ADB study involves a review of existing climate studies, modelling climate change and its impact, modeling economic impact of climate change, as well as results of national and sub-regional consultations with experts and policy makers. The ADB undertaking covering South East Asia (ADB, 2009) has been completed, while ADB studies are on-going for South Asia, the Pacific, Northeast Asia, as well as Central and West Asia.

1.3. Increased frequency of disasters should generate economic consequences. Investments undertaken on infrastructure and projects likely to be affected by disaster events have to adapt to these trends. People living in more risk prone areas will need to be have more access to catastrophe insurance, and more incentives to precautionary savings that will mitigate the adverse effects of these events should they occur. Often, those who have less in life are more at risk, especially when they live in these disaster-prone areas, so that in consequence, risk reduction is ultimately connected to social and economic development. Cognizant of these significant threats to development, the ADB has also been engaged in escalating its partnerships with governments, the private sector and civil society. Governments need to work on investing in hardened infrastructure and flood barriers, including improvement on infrastructure designs and standards, proper enforcement of building codes, as

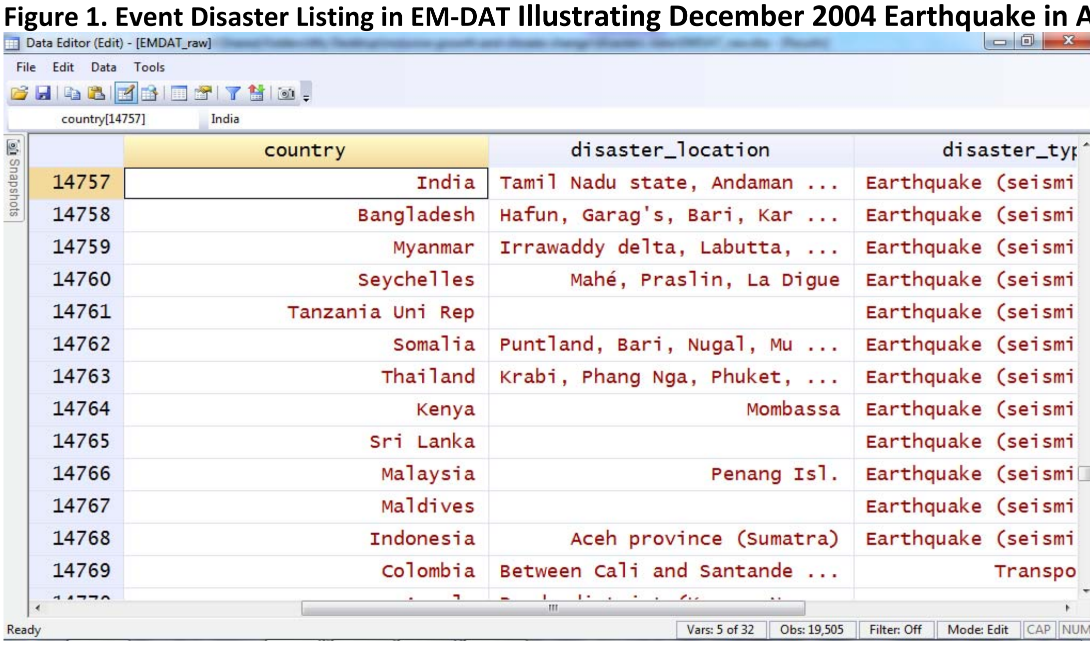
[1] The United Nations International Strategy for Disaster Reduction (UNISDR) defines a disaster as "a serious disruption of the functioning of a community or a society causing widespread human, material, economic, or environmental losses that exceed the ability of the affected community or society to cope using its own resources."

well as develop public policies for reducing the exposure to natural disasters by making changes on land zoning and urban planning. Mainstreaming disaster management and climate adaptation is ultimately about reducing disaster risks, aside from mitigating the impact of the consequences of disasters. Toward such ends, it is important to examine available data on disasters, particularly climate-related disasters, and uncover whether some regions, sub-regions and economies, are more at risk from these disasters toward planning for better disaster mitigation and prevention as well as climate change adaptation.

2. Trends in Intense Natural Disasters, especially Climate-Related Types

2.1. The Centre for Research on the Epidemiology of Disasters (CRED) monitors global disasters[2], and categorizes them into natural and technological groups. The natural disasters are further divided into five subgroups: (a) geophysical events including earthquakes, volcanoes, dry mass movements; (b) meteorological events, such as storms; (c) hydrological events, including floods, wet mass movements, (d) climatological events, including extreme temperature changes, drought, wildfire, and, (e) biological disasters, such as epidemics, insect infestations, animal stampedes. The CRED's EM-DAT[3] database of disasters[4] lists these events by country affected. In consequence, an event, such as the December 2004 undersea earthquake in Aceh, Indonesia that resulted in tsunamis in several countries, would have multiple entries in the event listing (see Figure 1).

Figure 1. Event Disaster Listing in EM-DAT Illustrating December 2004 Earthquake in Aceh



	country	disaster_location	disaster_typ
14757	India	Tamil Nadu state, Andaman ...	Earthquake (seismi
14758	Bangladesh	Hafun, Garag's, Bari, Kar ...	Earthquake (seismi
14759	Myanmar	Irrawaddy delta, Labutta, ...	Earthquake (seismi
14760	Seychelles	Mahé, Praslin, La Digue	Earthquake (seismi
14761	Tanzania Uni Rep		Earthquake (seismi
14762	Somalia	Puntland, Bari, Nugal, Mu ...	Earthquake (seismi
14763	Thailand	Krabi, Phang Nga, Phuket, ...	Earthquake (seismi
14764	Kenya	Mombassa	Earthquake (seismi
14765	Sri Lanka		Earthquake (seismi
14766	Malaysia	Penang Isl.	Earthquake (seismi
14767	Maldives		Earthquake (seismi
14768	Indonesia	Aceh province (Sumatra)	Earthquake (seismi
14769	Colombia	Between Cali and Santande ...	Transpo

[2] CRED defines disaster as "a situation or event which overwhelms local capacity, necessitating a request to a national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction and human suffering."

[3] The Emergency Events Database (EM-DAT), established and maintained since 1988 by CRED, is the only international database on disasters that is publicly available. The archive is available in the CRED website: www.cred.be/emdat).

[4] For a disaster to be recorded in EM-DAT, it has to meet one or more of the following four criteria:
(a) 10 or more people are killed; (b) 100 people or more are reported affected; (c) a state of emergency is declared; (d) an international call for assistance is issued.

2.2. The EM-DAT database is recognized as the most comprehensive publicly available database on disasters. Clearly, there are possible reporting biases in the EM-DAT disaster listing.[5] Reports of increases in disaster events and their costs in EM-DAT may be partly affected by improved disaster reporting from improved information and communications technology, or to a more extreme view (Kirschenbaum, 2004), a consequence of widespread establishment of disaster management agencies, which dramatizes mere incidents into full-fledged disasters. Hazards of nature are after all, not a new phenomenon: they have been a recurrent and integral part of history. Some may even suggest that even if there are increases in the number of such events in the past three decades, these increases may be merely part of a long cycle stretching more than a century, so that at least generations past may have already seen such seeming rises in the frequency of disasters. To control for information biases, the examination of EM-DAT natural disasters given in this report is restricted to "*intense*" natural disaster events, i.e., those which killed 100 or more people, or affected 1,000 or more persons (which are likely to be better recorded and reported than the less intense ones, even outside of fairly recent history). More attention is also given in this report to EM-DAT disaster data starting in the 1970s as a result of the seemingly limited disaster information recorded prior to this period. Total natural disasters recorded in EM-DAT from 1971 to 2010 were 9509, of which, 5442 were intense. During this period, the share of the annual number of intense natural disasters to total annual natural disasters has ranged from 37% (in 1975) to 73% (in 1995).

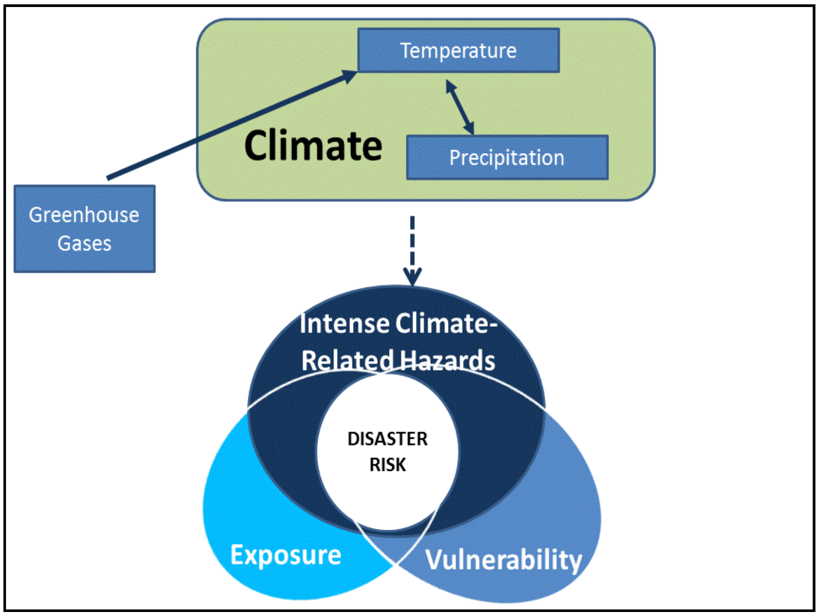
2.3. Any natural disaster has to be viewed within a framework of risks, which includes the hazard itself, as well as a community's vulnerability to the hazard (IPCC, 2001; IPCC, 2007). That is, natural disasters cannot be examined solely by the characteristics of the hazards (e.g., the scale of an earthquake, the amount of winds and rains that go with a storm), but also in the context of the damage they inflict to humans. A hazard will not yield human casualties if there are no people residing in an area where the hazard strikes. An earthquake may have less damage in a community where people are more prepared than in another which has less adaptive capacity (such as populations that are poor and/or in conflict situations). Fragile dwellings are less likely to escape the wrath of cyclones than sturdy residences. Hazards of nature may also have secondary effects. For instance, an earthquake near a coastline may incite a tsunami, a storm may cause flooding, and a volcanic eruption could result in ash showers. Figure 2 illustrates the framework for examining climate-related disasters in this paper. This framework also relates intense climate-related hazards to climate change, particularly human-induced climate change (through GHG emissions). It also adopts the hazard-exposure[6]-vulnerability[7] model of disaster risks (IPCC 2007; 2012), which suggests how exposure, and vulnerability turn a hazard of nature into a natural disaster.

[5] Disaster data in EM-DAT were obtained from insurance companies (Munich Re, Suisse Re and Lloyds of England), Federation of Red Cross, UN-OCHA, WHO, Reuters and governments. Data is not considered to be standardized, accurate or complete, but since 1975 there was a substantial improvement in reporting and data collection, and since the 1990s more than 90% coverage was reported to have been achieved. Several studies (e.g., Tschoegl *et al*., 2006; Below *et al*., 2010) have described various global disaster databases, and country-level databases vis-à-vis EM-DAT.

[6] Exposure is defined in IPCC (2012) as the presence of people; livelihoods; environmental services and resources; infrastructure; or economic, social, or cultural assets in places that could be adversely affected.

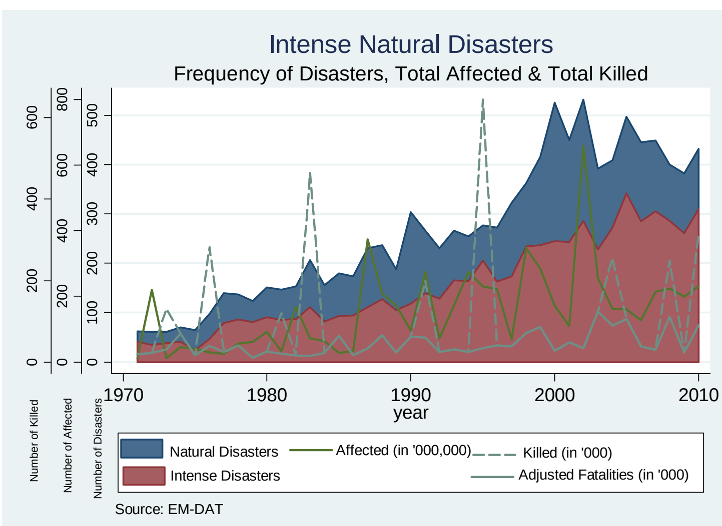
[7] Vulnerability is defined in IPCC (2012) as the propensity or predisposition to be adversely affected.

Figure 2. Linkage of Greenhouse Gas Concentration, Climate Variables, and Intense Climate-Related Disaster Risks



2.4. Since 1971, intense natural disasters (recorded in EM-DAT) seem to be rising. In the period 1971 to 1980, there were 539 intense natural disasters that occurred. The figures increased by 80% in the next decade, and the figures have kept rising across decades. The total intense disasters in 2001 to 2010 are four times those of the counts in the period 1971 to 1980 (Figure 3). In addition, it can be noted that the number of people affected[8] have also been rising. The annual average number of people affected by intense disasters in 2001 to 2010 is about 234 million per year, which is about four times the figure in 1971 to 1980.

Figure 3. Annual Occurrence of Intense Natural Disasters, Number of Killed and Number of Affected in these Events. 1971-2010.



[8] The number of people affected by disasters in EM-DAT is subject to multiple counting as some people may get affected by several disasters.

2.5. Deaths from intense natural disasters are very much influenced by singular events: over the period 1971-2010, eight out of 12,560 intense events registered at least 100,000 fatalities. In the 1970s, a 1973 drought in Ethiopia is reported to have 100 thousand fatalities, while a 1976 earthquake in China led to nearly a quarter million deaths. Two droughts in Africa occurred in the 1980s, viz., a 1981 drought in Mozambique (resulting in 100 thousand deaths), a 1983 drought in Sudan and Ethiopia (that led to 300 thousand and 150 thousand fatalities, respectively). In the 1990s, one intense disaster led to huge fatalities in Asia: the severe Bay of Bengal cyclone of 1991 (with more than 138,000 dead). From 2001 to 2010, a huge number of deaths were recorded from Typhoon Nargis in Myanmar in 2008 (that reportedly led to over 138 thousand deaths), and from two earthquakes: the 2004 Aceh earthquake (which killed over 160 thousand in Indonesia alone, and another 60 thousand in other countries from resulting tsunamis) and the Haiti earthquake of 2010 (that led to over 222 thousand fatalities). Accounting thus for such outliers in the deaths from intense disasters, we find that fatalities from intense natural disasters do not appear to be increasing, unlike the incidence of disasters and the number of affected from intense natural disasters.

2.6. In the past decade, the average annual number of people affected by intense weather-related (i.e. hydro-meteorological) disasters was estimated at nearly 150 million people (compared to about 170 million in the previous decade, 60 million in the 1980s and 30 million in the 1970s). When the figures are examined across affected countries per thousand population, we find that a substantial share of these affected are from low and lower middle income countries (see Table 1).

Table 1. Number of People Affected by Intense Disasters Per Thousand Population Per Year by Income Category of Economies, and by Type of Disaster: 2001-2010.

Income Category	Geophysical	Meteorological	Hydrological	Climatological	Biological
Low Income	527	829	2469	8471	244
Lower Middle Income	994	2902	2844	4382	136
Upper Middle Income	401	1411	1028	282	103
High Income	3	850	78	21	0
All Income Categories	1925	5992	6418	13157	484

Data Sources: EM-DAT, CRED; WDI Population projections, World Bank (2011); and WDI Gross National Income per capita data (in purchasing power parity terms), World Bank (2011).

2.7. Storms and floods also account for most of the damages[9] in the past two decades, with costs rising in absolute terms compared to the corresponding damage costs in the 1980s. In particular, weather-related damages in the most recent decade are five and a half times those pertaining to two decades earlier.

2.8. Over the last twenty years, the bulk of the 1.6 million deaths resulting from intense natural disasters are from lower middle income and low income countries (Table 2). The Asia-Pacific region accounts for a rather large share (about two thirds) of the total lives lost to natural disasters, even when these deaths are calculated as a proportion of regional population.

[9] Data on disaster damage costs reflect direct and indirect consequences of a disaster on the local economy. These are in nominal US$ ('000), and corresponds to the estimated damage value at the moment of the event. These data are likely subject to issues of comparability, whether across countries, or even among disaster events within a country. Note that damage costs are not available in EM-DAT for biological disasters.

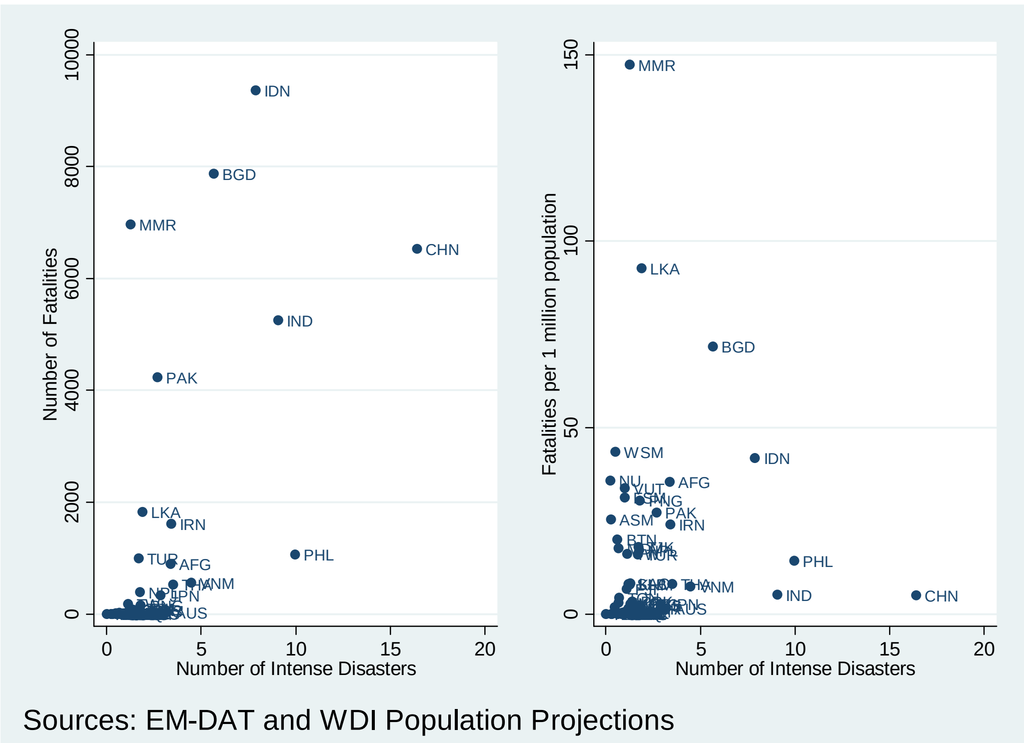
Table 2. Distribution of Deaths from Intense Disasters Across Asia-Pacific and Outside the Region, by Income Category of Economies: 1991-2010

Income Category	Asia Pacific	Outside Region	World
Low Income	42.6%	22.5%	**35.0%**
Lower Middle Income	52.1%	52.6%	**52.3%**
Upper Middle Income	4.2%	11.2%	**6.8%**
High Income	1.1%	13.7%	**5.9%**
All Income Categories	100.0%	100.0%	**100.0%**
Memo Note:			
Total No. of Deaths	984,869	594,111	**1,578,980**

Data Source: EM-DAT and World Bank Gross National Income per capita data (in purchasing power parity terms)

2.9. Fatalities from natural disasters (whether in absolute numbers or in relative terms to the country's population) are not a function merely of the strength of the hazard event experienced and exposure to the hazard, but also of a country's preparedness to cope with hazards (see Figure 4). Risk and vulnerability to natural disasters are tied to the occurrence of extreme events and to human issues.

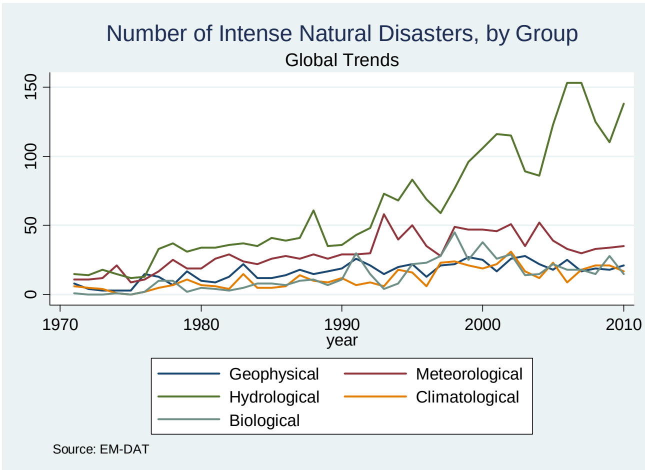
Figure 4. Average Disaster-related Deaths per Year and Annual Average Frequency of Intense Disasters in Asia-Pacific Countries in 1991-2010. (a) Fatalities versus Disaster Incidence (b) Fatalities as a proportion of country population (in millions) versus Disaster Incidence.



Note: Data on disasters and deaths represent country averages per year for the period 1991 to 2010

2.10. When the natural disasters are broken down by major sub-groups, we observe that from 1971, what has considerably risen, especially in the past two decades are climate-related (i.e. climatological and hydro-meteorological disasters), especially hydrological ones. The frequency of geological disasters (i.e., earthquakes and volcano eruptions) across the years is rising only mildly and as Jennings (2011), suggests when this is used as proxy for reporting bias, we still observe increasing trends in climate-related disasters(see Figure 5). Munich Re (2011) reports similar trends.

Figure 5. Frequency of Intense Natural Disasters, by Disaster Group. 1971-2010.



2.11. About two thirds of intense disasters in the period 1971 to 2010 are hydro-meteorological, and the rest are split up nearly evenly among climatological, geophysical and biological disasters. The occurrence of hydro-meteorological disasters throughout the world rose by about 72% during the 1991-2000 from their figures in the previous decade, and they increased in the subsequent decade (compared to 1991-2000) by about 41%. Droughts occur less frequently than weather-related disasters, and they appear to be also increasing across decades. Note that two thirds of the global droughts in the period 1971 to 2010 occurred outside Asia-Pacific.

2.12. The rise in intense natural disasters may be the effect of a compendium of demographic factors, including population growth, and migration of people toward more disaster prone areas such as cities and mega-cities built up along coastlines and water highways. Undoubtedly, more people are affected by natural disasters in the recent past in large part since there are currently more people in the world, and consequently, more people to be affected. People migrate toward cities near coasts in large part to seek jobs, with such cities flourishing in economic activity as a result of maritime trade and transport. But such migration and population growth result in increasing risks to disasters, the definition of which depends on counts (of people killed and/or affected). Increases in damages from disasters may almost certainly be rising on account of the increased concentration and high value property in urban coastal areas.

2.13. Trends in intense natural disasters are undoubtedly affected by issues about the reporting of disasters, and population concentrations. Jennings (2011) adjusts EM-DAT disaster counts to account for population effects and reporting biases, and still observes increased trends in disasters. The effect of information bias is further minimized here by inspecting trends only after 1970, and by way of examining only intense disasters in EM-DAT. As far as hydrological disasters, Thomas (2011) observes from hydrological disasters reported in the EM-DAT database that "the proportion of less severe flooding events reported over the total number of flooding events has remained practically constant over the 1985-2008 period at about 55 percent" (Thomas, 2011). This suggests that the increase in the reported disasters (in EM-DAT), at least for hydrological events, is unlikely to be merely due to better reporting and recording of these incidents. An examination (Hoeppe, 2007) of another disaster database, organized by Munich Re (one of the world's largest leading insurers), shows independently increasing trends in the number of weather-related disasters. See also (Munich Re, 2011). In addition, flood data from Darthmouth Flood Observatory (http://www.dartmouth.edu/~floods/) also suggests a rising number of large floods, as well as extreme floods.

2.14. The rising incidence of weather-related disasters especially in some sub-regions of Asia-Pacific, (see Table 3) deserves further explanation. The incidence of weather-related disasters, and their changes across the years, varies considerably across geographic areas, partly because of natural variability of climate. An example of the natural variability of the climate system is the fluctuations of seas surface temperatures in the tropical eastern Pacific, called the El Niño Southern Oscillation (ENSO). The extremes of the ENSO, El Niño (warming) and La Niña (cooling), cause extreme weather (such as floods and droughts) in many regions of the world. The warm phase typically accompanies high air surface pressure in the western Pacific. With the variability in incidence of weather-related disasters across geographic areas, it may well be that climate change adds to the incidence of weather-related disasters in some areas, and subtracts from others. However, even if there may not be changes in incidence of hazards, the characteristics associated with the hazards such as the concomitant temperature and amount of rainfall may be changing. Extreme precipitation has been causally linked to changes in global temperature (Lenderink, and van Meijgaard, 2010).

Table 3. Total Number of Intense Weather-Related Disaster in Geographic Sub-Regions of the World by Five Year Periods: 1971-2010.

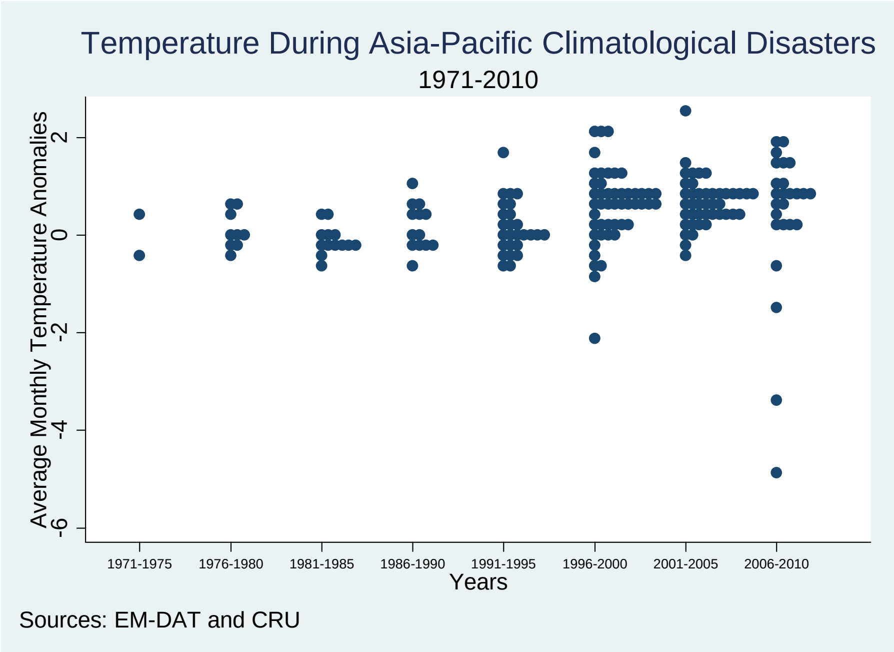
Geographic Sub-Region	1971-1975	1976-1980	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2010
Eastern Asia	16	23	35	59	68	79	116	96
Southern Asia	25	48	58	57	94	89	108	119
South-Eastern Asia	28	61	65	59	115	83	131	185
Australia and New Zealand	2	4	2	4	10	15	6	15
Melanesia	5	3	10	9	9	5	8	9
Micronesia	0	0	0	0	2	1	5	0
Polynesia	0	1	3	5	1	2	2	2
Central Asia	0	0	0	0	7	6	14	10
Western Asia	1	3	1	3	10	10	9	14
Asia-Pacific	**77**	**143**	**174**	**196**	**316**	**290**	**399**	**450**
South America	20	21	41	47	40	58	79	68
Western Africa	2	1	11	11	15	33	33	71
Central America	8	17	12	16	29	41	52	69
Eastern Africa	9	19	18	22	21	42	72	100
Northern Africa	6	6	7	4	9	10	12	24
Middle Africa	1	0	1	6	3	14	15	35
Southern Africa	1	1	4	3	5	7	12	16
Northern America	6	8	15	8	22	40	33	25
Caribbean	3	14	9	30	20	17	43	49
Southern Europe	2	5	7	4	9	13	17	20
Eastern Europe	1	2	7	4	22	38	36	25
Northern Europe	0	0	0	0	3	5	3	4
Western Europe	0	2	1	1	8	9	10	4
Outside Asia Pacific	**59**	**96**	**133**	**156**	**206**	**327**	**417**	**510**
World-wide	**136**	**239**	**307**	**352**	**522**	**617**	**816**	**960**

Data Source: EM-DAT, CRED.

2.15. While the trends in weather disasters are not uniform, i.e., some sub-regions are more affected than others, it is important to explain what else aside from population and reporting effects may account for the rise in weather related disasters. There is suspicion that climate change may contribute to trends in climate-related disasters, after all droughts, extreme temperature events, storms and floods are influenced by the climate. If temperature rises, the moisture-holding capacity of the atmosphere increases leading to increased moisture content, and correspondingly, this may lead to increased rainfall and even possibly enhanced storm intensity, thus leading to increased risk of flooding events. Rises in temperature may be partly explained by the result of natural variability. The ENSO suggests that oceans store and release heat, and therefore also influence measured global surface temperatures. However, the IPCC (2000, 2004, 2007) has indicated that rises in temperature in the past century cannot be attributed solely to natural variability. Man-made GHG emissions are further contributing to climate change. The IPCC (2004, 2007) explains that climate change is a result of a compendium of natural variability, external anthropogenic forcings (such as emissions of human-caused greenhouse gases), and external natural forcings (such as volcanic eruption). Recent scientific research suggests that a huge part of climate change (see, e.g. Huber and Nutti, 2011), particularly the increased occurrence of extreme precipitation (O'Gorman, and Tapio, 2009; Min et al., 2011; Scott et al., 2004) is man-made. Thus, to complete the profile of disaster trends, disasters should be viewed not only within the perspective of the hazards themselves but also in the framework of disaster risks (See Figure 2).

2.16. As regards climatological disasters in Asia-Pacific, the average monthly temperature anomalies recorded during these disasters appear to have changes in their distribution across the years (Figure 6). Not only do we readily observe shifts across time in the means, but also more variability, indicative that these extreme events have changing characteristics across time.

Figure 6. Distributional Shifts Across Five Year Periods in Monthly Temperature Anomalies During Occurrence of Climatological Disasters in Asia-Pacific: 1971-2010.



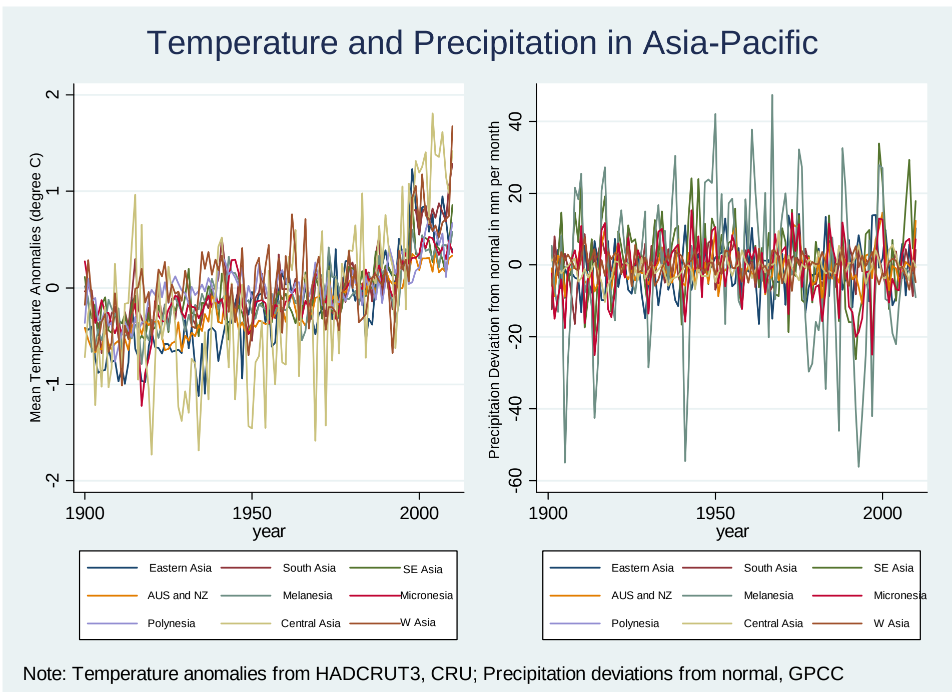
Note: Temperature anomalies data represent monthly combined land and marine sea surface temperature (SST) anomalies with respect to 1961-90 °C sourced from CRU in http://www.cru.uea.ac.uk/cru/data/temperature/

2.17. Global temperature data[10] from the twentieth century up to current periods clearly show rising land and marine temperatures in the world, with the current rate of increase steeper than in the

[10] Global temperature anomaly data sourced from the Climatic Research Unit (CRU) of the University of East Anglia (http://www.cru.uea.ac.uk/cru/data/temperature/).

past (Brohan *et al.* 2006; Royal Society, 2010). In Asia-Pacific, monthly temperature anomalies (averaged per year) from baseline temperatures in 1960-1990 are rising across various geographic sub-regions (see Figure 7a), with some areas having more variability in temperature anomalies than others. While precipitation deviations from normal (Rudolph et al., 2010) have not changed, on the average, but these precipitation deviations appear to be more variable in recent times across some Asia Pacific sub-regions (see Figure 7b). Such observations are consistent with the most recent report of the IPCC which mentions (a) increasing trends in temperature; (b) average precipitation globally remains largely unchanged, but there are indications that precipitation variability and extreme precipitation events appear to have increased in recent history (IPCC 2007).

Figure 7. Trends in Climate Indicators across Asia-Pacific Sub-regions: 1900-2010. (a) Monthly Temperature Anomalies (averaged per year); (b) Precipitation Deviations from normal (averaged per year)



Remark: Temperature anomalies data represent monthly combined land and marine sea surface temperature (SST) anomalies (averaged per year) with respect to 1961-90 °C sourced from CRU in http://www.cru.uea.ac.uk/cru/data/temperature/ while precipitation deviations data represent monthly precipitation deviations (averaged per year) with respect to 1951-2000 means sourced from http://gpcc.dwd.de/

2.18. Across Asia and the Pacific, the incidence of storms and floods far exceeds the number of droughts, earthquakes as well as biological disasters. In the past twenty years, the number of intense meteorological events accounts for about a quarter of all intense disaster events, while floods constitute nearly half of the total number of intense disasters. The frequency of hydrological events is visibly increasing, with a rate of increase surpassing those of other natural disasters.

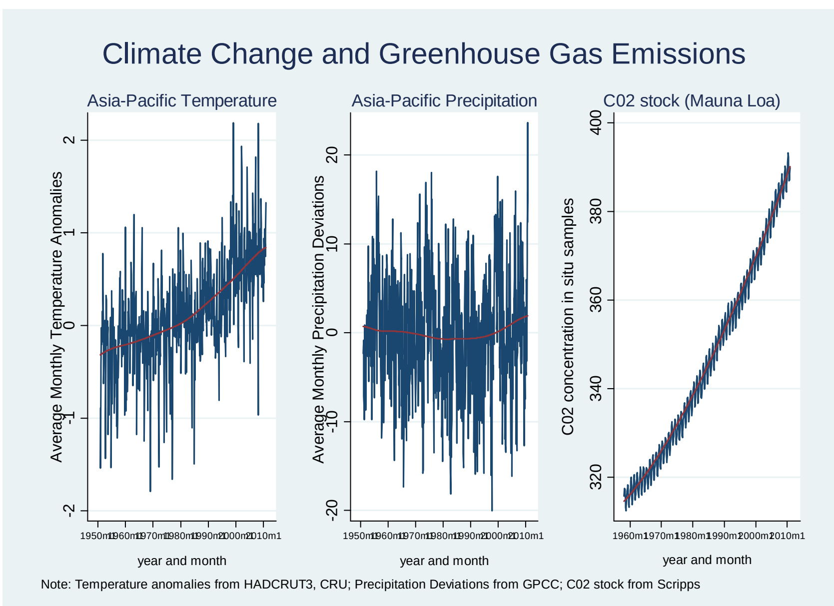
2.19. Although the number of deaths due to storms and floods across the Asia Pacific region in the past two decades only accounts for half of the total deaths, the number of people affected from natural weather-related disasters comprises three quarters of total people affected from intense natural disasters. The actual impact of different types of disasters varies across sub-regions. Less than twenty percent of deaths from intense disasters in Australia, New Zealand, Melanesia, and

Polynesia are due to floods and storms, but in Polynesia, more than 90% of people affected from disasters are those who got affected from weather-related disasters.

2.20. Such trends in the various types of natural disasters are of relevance since each type of disaster has destructive impacts to life and property in different ways. For instance, earthquakes can be very deadly and have severe economic costs. As Thomas (2011) points out: "the 2011 Great East Japan earthquake and tsunami killed 15,457 people with estimated damages ranging from US$122 billion to $235 billion, or 2.5-4.0 percent of the country's GDP." Floods, which may come with storms, affect infrastructure, displace people and affect livelihood, but floods tend to be less deadly (at least in recent times) and more readily amenable to forecasting than earthquakes. In consequence, the interventions for floods go beyond mere disaster relief, to that of disaster prevention. In addition, the linkage of increased floods to human-induced climate change also suggests climate adaptation issues.

2.21. The linkage of climate change and GHG emissions is further examined by looking into monthly average temperature anomalies in Asia-Pacific from 1951 to 2010, monthly average precipitation deviations from normal in Asia-Pacific in the period 1951 to 2010,and monthly atmospheric carbon dioxide (CO2) stock data (in ppmv) [11] from 1959 to 2010 (see Figure 8). The latter serves as a proxy for GHG concentration.

Figure 8. Average Temperature Anomalies in Asia-Pacific (1951-2010) and C02 concentration from Air-Situ Samples in Mauna Loa (1959-2010)



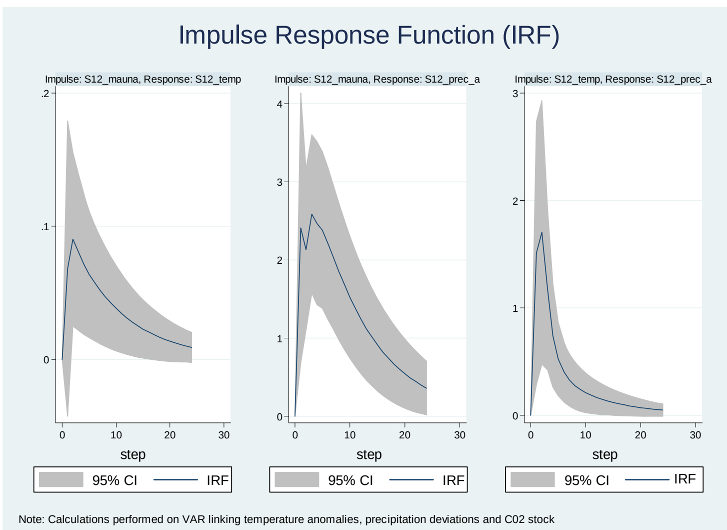
2.22. Since all these three time series have seasonal components, they were subjected to seasonal differencing to remove their respective seasonal effects, and thus make trends more amenable to analysis. The resulting seasonally differenced series were observed to be stationary[12] and subjected

[11] Data sourced from Scripps Carbon Dioxide Program of UCSD Scripps Institute of Oceanography derived from in situ air samples collected at Mauna Loa, Hawaii, USA (http://co2now.org/Current-CO2/CO2-Now/scripps-co2-data-mauna-loa-observatory.html).

[12] A time series is said to be stationary when its joint probability distribution does not change when shifted in time or space, and in consequence, its mean, variance, autocorrelation, and other statistical properties are all constant over time. Many

to a vector auto regression[13] model. Least squares regressions on the levels of the time series cannot be employed due to trends and seasonal behaviour in the data, otherwise spurious regressions result. The resulting econometric model on the seasonally differenced time series suggests that monthly precipitation deviations from normal depended on past precipitation as well as on monthly average temperature anomalies and C02 stock concentration. While seemingly temperature anomalies are more affected by past temperature anomalies than by the other variables, because of the inherent dynamics in a VAR model, it is helpful to look into the associated impulse response functions of the VAR. Figure 9 shows that a one-time shock to C02 stock concentration results in a positive change in (the seasonally differenced) temperature anomalies as well as to precipitation, with the effects lingering even after two years. The effect of the C02 shock on temperature is likely to start two months later. A one-time shock to temperature anomalies was also found to have significant, lingering effects on precipitation deviations (from normal), with likely dissipation as early as 15 months from the shock.

Figure 9. Impulse Response Function of Changes to Precipitation and Temperature to a One Time One Unit Shock on Change in C02 Concentration.



2.23. Granger causality tests[14] on the VAR model suggest that there is evidence that temperature anomalies in Asia-Pacific and global C02 concentration both Granger-cause precipitation deviations in Asia-Pacific. In addition, C02 concentration Granger-causes temperature anomalies in Asia-Pacific.

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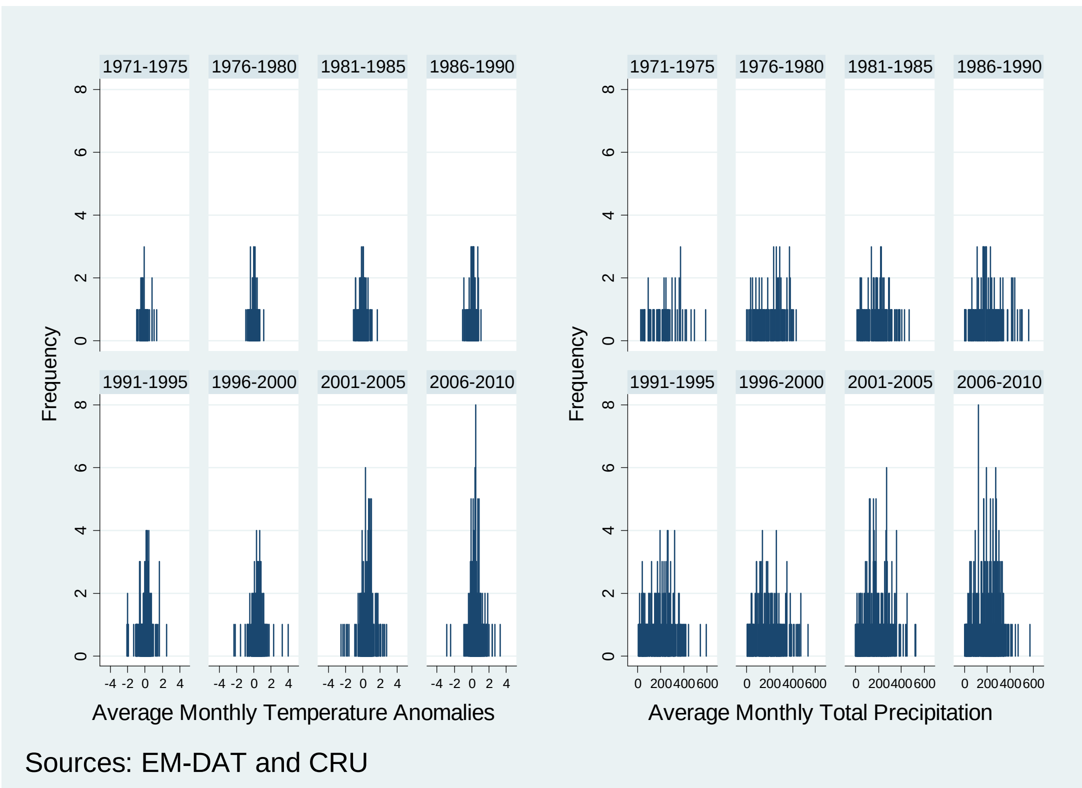
statistical forecasting methods are based on the assumption that the time series is stationary or can be rendered approximately stationary. A stationary series is rather easy to predict, since its statistical properties will be the same in the future as they have been in the past. A non-stationary time series is said to be difference stationary if the levels of the time series are non-stationary, but the changes in the time series are stationary. First difference stationary means that the changes in the time series are stationary, while second difference stationary means that the changes in the changes are stationary.

[13] A Vector Auto Regression (VAR) is an econometric model in which K variables are specified as linear functions of p of their own lags, p lags of the other K-1 variables, and possibly additional exogenous variables. See Annex for more details. Various criteria, such as final prediction error (FPE) and Akaike's information criterion (AIC) suggest the use of 4 lags for the VAR. Diagnostics on the residuals of the VAR with the Lagrange Multiplier Test suggested that the residuals were not serially correlated.

[14] Granger causality tests are statistical tests of causality in the sense of determining whether there is evidence that lagged observations of another variable have incremental forecasting power when added to a univariate

2.24. As was pointed out earlier, the EM-DAT database does not have complete coverage of all hazards occurring, since hazards are screened according to the disaster definition, which depends on the impact of the hazard on people (either in terms of number of people affected and number of people killed). However, the intense disasters examined here can serve as proxy for extreme hazards. To understand the nature of the hazards that led to these disasters, it is important to examine the associated average temperature anomalies and total precipitation during the months when these extremes events occurred. Figure 10 suggests that the temperature anomalies during weather-related disasters have averages that are rising across time (similar to observations from Figure 7), and that total precipitation (during months when intense disasters occurred) appears to be having slightly more variability, but not considerably.

Figure 10. Distribution of Mean Temperature Anomalies and Average Total Precipitation During Month when Weather-Related Disasters Occurred.



2.25. A substantial proportion of weather-related disasters in Asia-Pacific occur in ADB-member economies. Among the twenty economies in the entire world with the most frequent number of intense hydro-meteorological disasters in the period 1991-2010, fourteen are regional ADB-member economies (People's Republic of China, Philippines, India, Bangladesh, Japan, Indonesia, Viet Nam,

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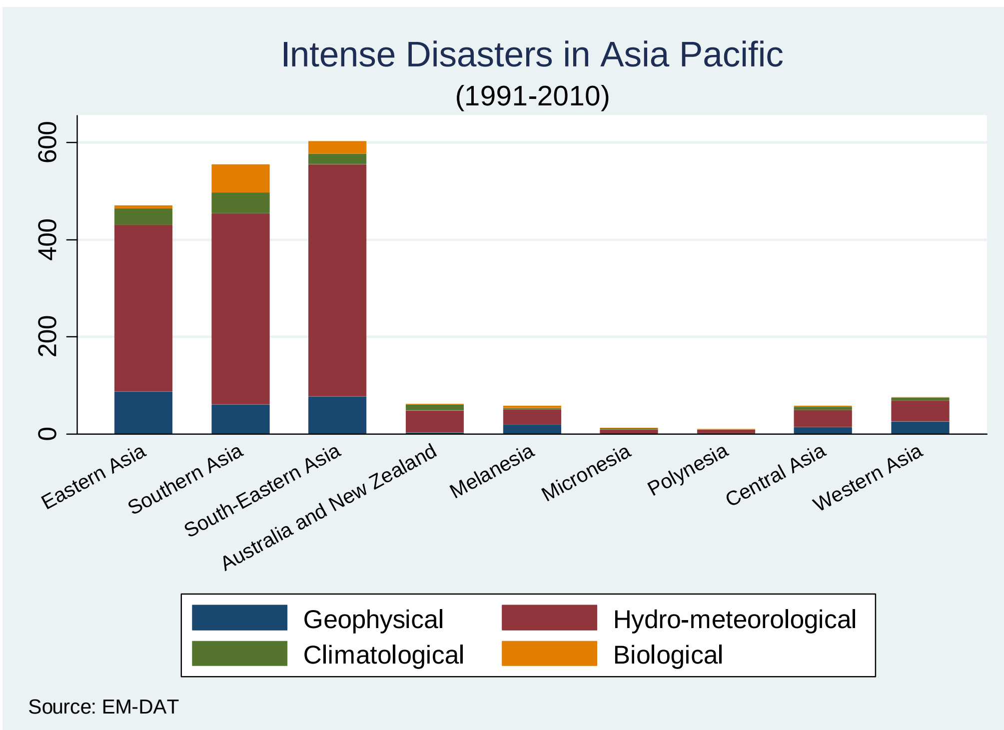
autoregressive representation of a variable. Note that the null hypothesis is stated as non-Granger causality, so that the tests should actually be better referred to as Granger non-causality tests. Also, it is important to understand that though that Granger causality is not causality in a theoretical sense. The presence of a rooster may Granger cause a sunrise, for instance. See also, Hamilton (1994) pp. 302-309, or Enders (2004), pp. 283-287 and 357-358 for more details.

Australia, Thailand, Republic of Korea, Afghanistan, Hong Kong, China Special Administrative Region and Pakistan), one is a non-regional ADB member (USA), while one is a non-ADB member economy in the region (Iran).

3. Climate Classification and Climate-Related Disasters in Asia and the Pacific

3.1. Although some recent scientific research (see Landsea *et al*., 2006; and Knutson *et al.*, 2010) has suggested that existing tropical cyclone databases are insufficiently reliable to detect trends in the frequency of extreme cyclones, climate science projections suggest that climate change, particularly increased temperatures, will lead to more extreme cyclones, and thus, there is growing interest in managing and predicting extreme weather-related catastrophes (Lubchenco and Karl, 2012). Across Asia and the Pacific, economies in South East Asia, Southern Asia and East Asia bore the brunt of weather-related disasters (nearly 500 for East Asia, and over 500 each for Southern Asia and South East Asia) in the past two decades (Figure 11). These sub-regions in the Asia-Pacific Region are also the areas which are battered by other types of natural disasters.

Figure 11. Number of Intense Disasters in Asia-Pacific Region: 1991-2010.

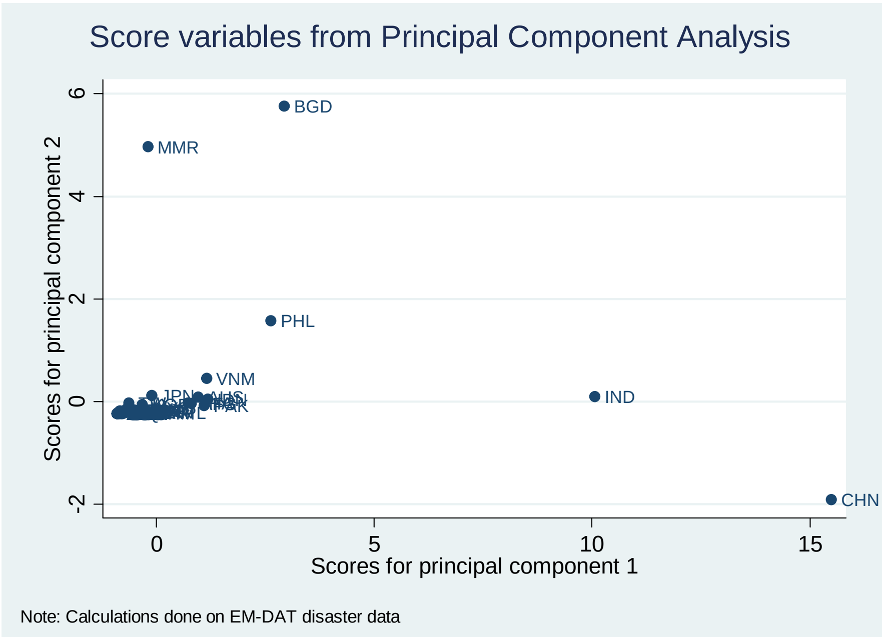


3.2. Economies in the Asia-Pacific Region vary in vulnerability to weather-related disasters. A principal component analysis[15] of data on hydrological, meteorological and climatological disasters was performed using the frequency of intense disasters, number of people affected and number of people killed in the past two decades. The results suggest that some economies are more vulnerable than the rest (see Figure 12). In particular, China, India, Bangladesh and the Philippines are found to be extremely vulnerable to climate-related disasters (using the first principal

[15] Principal component analysis (PCA) is a dimension reduction technique that uses an orthogonal transformation to convert a set of data of possibly correlated variables into a set of values of uncorrelated variables called principal components. The first two PCs explain 85% of total variability of data examined.

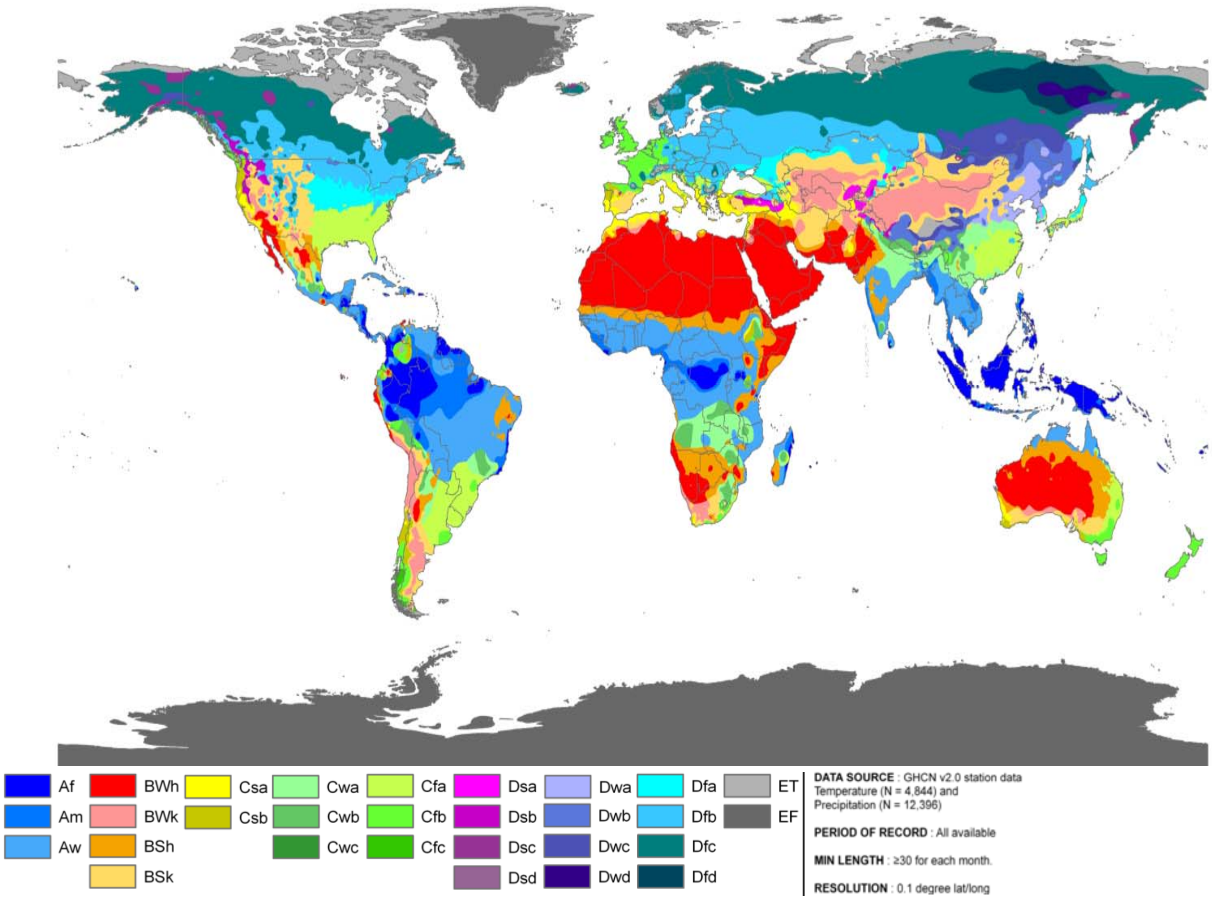
component). It was also noted (from the second principal component, which largely accounts for deaths from storms) that Bangladesh, Myanmar and Philippines are the economies more prone to deaths from storms than the rest of the economies in the Asia-Pacific Region.

Figure 12. Economies in Asia-Pacific Vulnerable to Weather Related Disasters (1991-2010).



3.3. The results of the principal component analysis are not surprising. Geography explains a lot about climate-related disasters. India and China are vast in size. The Philippines, an archipelago, lies in a typhoon belt between 10 and 40 degrees North latitude in the Pacific. In consequence, it may be helpful to describe climate-related disasters in relation to geographic zones, particularly by way of the Köppen Geiger climate classification (Figure 13). As explained in Peele (2007), the categories of the Köppen Geiger system are based on the annual and monthly averages of temperature and precipitation, yielding five major climatic groups, *viz.,* tropical (A), arid (B), temperate (C), cold (D), and polar (E). Each of the groups may have types and subtypes. For instance, in tropical climates, all months have average temperatures greater than 18° Celsius. Three Köppen Geiger climate types are defined in the tropical climate A group, based on seasonal distribution of rainfall: the tropical wet (Af) climates have precipitation occurring all year long; tropical monsoon (Am) climates have annual rainfall equal to or greater than tropical wet climates, but most of the precipitation falls in the 7 to 9 hottest months, while during the dry season, very little rainfall occurs; and, tropical savannah (Aw) climate has an extended dry season during winter, with precipitation during the wet season usually less than 1000 millimeters, and only during the summer season. More details characterizing the Köppen Geiger climate classification types and the rules on precipitation and temperature data used for identifying the specific climate types are provided in Table A-3 in the Annex (which is reproduced from Peele, 2007).

Figure 13. World Map with Köppen Geiger climate classification.



Source: http://people.eng.unimelb.edu.au/mpeel/Koppen/World_Koppen_Map.png

3.4. The climate classification groups across economies in the Asia-Pacific Region are provided in Table A-5. A summary of the climate classification in sub-regions of Asia-Pacific is given in Table 5. About half of the economies in Asia and the Pacific are in arid climates. South-east Asia, which is the most affected by weather-related disasters, is primarily tropical. Eastern Asia and South Asia, the other two sub-regions which are battered by weather-related disasters, are much more temperate than the rest of Asia and the Pacific, with South Asia also having tropical climate in portions of its land. How weather-related disasters affect economies appears to depend on both the specific location and the climates in the area. In fact, among the ten economies with the most number of weather-related disasters in Asia-Pacific, seven of these economies have both tropical and temperate climates, two (Indonesia and Thailand) have fully tropical climate, while one (Pakistan) has arid and temperate climates.

Table 5. Distribution of Sub-regions in Asia-Pacific by Climate Classification.

Sub-Region	Köppen Geiger Climate Group						Memo Note: Land Area (in 10,000 sq m)
	A (tropical)	B (arid)	C (temperate)	D (cold)	E (polar)	All Climates	
Eastern Asia	0.3%	41.8%	24.1%	33.9%	0.0%	100.0%	1126.18
Southern Asia	18.3%	53.5%	21.7%	2.6%	3.9%	100.0%	689.25
South-Eastern Asia	92.5%	0.0%	7.1%	0.3%	0.0%	100.0%	448.57
Australia and New Zealand	7.4%	75.0%	17.7%	0.0%	0.0%	100.0%	797.30
Melanesia	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%	54.49
Micronesia	70.6%	29.4%	0.0%	0.0%	0.0%	100.0%	0.36
Polynesia	100.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.74
Central Asia	0.0%	63.6%	0.8%	35.7%	0.0%	100.0%	397.49
Western Asia	0.0%	93.0%	5.1%	1.8%	0.0%	100.0%	374.06
All Sub-Regions	16.9%	52.4%	15.8%	14.1%	0.7%	100.0%	3890.00

3.5. Disasters have to be understood from a disaster risk framework. To assess the disaster risks faced by economies across Asia-Pacific, each economy was examined in terms of the disaster indicators on the frequency of intense hydrological disasters, the number of people affected by these catastrophes, the number of people killed from these events, as well as the corresponding three indicators for meteorological disasters. Economies were considered at risk in a particular year if at least one of these six indicators was at least two standard deviations above the Asia-Pacific wide averages. A set of panel logistic[16] regression models was then generated using the weather-related disaster data across economies and across time, to help identify factors that make an economy more weather-disaster risk prone. Explanatory variables considered in the panel logistic regression, include (a) climate variables such as annual average temperature anomaly and annual average precipitation deviations from normal; (b) a measure of exposure, viz., population (in logarithmic scale); (c) a measure of adaptive capacity, an indicators of whether the economy is low or lower middle income class, and if the population density is rather high; and, (d) variables pertaining to climate zone character of the economy, namely, the percentage of land area that is tropical and the percentage of land area. The econometric model made use of the framework shown in Figure 5, but was constrained by data availability. Other factors, such as land use (see Brath *et al*., 2006), which may explain hydrological disasters, were not considered in the models since these data are not regularly available across economies. The panel regressions[17] were developed for all economies in Asia-Pacific, and separately for economies in three sub-regions: East Asia, South Asia and South East

[16] Logistic regression is a type of regression model used for explaining a binary outcome (here, whether an economy is at risk or not) based on one or more explanatory variables. The model attempts to describe the log-odds of the probability of one outcome (say, that the economy is at risk) using a linear function of the explanatory variables. More details are given in the annex.

[17] Panel data contains observations on multiple phenomena observed over multiple time periods for the same subjects (here, countries). Rather than have a pooled regression that considers each subject across time as an observation, panel regressions account for the temporal changes within subjects, and the cross-section differences across subjects.

Asia, and in the rest of the sub-regions across Asia-Pacific. Sub-regional models for East Asia, South Asia and South East Asia were developed based on the observation from Figure 11 that these sub-regions in Asia-Pacific are the most at risk from frequent weather-related disasters. The odds ratios of the resulting panel logistic regressions are found in Table 6.

Table 6. Odds Ratios of Panel Logistic Regression Models Identifying Determinants of Weather-Related Disaster Risk in Asia-Pacific Economies: 1971-2010

Variables	**Asia-Pacific**	**East Asia**	**South Asia**	**South East Asia**	**Other Asia Pacific Sub-regions**
Annual Average Temperature Anomalies	1.53	5.19**	1.29	1.44	0.75
Annual Average Precipitation Deviations from Normal	1.02*	0.98	1.07***	1.03**	0.99
Population (in natural log)	4.69***	3.53**	4.49***	3.83**	10.37***
Indicator on whether (or not) economy is low income or lower middle income class, and population density is at least 75 per square km	1.65	0.56	0.16	3.51*	5.07
Percentage of Land that is Tropical	1.01		1.03**	0.99	1.09***
Percentage of Land that is Temperate	0.97*	0.98	0.99	1	0.97
lnsig2u					
_cons	6.45***	3.94	0.21	2	9.30***
Memo Notes:					
Model Fit Statistics					
Chi2	90.82	20.05	45.71	37.21	29.66
N	2320	320	320	440	1240
Akaike Information Criterion	867.34	150.25	216.87	292.23	194.58
Schwarz Bayesian Information Criterion	907.58	172.86	243.25	320.84	230.44
Legend:	*p<.05; **p<.01; *** p<.001				

Note: Table entries reflect odds ratios. Data sourced from EM-DAT and WDI Indicators, World Bank (2011).

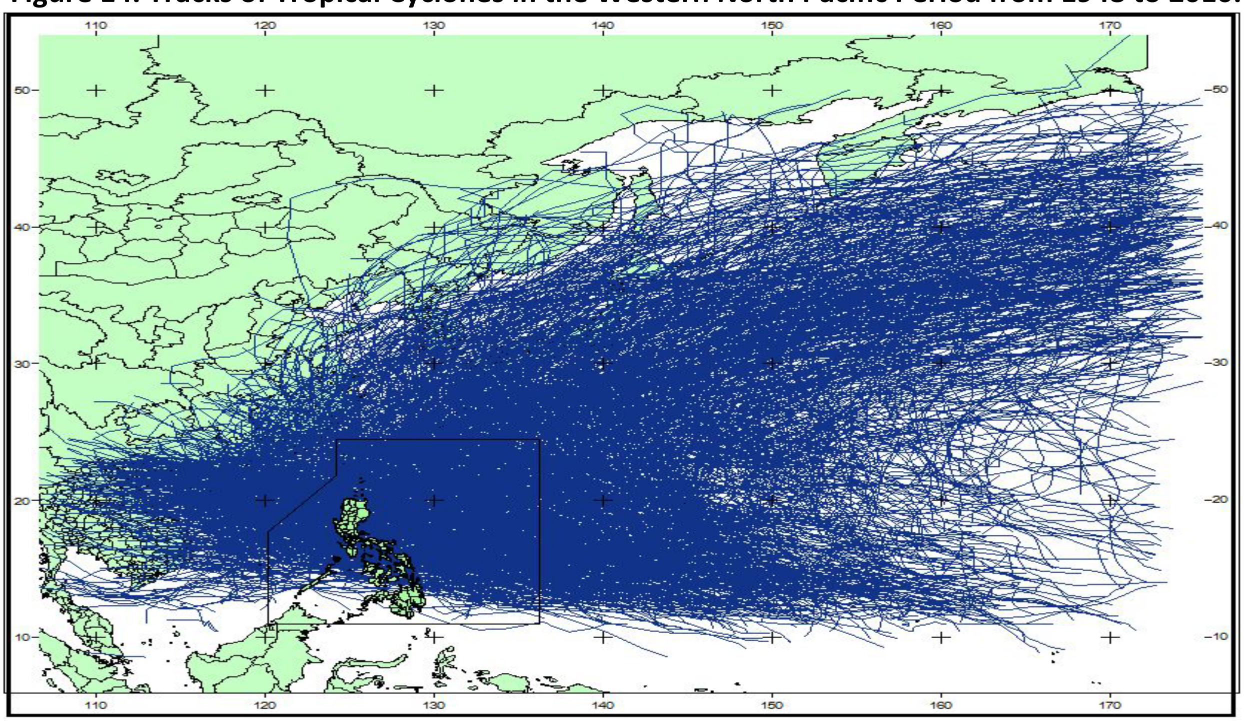
3.6. The regression results suggest that exposure matters considerably. Whether across Asia-Pacific, or in specific sub-regions, the higher the population, the greater the risk an economy faces. All other things being equal, the amount of precipitation (deviations from normal) explains weather-disaster risk faced by economies, especially in South Asia and South East Asia. In East Asian economies, temperature anomalies, rather than precipitation deviations, explain weather-related disaster risks. Seemingly, the lower the adaptive capacity (indicated by high population density together with low income), the greater the risk, but the evidence for this is strong in South East Asia. Climate zone also matters, particularly in South Asia and for economies outside of East, South and South-East Asia, the bigger the proportion of land of an economy that is tropical, the more likely the economy is prone to weather-disasters.

4. Case Study: Climate Conditions in the Philippines

4.1. In the previous section, it was noted that some economies in Asia-Pacific are more at risk from hydro-meteorological disasters than others. One of these countries is the Philippines, the home to the headquarters of the Asian Development Bank. In the Philippines, all the elements of risks are changing: hazards, vulnerability and exposure. This section limits its discussion to how (climate and weather-related) hazards have changed in the Philippines, as such examination is more relevant in terms of greenhouse gas emissions and climate change.

4.2. From the examination of EM-DAT data in the previous section, it can be also ascertained that from 1971 to 2010, the Philippines was a hot spot from weather-related disasters for 34 years. Only India managed to have a higher record (35 years) in Asia-Pacific and by a rather negligible margin. Across Asia-Pacific, the Philippines had the fourth highest record (98) of intense hydrological disasters in the period 1971 to 2010, topped only by Indonesia (124), India (167) and China (172). The Philippines is an archipelago composed of 7,100 islands. It has a number of low lying areas and is thus highly susceptible to flooding and inundations. The Philippines also had the highest incidence (218) of intense meteorological disasters in the Asia-Pacific region across the span of four decades covering 1971 to 2010. The latter is not surprising since the Philippines has one of the longest coastlines in the world (32,400 km.) and it is located in the basin with the most number of tropical cyclones[18] across the globe. In the period 1948 to 2010, out of over a thousand six hundred (1641) tropical cyclones that were formed in the Western North Pacific[19], about 70 percent (1154) entered or formed within the Philippine Area of Responsibly (PAR). On average, about 19 to 20 tropical cyclones affect the PAR per year, with variations in the figures across the years: the annual number of cyclones affecting the PAR ranged from as low as 10 tropical cyclones to as high as 32 tropical cyclones.

Figure 14. Tracks of Tropical Cyclones in the Western North Pacific Period from 1948 to 2010.



Source: Japan Meteorological Agency

[18] Atmospheric low pressure systems generated in the tropical and subtropical regions are called tropical cyclones (TCs).

[19] Range: north of the equator and west of 180°E

4.3. Data from the Philippine government's meteorological office (PAGASA) [20] suggests that from 1951 to 2010, there is no indication of an increase across time in the frequency of tropical cyclones that affect the Philippines. A comparison of the 30-year average number of tropical cyclones even shows that the mean for the last 30 years has slightly decreased to 18.8 tropical cyclones per year in the period 1981 to 2010 (from 19.8 tropical cyclones per year in the period 1951 to 1980). Such trends in the data, however, should be taken with a grain of salt given the difference in the tools for detection of cyclones. The use of radars and satellites for detecting cyclones started in the early 1970's, so that in consequence, the only real comparison is between the last two 30-year means, which also shows practically no difference in the average annual occurrence of tropical cyclones (whether from the period 1971-2000 to the period 1981-2010).

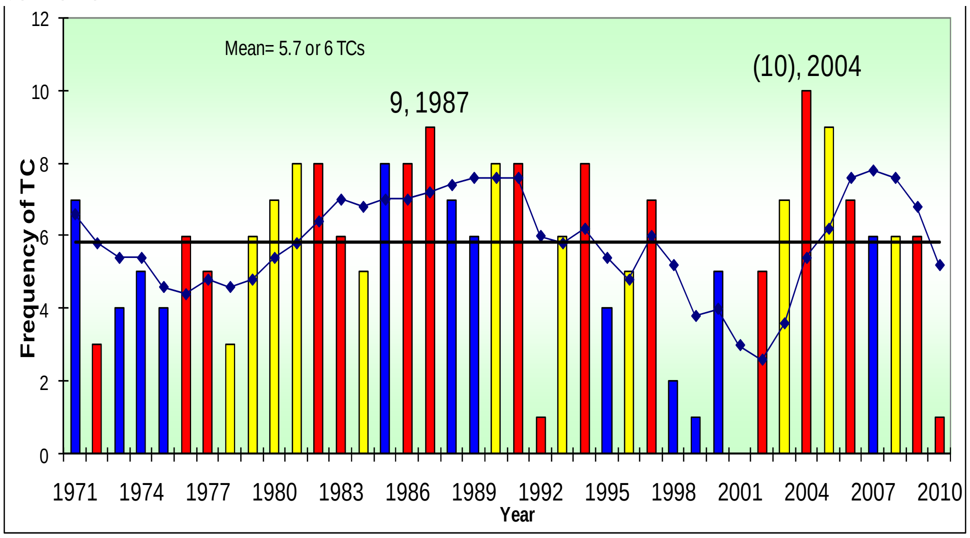
Table 7. Thirty Year Running Averages of Number of Tropical Cyclones Affecting the Philippines: 1951-2010.

	1951-1980	1961-1990	1971-2000	1981-2010
Number of Tropical Cyclones Affecting PH	19.8	20.2	19.5	18.8

Source: *PAGASA*

4.4. In the forty-year period 1971 to 2010, around 6 extreme typhoons[21] with maximum sustained winds of greater than 150kph and above affected the Philippines. No significant trends are observed regarding the incidence of extreme typhoons, but there are clearly more strong typhoons during years with El Niño (see Figure 15).

Figure 15. Frequency of Extreme Typhoons (150 kph and above) in the Philippines from 1971 to 2010.



Source: PAGASA

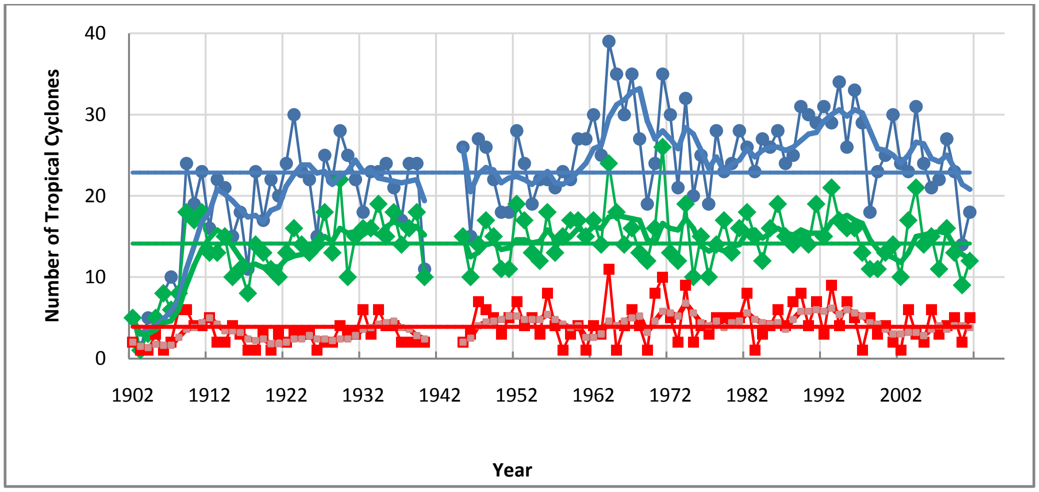
4.5. Aside from the Philippine government's meteorological office, the Manila Observatory also tracks weather events. Historical data, for tropical cyclones, typhoons and extreme typhoons, also do not

[20] PAGASA is the Philippine Atmospheric, Geophysical and Astronomical Services Administration

[21] In the Western North Pacific, when a tropical cyclone has maximum sustained wind speeds near its center (10-minute average) of 33 m/s or more, it is called a typhoon.

appear to have clear trends. It may be observed, that in many recent years, the number of tropical cyclones has been above normal, but the number of landfalls has been below normal.

Figure 16. Frequency of Tropical Cyclones in the PAR, and Their Landfalls in the Philippines from 1902 to 2010.

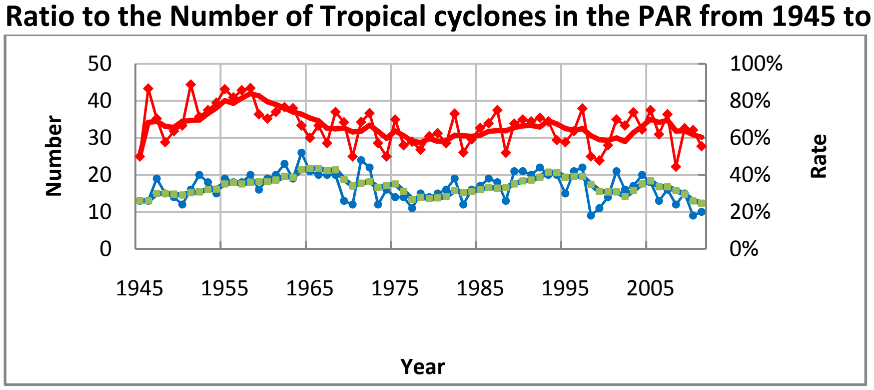


Notes: (a) The thin solid lines show the number of Tropical Cyclones formed on the Western Pacific Region (blue); the number of Tropical Cyclones that either formed within PAR or approaches PAR (green); and the number of Tropical Cyclones which made landfall in the Philippines (red). (b) The heavy solid lines give the five-year running means for the data. (c) The dashed lines show the normal values (average from 1971 to2000). (d) No data was available for 1941 to 1944.

Sources: "Monthly Bulletins of the Philippine Weather Bureau" of Manila Observatory; Kubota and Chan, 2009 (1902-1940)

4.6. Figure 17 portrays the number of typhoons and their ratio to the number of tropical cyclones from 1945 to 2010. While the number of typhoons in the Philippines varies between 9 and 26, there are no visible long-term trends in the frequency of typhoons. The ratio to tropical cyclones also varies between 42% and 90%, but the ratio has been around 60% in recent years.

Figure 17. The Number of Typhoons in the Philippine Area of Responsibility (PAR) and their Ratio to the Number of Tropical cyclones in the PAR from 1945 to 2010.



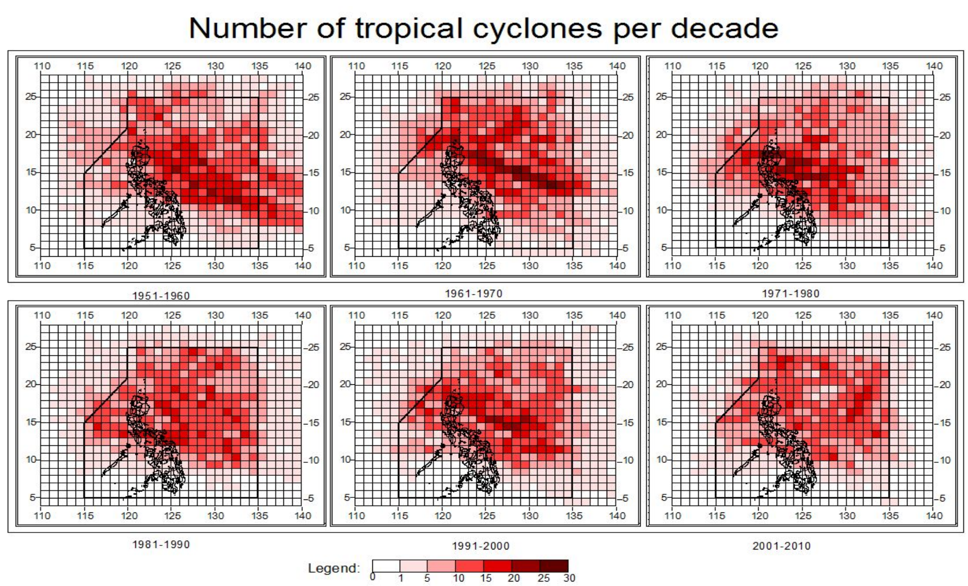
Notes: (a) Data in blue represent the number of Typhoons formed, while those in red are the ratios of the number of Typhoons to the number of Tropical Cyclones; (b) Heavy solid lines represent 5 year running averages.

Source Data: US Joint Typhoon Warning Center, Best Tracks (1945 to 2011)

4.7. While there may be no clear trends in the frequency of tropical cyclones and extreme typhoons affecting the Philippines, there is evidence of changes in the nature of these hazards. As Table A-7 shows, for the period 1971 to 2010, among the twenty most costly tropical cyclones (in terms of damage costs), seventeen of these occurred in the past two decades. Out of the top five costliest tropical cyclones, four are from the 2001-2010 decade. Thus, costs of damages from these hazards are found to be increasing with time. In contrast, as regards the deadliest tropical cyclones that affected the Philippines in the period 1951 to 2010 (see Table A-8), less than about half were from 1991 to 2010. Tropical Storm *Uring* is recorded as the deadliest tropical cyclone with over five thousand (5101) casualties in 1991. Table A-9 reports that the two tropical cyclones with the highest ever recorded maximum gustiness, Typhoons Reming and Loleng, occurred during the last two decades. Also, it must be noted that the damages in the more recent decade were caused by the less intense tropical cyclones (i.e. tropical storms, which are less intense than typhoons in terms of central winds). In the last decade (and even for the most recent tropical cyclones in December 2011), the damages were caused by the very intense rains associated with these cyclones. Usually the amount of rain that fell within 24 hours equal or exceeded the climatological average[22] during the month when the cyclone occurred (e.g., tropical storm Ketsana in September 2009 and Tropical Depressions[23] Violeta and Winnie in 2004).

4.8. It is also worth noting that typical paths of tropical cyclones per decade have been dynamic. As Figure 18 shows, during the decades of the 1950s and the 1960s, the maximum area of tropical cyclone activity is in the eastern part of the country, but by the 1970s, the activity shifted toward the northern Luzon, with the frequency becoming lesser in the last two decades.

Figure 18. Spatial Distribution of the frequency of tropical cyclones per decade in the PAR from 1951 to 2010.



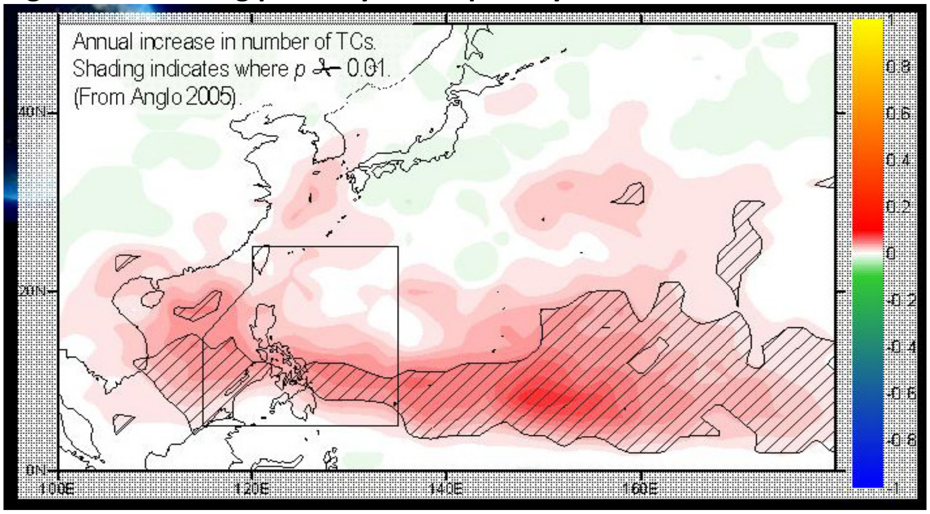
Source: PAGASA

[22] Climatological average or normals are the averages for a period of 30 years.

[23] Tropical Depression is a tropical cyclone classification which has the least intense winds at the center. Usually no name is given for this classification in the NW Pacific Basin outside PAR. Tropical depression Violeta became a tropical storm which was named Merbok in the NW Pacific basin.

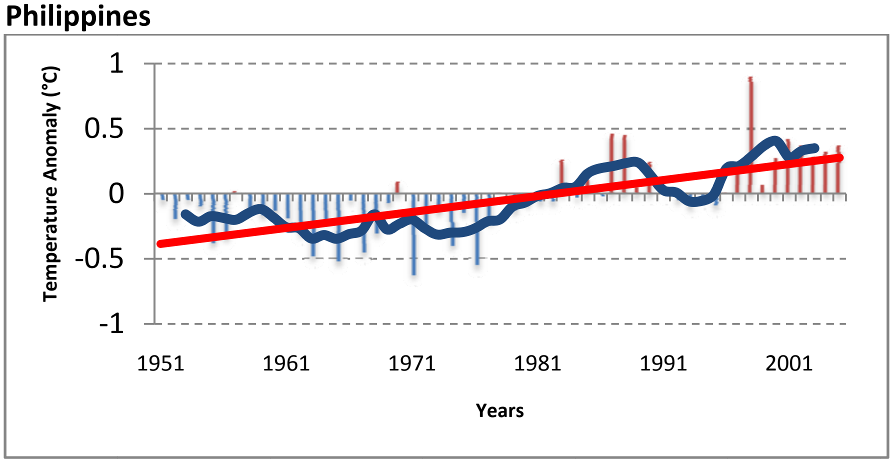
4.9. A more recent srudy by Anglo(2005) indicated that the tropical cyclone pathway has shifted to the Central Philippines . This is depicted in Figure 19.

Figure 19: Shifting pathways of tropical cyclones in the most recent decade



4.10. It is also worth pointing out that climate is changing in the Philippines. Like most parts of the world, the Philippines has exhibited increasing temperatures (see Figure 20), with the annual temperature in the country rising at a rate of 0.65 °C during the period 1951 to 2010, or an average of 0.0108 °C per year-increase. The rate of increase in temperature during the last thirty years (.0164°C per year) is also found to be faster as compared to the long term rate of increase. As in the case of the global changes in temperature, the warming trends are attributed to both natural variations in temperature and man-made climate change, i.e., increased emissions of GHGs.

Figure 20. Observed Annual Mean Surface temperature Anomalies from 1951 to 2005 in the Philippines

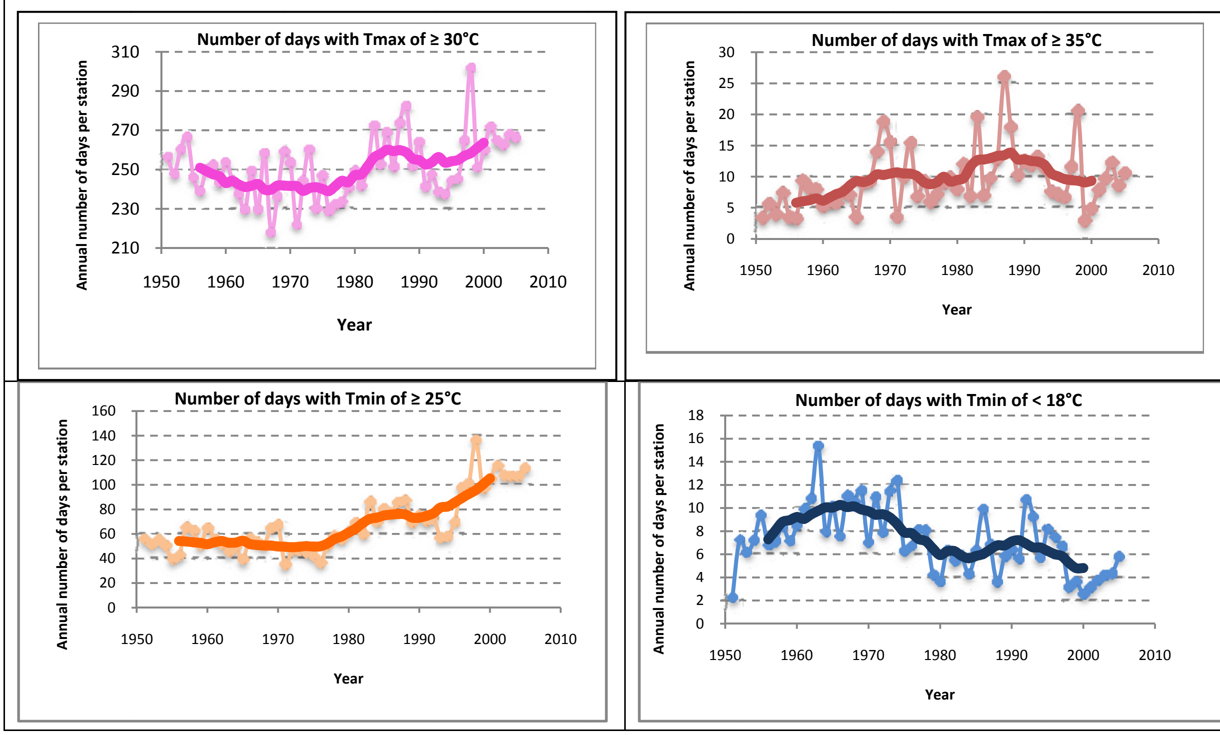


Source: Manila Observatory with data obtained from PAGASA

Note: (a) Data obtained at 28 observation stations of PAGASA: Aparri, Cagayan; Casiguran, Quezon; Iba, Zambales; Alabat, Quezon; Masbate, Masbate; Romblon, Romblon; Coron, Palawan; Cuyo, Palawan; Tagbilaran, Bohol; Catarman, Northern Samar; Guiuan, Eastern Samar; Dipolog, Zamboanga del Norte; Malaybalay, Bukidnon; Surigao, Surigao del Norte; Hinatuan, Surigao del Sur; Basco, Batanes; Vigan, Ilocos Sur; Calayan, Cagayan; Itbayat, Batanes; Ambulong, Batangas; Infanta, Quezon; Pagasa Island, Palawan; Sangley Point, Cavite; Tayabas, Quezon; Daet, Camarines Norte; Virac, Catanduanes; Iloilo City, Iloilo; Maasin, Southern Leyte. (b) Temperature anomalies represent departures from 1971-2000 normal values.

4.11. Since 1950, temperatures in the Philippines have risen but they began to rise abruptly in the latter half of the 1980s. The trend in rising temperatures in the Philippines can also be noticed in Figure 21 which illustrates (upper left) the number of days with maximum temperatures (***Tmax***) of ≥ 30°C and (lower left) the numbers of days with minimum temperatures (***Tmin***) of ≥ 25°C. The respective frequencies of these days are increasing, while (as shown in the lower right) the number of days with ***Tmin*** < 18°C is decreasing. The rather rare occurrence of days with ***Tmax*** ≥ 35°C is observed (in the upper right) to be generally more frequent in the period after the 1980 than in the period before 1970. The years that recorded significantly high temperatures are more concentrated in the period after 1995.

Figure 21. Changes in the annual number of days with *Tmax* of ≥30°C (upper left), days with *Tmax* of ≥35°C (upper right), days with *Tmin* of ≥25°C (lower left), and days with *Tmin* of < 18°C (lower right) in Philippines



Source: Manila Observatory with data obtained from PAGASA

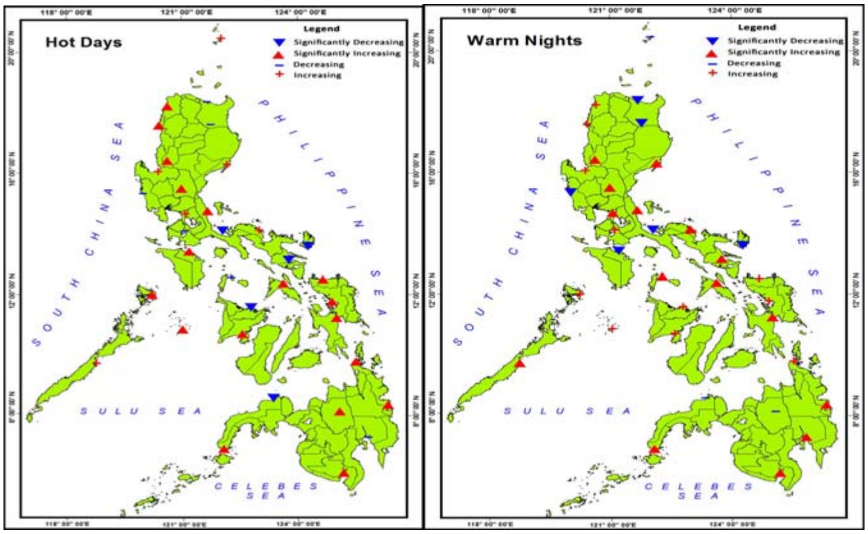
Notes: (a) Annual number of occurrence days per station calculated from data taken at 28 observation stations. (b) The thin line shows the annual number of days per station. (c) The heavy line shows the 11-year running mean.

4.12. Both maximum and minimum temperatures are generally getting warmer. In many parts of the country (see Figure 22), there are a statistically significant increasing number of hot days[24] and warm nights[25]. In addition, the number of cold days and cool nights are found to be decreasing.

[24] Hot days refer to days with maximum temperature (day time temperature) above the 1971-2000 mean 99th percentile.

[25] Warm nights are the days with minimum temperature (night time temperature) above the 1971-2000 mean 99th percentile.

Figure 22. Spatial Trends in Extreme Daily Temperatures in the Philippines Period: (1951 – 2008)

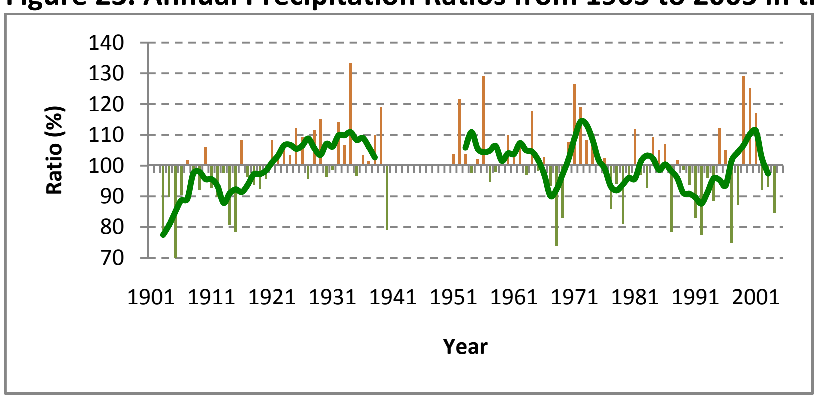


Source: PAGASA

Note: Data taken from 28 observation stations of PAGASA.

4.13. In the period 1903 to 2005, considerable wet periods were observed in the early to mid-1970s and in the late 1990s, and rather dry periods were seen in the mid-1960s and in the mid-1990s, but no clear trends can be observed (see Figure 23).

Figure 23. Annual Precipitation Ratios from 1903 to 2005 in the Philippines

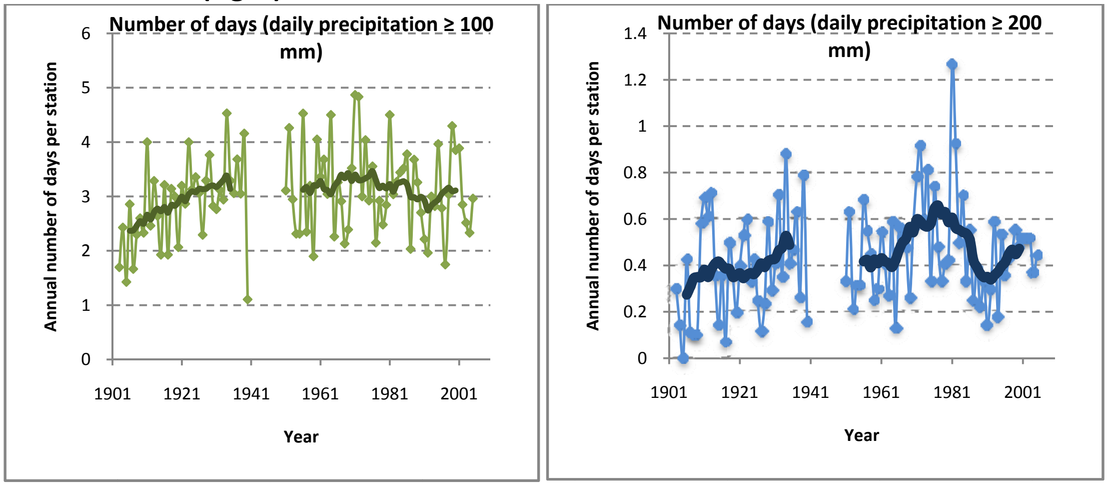


Sources: "Monthly Bulletins of the Philippine Weather Bureau" of Manila Observatory; Kubota and Chan, 2009 (1901-1940)

Note: Changes in annual precipitation ratio taken at 28 stations in the Philippines. Data represents annual precipitation ratios to the normal (i.e. the 1971 – 2000 average), with the heavy line (green) showing the five-year running mean.

4.14. Although no trends can be seen in the historical data of annual precipitation ratios, in contrast, Figure 24 shows that the number of days with heavy precipitation in the later part of the 20th century appears to be higher than the corresponding occurrence in the early part of the 20th century. This is consistent with IPCC AR4 (2007) finding.

Figure 24. Changes in the annual number of days with a daily precipitation of ≥ 100 mm (left) and ≥ 200 mm (right)

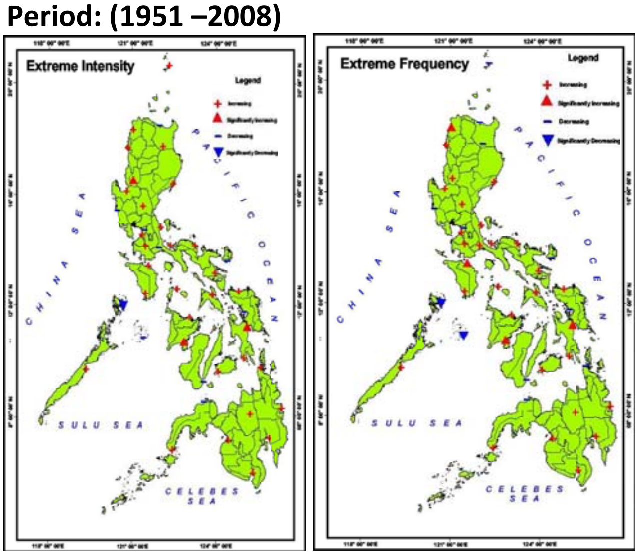


Note: The annual number of days per station derived from the number of occurrence days at 28 stations. The thin and heavy lines show annual values and the 11-year running mean values, respectively.

Sources: "Monthly Bulletins of the Philippine Weather Bureau" of Manila Observatory; Kubota and Chan, 2009 (1901-1940)

4.15. For the latter part of the century, the intensity of rainfall (Figure 25) appears to be increasing in most parts of the country, but not all of these increases are statistically significant. There is evidence of statistically significant increase in rainfall intensity in a few places, namely, Baguio, Tacloban and Iloilo. Figure 23 also shows that most parts of the Philippines also have a generally increasing trend in the frequency of extreme daily rainfall, but it is worth noting that not all of these trends are statistically significant. Trends are significant only in Calapan, Laoag, Iloilo and Tacloban, while in Palawan, the trends, though significant, are in the reverse direction.

Figure 25. Spatial Trends in Extreme Daily Rainfall (Intensity and Frequency) in the Philippines Period: (1951 –2008)

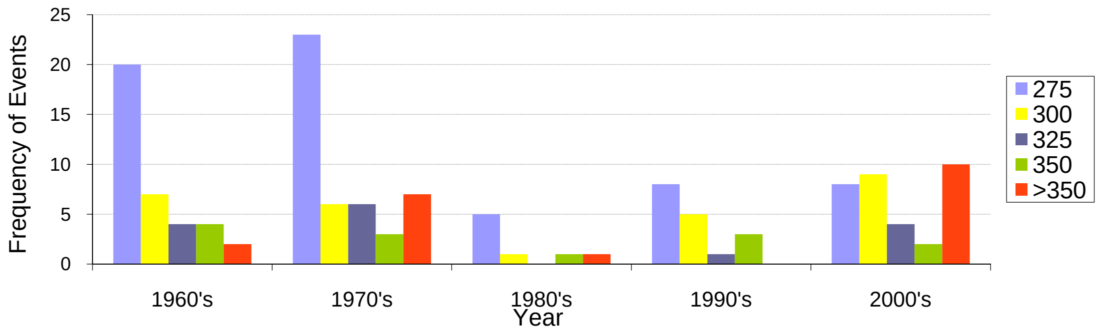


Source: PAGASA

Note: Data taken from 28 observation stations of PAGASA.

4.16. Though the frequency of extreme rainfall events may not be changing much across the decades, there is clear evidence that nature of these extreme events are changing. For example, over Luzon (the northern major island in the country), more frequent rainfall of greater than 350 millimeters are recorded in most recent years of 2000, than the 275 millimeters rainfall events of the 1960s and 1970s (see Figure 26).

Figure 26. Frequency of Heavy Rainfall Events in Luzon

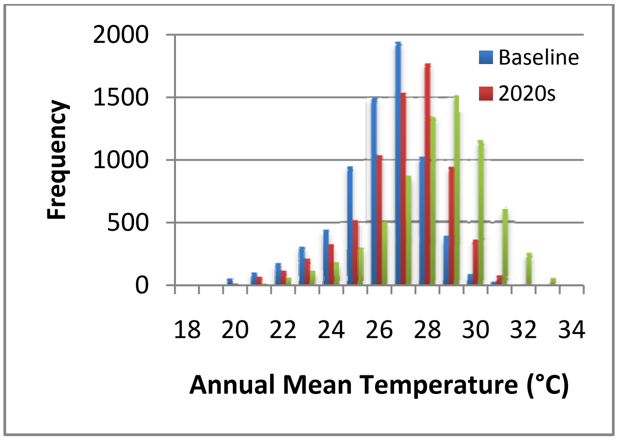


Source: Manila Observatory, based on RIHN, MRI/JMA Aphrodite data

4.17. Trends in climate indicators can help project future climate conditions. Alternatively, climate models may be used to foretell climate conditions decades into the future. Global climate models (GCMs) or regional climate models represent the dynamics in the factors that influence the climate system, and given specific scenarios, computer simulations may be generated on likely future outcomes. In its Special Report on Emission Scenarios (SRES), the IPCC outlined various GHG emission scenarios for projecting future climate conditions with climate models. These SRES scenarios, which were extensively used in IPCC's Third Assessment Reports (2001) and Fourth Assessment Report (2007), were based on the established relationship between atmospheric concentration of GHGs and changes in the climate, especially temperature. These scenarios can roughly be categorized into four: two categories that pertain to the focus of development: (A) economic or (B) environmental; and two categories that describe the homogeneity or heterogeneity of economies: (1) an advancement of globalization versus (2) more intensified regional uniqueness. These scenarios will influence the amount of GHG emissions. For instance, GHG emissions are high for the A2 scenario, low for B1, and medium for A1B.

4.18. Research undertaken at the Manila Observatory (2010) involved downscaling of the output of the ECHAM5 GCM (established by the Max Planck Institute for Meteorology) with the Regional Climate Model 3 (RegCM3) of the International Center for Theoretical Physics. Results of the Manila Observatory research on projected temperature in the Philippines using the medium A1B scenario is illustrated in Figure 27. Average temperature is projected to increase by 0.8°C to 2.2°C by 2020 and 2050, respectively over the entire country for the A1B IPCC scenario compared to baseline conditions. There is a noticeable shift of more frequent days having 28 °C in 2020 and 29°C in 2050 compared to the baseline. Detailed distribution of projected temperature over the Philippines shows varying degrees of warming in different areas, with the southern regions in the country expected to experience a greater degree of warming than those in the north. In particular, Mindanao and Southern Visayas is expected to be warmer in 2020 and 2050 compared to Luzon. A particular region in Mindanao, Zamboanga Peninsula, is expected to have the highest increase in temperature.

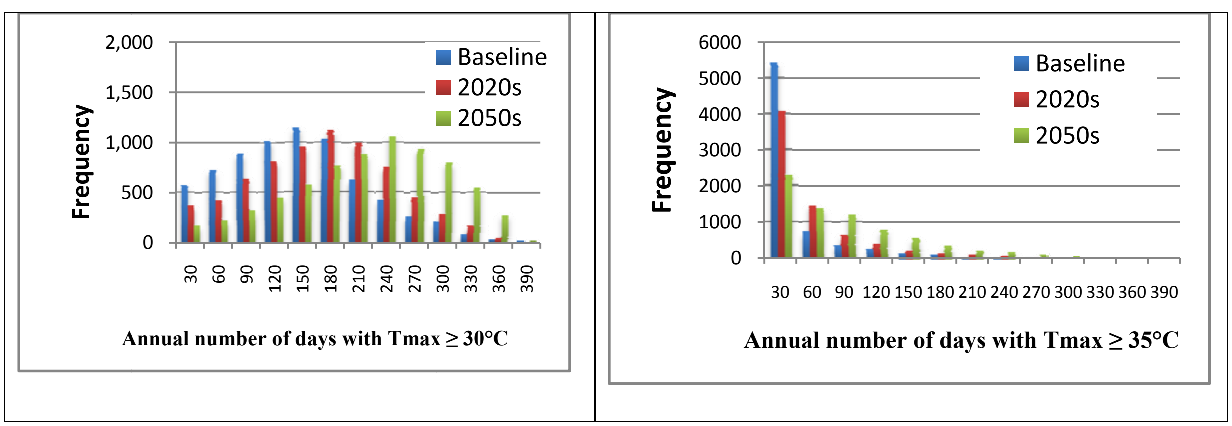
Figure 27. Projected Temperature over the Philippines by 2020 and 2050



Source: Manila Observatory

4.19 With such warming in the future, the numbers of cold days and hot days are expected to change as well. Using temperature projections in the medium–range scenario (A1B), the number of hot days, such as days with ***Tmax*** [26] of ≥30°C days or with ***Tmax*** of ≥35°C is projected to increase over the Philippines (Figure 28a). Days with ***Tmin***[27] of ≥25°C will also increase in 2020 and 2050 (Figure 28 b). In addition, for the annual number of years with Tmin < 18°C, there is an increase in frequencies in the 30 days range in the 2020s and 2050s, but declines in all the other higher range after that. This implies then that in the baseline climate, we would get more than 30 days and as many as 270 days of cold nights. But by 2020 and 2050, the frequency of many nights (that is more than 30) that will have cold temperature will decrease. Most of the years will just have 30 days or so of cooler nighttime temperature and nothing longer.

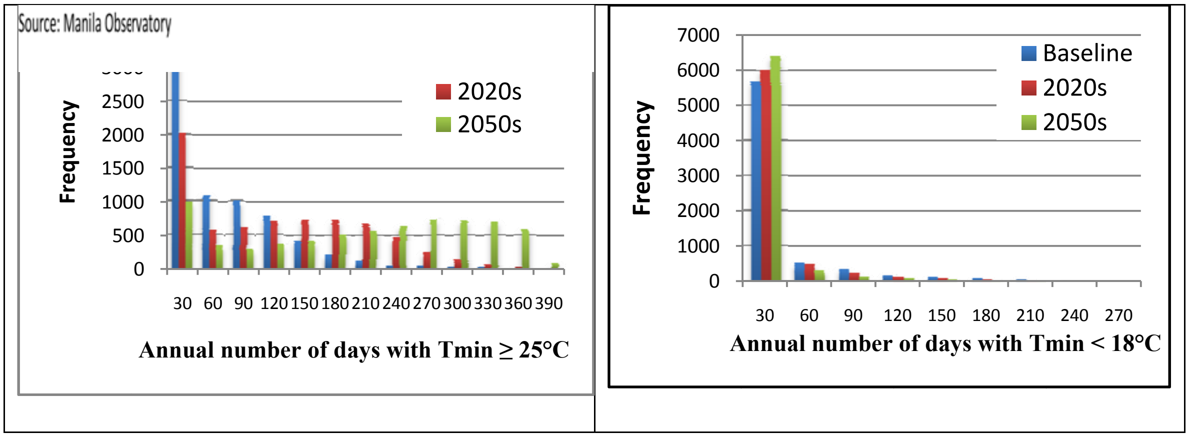
Figure 28a. Projected Number of Hot Days over the Philippines by 2020 and 2050



Source: Manila Observatory

[26] Tmax or maximum temperature is also known as the daytime temperature (from 6 am to 6 pm).
[27] Tmin or minimum temperature is also known as the nighttime temperature (from 6 pm to 6 am).

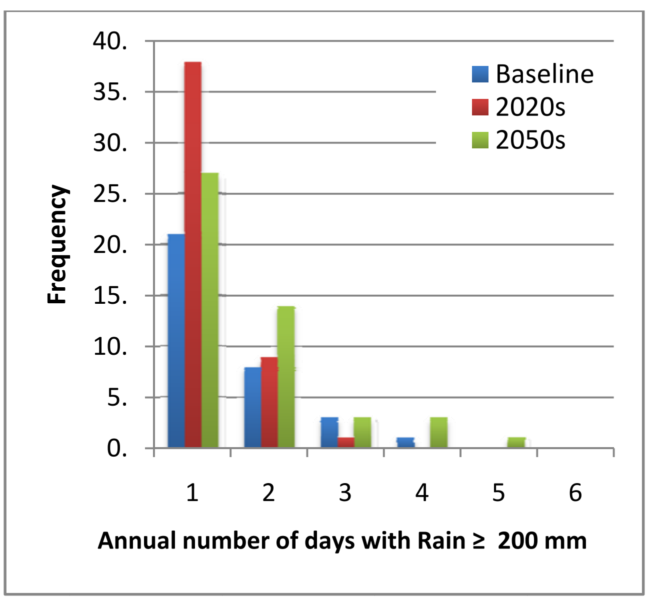
Figure 28b. Projected Number of Cold Days over the Philippines by 2020 and 2050



Source: Manila Observatory

4.19. While climate models project temperature increases practically everywhere as GHG concentration increases, the IPCC (2007) suggests that precipitation will increase in some regions and decrease in other regions. In particular, precipitation is expected to increase in high-latitude regions and to decrease in the tropics. The Manila Observatory (2011) reports that the downscaled output of the ECHAM5 model under the A1B scenario suggests a decrease in rainfall by 2020 in most parts of the country except for Luzon, where there is either an increase or no change in rainfall. In addition, by 2050, it is expected that Visayas and Mindanao will be drier than normal. As far as extreme precipitation in the Philippines, the number of days with heavy precipitation (e.g., greater than 200 mm) is expected to increase with global warming by the year 2020 and 2050 (see Figure 29).

Figure 29. Projected Number of Days with Heavy Precipitation over the Philippines by 2020 and 2050



Source: Manila Observatory

5. Conclusions

5.1 The incidence of intense climate-related disasters is rising, particularly in some sub-regions of Asia and the Pacific. The concomitant distribution of temperature and precipitation conditions of these events is becoming more variable and extreme. These emerging trends suggest that some of the main effects of climate change may already be taking place. Thus the increasing frequency of intense hydro-meteorological disasters would seem to be caused by not only rising population exposure and limited adaptive capacity, but also man-made climate change. The main effects of man-made climate change may still well be in the near future.

5.2 The disaster risks across economies in Asia-Pacific vary, with coastal economies in South East Asia, South Asia and East Asia being more prone to these weather-related disasters. There is evidence that these risks to weather related disasters are also related to socio-demographic indicators, such as population, population density that reflect exposure and adaptive capacity to disasters. There is also evidence that the disasters are having a heavier toll on low and lower middle income economies.

5.3 The main effects of climate change may well be in the near future. There is evidence that the increasing frequency of intense weather-related disasters is caused by a confluence of the changing nature of hazards that are affected by climate change, including human-induced climate change, rising population exposure, and limited adaptive capacity.

5.4 Disaster risk varies from country to country, with coastal countries in Southeast, South, and East Asia more prone to hydro-meteorological disasters, particularly Bangladesh, the People's Republic of China, India, Myanmar, and the Philippines. The evidence suggests that disasters are taking a heavier toll on such low-income and lower-middle-income countries.

5.5 The Philippines, one of the economies that are hot spots for climate-related disasters, does not necessarily have rising frequency of occurrence of tropical cyclones and typhoons. But various data suggests that these extreme weather-related events in the Philippines are getting more costly, deadly, and having dynamics in their path and intensity. The bigger damages in the recent past are not even from typhoons, but tropical cyclones of lower intensity (in terms of central winds). Although these more deadly and more costly tropical cyclones have less central winds, they have very intense rains associated with them. In addition, there is evidence of increasing temperature and more occurrence of extreme precipitation in the Philippines (at least in comparison to the early twentieth century). While the frequency count of extreme rainfall events may seem not to be increasing, but the amount of rainfall for these events are getting more intense with time. Since disaster risks are ultimately a function of the hazards, vulnerability and exposure, the results shown here highlight the need for more concerted action to minimize the impact of such climate-related events and adapt to these climatic trends.

Better climate mitigation and climate adaptation, such as accelerating plans for the clean development mechanism of the Kyoto Protocol, as well as refining hazard mapping and various risk assessment systems, are needed. Mainstreaming disaster management and climate adaptation is ultimately about reducing disaster risk, aside from mitigating the impact of the consequences of disasters. Often, those who have less in life are more at risk, especially when they live in these disaster-prone areas, so that in consequence, risk reduction is ultimately connected to social and economic development.

5.6 Since GHG emissions are at the centre of climate change, it is important to develop more efficient furnace systems and new low-energy technologies for industry and transport. All countries need to improve on reducing consumption of energy-intensive products, and switch to renewable forms of energy. Forests, vegetation, soils and other natural carbon sinks can be managed to absorb carbon dioxide. More research and development should be geared to develop technologies for capturing carbon dioxide at industrial sources as well as for inject it into permanent storage deep underground.

5.7 In addition to climate mitigation, it is also important to invest in climate proofing infrastructure, especially in areas prone to climate hazards. People living in more risk prone areas will need to be have more access to catastrophe insurance, and more incentives to precautionary savings that will mitigate the adverse effects of these events should they occur. Governments need to work on improving infrastructure designs and standards, proper enforcement of building codes, as well as develop public policies for reducing the exposure to natural disasters by making changes on land zoning and urban planning.

5.8 Adaptation and mitigation actions should be considered jointly, and these should be mainstreamed in development policy to reduce the risk to lives and livelihoods and increase the resilience of communities to these hazards.

Annex Tables

Table A-1 Results of Non-Stationarity Tests on Seasonally Differenced Monthly Average Temperature Anomalies in Asia-Pacific, Seasonally Differenced Monthly Average Precipitation Deviations from Normal in Asia-Pacific, and Seasonally Differenced C02 Concentration (in Mauna Loa).

Time Series	***Augmented Dickey Fuller Test for Specification with trends and twelve lags***	***Phillips-Perron***
Monthly Average Temperature Anomalies in Asia-Pacific*	Evidence that Series is Stationary, i.e. reject unit root hypothesis (p value < 0.01)	Reject unit root hypothesis (p value < 0.01)
Monthly Average Precipitation Deviation from Normals in Asia-Pacific*	Evidence that Series is Stationary, i.e. reject unit root hypothesis (p value < 0.01)	Reject unit root hypothesis (p value < 0.01)
Monthly C02 Concentration in Mauna Loa In Situ Samples*	Evidence that Series is Stationary, i.e. reject unit root hypothesis p value < 0.01)	Reject unit root hypothesis (p value < 0.01)

Note: * Time Series were Seasonally Differenced

Table A-2. Summary of Vector Auto Regression Model Linking Seasonally Differenced Monthly Time Series of Temperature Anomalies in Asia-Pacific, Rainfall Deviations from Normal in Asia-Pacific, and C02 Concentration from Mauna Loa In Situ Air Samples

Sample: 1959m5 - 2010m11					No. of obs =619
Equation	Parameters	RMSE	R-sq	chi2	P>chi2
Precipitation deviation from normals in Asia-Pacific	7	8.65	0.206	160.6885	0.00000
Temperature anomalies in Asia-Pacific	7	0.56	0.103	71.34938	0.00000
C02 Concentration	7	0.38	0.712	1532.925	0.00000

	Coef.		z	P>z
Precipitation Deviations from Normals in Asia- Pacific				
Precipitation deviation from normals in Asia-Pacific				
L1.	**0.26**	0.040	6.64	0.00
L2.	**0.15**	0.039	3.92	0.00
Temperature Anomalies in Asia-Pacific				
L1.	**1.51**	0.625	2.42	0.02
L2.	0.83	0.628	1.32	0.19
C02 concentration				
L1.	**2.41**	0.880	2.74	0.01
L2.	-0.10	0.895	-0.11	0.91
_cons	-3.28	0.849	-3.86	0.00
Temperature Anomalies in Asia-Pacific				
Precipitation deviation from normals in Asia-Pacific				
L1.	0.00	0.003	0.91	0.36
L2.	0.00	0.003	-0.52	0.60
Temperature Anomalies in Asia-Pacific				
L1.	**0.31**	0.040	7.67	0.00
L2.	**-0.08**	0.040	-2.07	0.04
C02 concentration				
L1.	0.07	0.057	1.20	0.23
L2.	0.02	0.058	0.37	0.71
_cons	-0.11	0.055	-2.10	0.04
C02 concentration				
Precipitation deviation from normals in Asia-Pacific				
L1.	0.00	0.002	-0.59	0.56
L2.	0.00	0.002	-0.39	0.70
Temperature Anomalies in Asia-Pacific				
L1.	0.00	0.027	0.12	0.91
L2.	**0.08**	0.028	3.08	0.00
C02 concentration				
L1.	**0.62**	0.039	16.06	0.00
L2	**0.25**	0.039	6.38	0.00
_cons	0.19	0.037	5.05	0.00

Table A-3. Granger Causality Tests on Seasonally Differenced Monthly Time Series of Temperature Anomalies in Asia-Pacific, Rainfall Deviations from Normal in Asia-Pacific, and C02 Concentration from Mauna Loa In Situ Air Samples

Equation	Excluded	chi2	Df	Prob > chi2
Precipitation Deviations	Temperature anomalies	10.35	2	0.01
Precipitation Deviations	C02 Concentration	20.68	2	0.00
Precipitation Deviations	Temperature anomalies and C02 Concentration	33.96	4	0.00
Temperature anomalies	Precipitation Deviations	0.89	2	0.64
Temperature anomalies	C02 Concentration	6.83	2	0.03
Temperature anomalies	Precipitation Deviations and C02 Concentration	9.02	4	0.06
C02 Concentration	Precipitation Deviations	0.72	2	0.70
C02 Concentration	Temperature anomalies	10.61	2	0.01
C02 Concentration	Precipitation Deviations and Temperature Anomalies	11.01	4	0.03

Table A-4. Characterization of Köppen Geiger climate classification groups, types and subtypes

Classification Type			Description	Criteria*
1st level	2nd level	3rd level		
A			Tropical	Tcold ≥ 18
	F		- Rainforest	Pdry ≥ 60
	M		- Monsoon	Not (Af) & Pdry ≥ 100–MAP/25
	W		- Savannah	Not (Af) & Pdry < 100–MAP/25
B			Arid	
	W		- Desert	MAP < 5×Pthreshold
	S		- Steppe	MAP ≥ 5×Pthreshold
		H	- Hot	
		K	- Cold	
C			Temperate	Thot ≥ 10 & 0 < Tcold < 18
	S		- Dry Summer	Psdry < 40 & Psdry < Pwwet/3
	W		- Dry Winter	Pwdry < Pswet/10
	F		- Without Dry season	Not (Cs) or (Cw)
		A	- Hot Summer	Thot ≥ 22
		B	- Warm Summer	Not (a) & Tmon10 ≥ 4
		C	- Cold Summer	Not (a or b) & 1 ≤ Tmon10 < 4
D			Cold	
	S		- Dry Summer	Psdry < 40 & Psdry < Pwwet/3
	W		- Dry Winter	Pwdry < Pswet/10
	F		- Without Dry season	Not (Ds) or (Dw)
		A	- Hot Summer	Thot ≥ 22
		B	- Warm Summer	Not (a) & Tmon10 ≥ 4
		C	- Cold Summer	Not (a, b or d)
		D	- Very Cold Winter	Not (a or b) & Tcold < –38
E			Polar	
	T		- Tundra	Thot > 0
	F		- Frost	

* MAP = mean annual precipitation, MAT = mean annual temperature, Thot = temperature of the hottest month, Tcold = temperature of the coldest month, Tmon10 = number of months where the temperature is above 10, Pdry = precipitation of the driest month, Psdry = precipitation of the driest month in summer, Pwdry = precipitation of the driest month in winter, Pswet = precipitation of the wettest month in summer, Pwwet = precipitation of the wettest month in winter, Pthreshold = varies according to the following rules (if 70% of MAP occurs in winter then Pthreshold = 2 x MAT, if 70% of MAP occurs in summer then Pthreshold = 2 x MAT + 28, otherwise Pthreshold = 2 x MAT + 14). Summer (winter) is defined as the warmer (cooler) six month period of ONDJFM and AMJJAS.

Note: Precipitation measured in millimeters (mm) and temperature in degrees Celsius (^{o}C)

Table A-5. Climate Distribution in Asia-Pacific Economies by Köppen Geiger climate classification groups

Economy	*Climate Classification Group*				
	A	*B*	*C*	*D*	*E*
Afghanistan	0.0%	94.0%	1.9%	4.2%	0.0%
American Samoa	100.0%	0.0%	0.0%	0.0%	0.0%
Armenia	0.0%	11.4%	0.0%	88.6%	0.0%
Australia	7.6%	77.6%	14.8%	0.0%	0.0%
Azerbaijan	0.0%	42.2%	45.1%	12.7%	0.0%
Bahrain	0.0%	100.0%	0.0%	0.0%	0.0%
Bangladesh	72.3%	0.0%	27.7%	0.0%	0.0%
Bhutan	0.0%	0.0%	65.8%	32.1%	2.2%
Brunei Darussalam	100.0%	0.0%	0.0%	0.0%	0.0%
Cambodia	100.0%	0.0%	0.0%	0.0%	0.0%
China	0.3%	38.5%	26.3%	32.0%	2.9%
China, Hong Kong Special Administrative	0.0%	0.0%	100.0%	0.0%	0.0%
China, Macao Special Administrative Region	0.0%	0.0%	100.0%	0.0%	0.0%
Cook Islands	100.0%	0.0%	0.0%	0.0%	0.0%
Cyprus	0.0%	51.9%	48.1%	0.0%	0.0%
Democratic People's Republic of Korea	0.0%	0.0%	1.0%	99.0%	0.0%
Fiji	100.0%	0.0%	0.0%	0.0%	0.0%
French Polynesia	100.0%	0.0%	0.0%	0.0%	0.0%
Georgia	0.0%	0.8%	60.7%	38.5%	0.0%
Guam	100.0%	0.0%	0.0%	0.0%	0.0%
India	35.7%	29.7%	33.4%	1.3%	0.0%
Indonesia	100.0%	0.0%	0.0%	0.0%	0.0%
Iran (Islamic Republic of)	0.0%	88.1%	9.3%	2.7%	0.0%
Iraq	0.0%	91.3%	7.8%	1.0%	0.0%
Israel	0.0%	59.9%	40.1%	0.0%	0.0%
Japan	0.1%	0.0%	50.3%	49.7%	0.0%
Jordan	0.0%	95.5%	4.5%	0.0%	0.0%
Kazakhstan	0.0%	54.6%	0.0%	45.4%	0.0%
Kiribati	0.0%	100.0%	0.0%	0.0%	0.0%
Kuwait	0.0%	100.0%	0.0%	0.0%	0.0%
Kyrgyzstan	0.0%	54.1%	0.0%	45.9%	0.0%
Lao People's Democratic Republic	82.4%	0.0%	17.6%	0.0%	0.0%
Lebanon	0.0%	0.0%	100.0%	0.0%	0.0%
Malaysia	100.0%	0.0%	0.0%	0.0%	0.0%
Maldives	0.0%	100.0%	0.0%	0.0%	0.0%
Marshall Islands	100.0%	0.0%	0.0%	0.0%	0.0%
Micronesia (Federated States of)	100.0%	0.0%	0.0%	0.0%	0.0%
Mongolia	0.0%	71.1%	0.0%	28.9%	0.0%
Myanmar	78.7%	0.0%	21.3%	0.0%	0.0%
Nepal	0.0%	0.0%	99.9%	0.1%	0.0%
New Caledonia	100.0%	0.0%	0.0%	0.0%	0.0%
New Zealand	0.0%	0.0%	99.9%	0.0%	0.1%
Niue	100.0%	0.0%	0.0%	0.0%	0.0%
Northern Mariana Islands	100.0%	0.0%	0.0%	0.0%	0.0%
Occupied Palestinian Territory	0.0%	0.0%	100.0%	0.0%	0.0%
Oman	0.0%	100.0%	0.0%	0.0%	0.0%
Pakistan	0.0%	84.1%	9.4%	6.5%	0.0%
Palau	100.0%	0.0%	0.0%	0.0%	0.0%
Papua New Guinea	100.0%	0.0%	0.0%	0.0%	0.0%
Philippines	98.3%	0.0%	1.7%	0.0%	0.0%
Qatar	0.0%	100.0%	0.0%	0.0%	0.0%

Republic of Korea	0.0%	0.0%	25.5%	74.5%	0.0%
Samoa	100.0%	0.0%	0.0%	0.0%	0.0%
Saudi Arabia	0.0%	100.0%	0.0%	0.0%	0.0%
Singapore	100.0%	0.0%	0.0%	0.0%	0.0%
Solomon Islands	100.0%	0.0%	0.0%	0.0%	0.0%
Sri Lanka	94.7%	0.0%	5.3%	0.0%	0.0%
Syrian Arab Republic	0.0%	76.7%	23.3%	0.0%	0.0%
Taiwan (China)	1.9%	0.0%	98.1%	0.0%	0.0%
Tajikistan	0.0%	49.9%	16.7%	33.4%	0.0%
Thailand	100.0%	0.0%	0.0%	0.0%	0.0%
Timor-Leste	0.0%	0.0%	0.0%	100.0%	0.0%
Tokelau	0.0%	0.0%	0.0%	0.0%	0.0%
Tonga	100.0%	0.0%	0.0%	0.0%	0.0%
Turkmenistan	0.0%	100.0%	0.0%	0.0%	0.0%
Tuvalu	100.0%	0.0%	0.0%	0.0%	0.0%
United Arab Emirates	0.0%	100.0%	0.0%	0.0%	0.0%
Uzbekistan	0.0%	88.4%	1.4%	10.2%	0.0%
Vanuatu	100.0%	0.0%	0.0%	0.0%	0.0%
Viet Nam	59.9%	0.0%	40.1%	0.0%	0.0%
Wallis and Futuna Islands	100.0%	0.0%	0.0%	0.0%	0.0%
Yemen	0.0%	100.0%	0.0%	0.0%	0.0%

Table A-7. List of Most Damaging Tropical Cyclones that Affected the Philippines From 1971 to 2010

TROPICAL CYCLONE NAME	YEAR	TOTAL DAMAGE (IN BILLION PESOS)	PERIOD
Typhoon PEPENG	2009	27.3	SEP 30 - OCT 10
Typhoon FRANK	2008	13.5	JUN 18 - JUN 23
Typhoon JUAN	2010	11.5	OCT 16 - OCT 21
Tropical Storm ONDOY	2009	11.0	SEP 24 - SEP 27
Typhoon RUPING	1990	10.8	NOV 08 - NOV 14
Typhoon ROSING	1995	10.8	OCT 31 - NOV 04
Typhoon KADIANG	1993	8.8	SEP 30 - OCT 07
Typhoon LOLENG	1998	6.8	OCT 15 - OCT 25
Typhoon MILENYO	2006	6.6	SEP 25 - SEP 29
Typhoon REMING	2006	5.4	OCT 21 - OCT 26
Typhoon UNSANG	1988	5.6	NOV 28 - DEC 03
Typhoon ILIANG	1998	5.4	OCT 10 - OCT 16
Typhoon COSME	2008	4.7	MAY 14 - MAY 20
Typhoon CALOY	2006	4.3	MAY 09 - MAY 15
Typhoon REMING	2000	3.9	OCT 25 - OCT 31
Typhoon NITANG	1984	3.9	AUG 31 - SEP 04
Typhoon EMANG	1998	3.8	SEP 16 - SEP 17
Typhoon GADING	1998	3.8	SEP 17 - SEP 21
Typhoon TRINING	1991	3.7	OCT 20 - OCT 31
Typhoon FERIA	2001	3.6	JUL 02 - JUL 05

Source: Office of Civil Defense, National Disaster Risk Reduction and Management Council, Philippines

Table A-8. List of Most Deadly Tropical Cyclones that Affected Philippines From 1951-2010

TROPICAL CYCLONE NAME	YEAR	NO. OF DEAD	PERIOD
Tropical Storm URING	1991	5101	NOV 01 - NOV 06 ***
Typhoon NITANG	1984	1029	AUG 31 - SEP 04 ***
Typhoon TRIX	1952	995	OCT 17 - OCT 23
Typhoon AMY	1951	991	DEC 06 - DEC 11
Typhoon ROSING	1995	936	OCT 30 - NOV 04
Typhoon UNDANG	1984	895	NOV 03 - NOV 06
Typhoon SISANG	1987	808	NOV 23 - NOV 26
Typhoon REMING	2006	734	NOV 28 - DEC 03
Typhoon TITANG	1970	631	OCT 18 - OCT 22
TD WINNIE	2004	593	NOV 27 - NOV 29 ***
Typhoon SENING	1970	575	OCT 11 - OCT 15
Typhoon FRANK	2008	557	JUN 18 - JUN 23 ***
Typhoon RUPING	1990	508	NOV 10 - NOV 14
Tropical Storm RENA	1949	505	NOV 10 - NOV 13
Typhoon PEPENG	2009	465	SEP 30 - OCT 10
Tropical Storm ONDOY	2009	464	SEP 24 - SEP 27 ***
Typhoon KADING	1978	444	OCT 25 - OCT 27
Typhoon LOLENG	1998	303	OCT 15 - OCT 24

Source: Office of Civil Defense, National Disaster Risk Reduction and Management Council, Philippines

Table A-9. List of Highest Ever Recorded Maximum Gustiness during the passage of Tropical Cyclones from 1951 to 2010.

T.C. NAME	STATION	MAX. WIND (KPH)	DATE OF OCCURRENCE	DURATION
Typhoon REMING	Virac Radar	320	11/30/2006	NOV 28 - DEC 03
Typhoon LOLENG	Virac S.	287	10/21/1998	OCT 15 - OCT 25
Typhoon ANDING	Virac R.	280	11/27/1981	NOV 21 - NOV 27
Typhoon SENING	Virac S.	276	10/13/1970	OCT 10 - OCT 16
Typhoon WENING	Aparri	269	10/27/1974	OCT 25 - OCT 29
Typhoon TRINING	Masbate	269	12/15/1987	DEC 14 - DEC 19
Typhoon FREDA	Casiguran	258	11/16/1959	NOV 12 - NOV 19
Typhoon YOLING	Alabat	258	11/19/1970	NOV 17 - NOV 21
Typhoon GARDING	Guiuan	258	12/21/1994	DEC 17 - DEC 24
Tropical Storm SALING	Ambulong	251	10/10/1989	OCT 08 - OCT 11
Typhoon ROSING	Virac R	251	11/2/1995	OCT 31 - NOV 04
Typhoon MAMENG	Basco	240	10/12/1975	OCT 09 - OCT 13
Typhoon ATANG	Guiuan	240	4/19/1978	APR 18 - APR 26
Typhoon SALING	Daet	233	10/18/1985	OCT 15 - OCT 20
Typhoon SISANG	Legaspi	233	11/25/1987	NOV 23 - NOV 27
Typhoon SUSANG	Aparri	230	10/10/1974	OCT 09 - OCT 12
Typhoon ARING	Virac R	230	11/4/1980	NOV 01 - NOV 07

Table A-10. List of Greatest 24-Hr. Rainfall during the passage of Tropical Cyclones from 1951 to 2010.

T.C. NAME	STATION	GREATEST 24-HR. RAINFALL (MM)	DATE OF OCCURRENCE	DURATION
Typhoon FERIA	Baguio	1085.8	7/4/2001	JUL 02 - JUL 05
Typhoon ILIANG	Baguio	994.6	10/14/1998	OCT 10 - OCT 16
Typhoon TRINING	Baguio	979.4	10/17/1967	OCT 14 - OCT 19
Typhoon SUSANG	Baguio	781.4	10/11/1974	OCT 09 - OCT 12
Typhoon TRINING	Baguio	760	10/27/1991	OCT 20 - OCT 31
Typhoon DITANG	Baguio	730.3	5/15/1980	MAY 10 - MAY 20
Tropical Storm CHEDENG	Dagupan	722.6	5/27/2003	MAY 25 - MAY 29
Typhoon GADING	Baguio	709.6	7/9/1986	JUL 06 - JUL 10
Typhoon ARING	Baguio	698.7	11/5/1980	NOV 01 - NOV 07
Typhoon WENING	Baguio	678.8	10/28/1974	OCT 25 - OCT 29
Tropical Depression SISANG	Alabat	673	12/27/1975	DEC 26 - DEC 28
Typhoon NITANG	Baguio	649.7	9/28/1968	SEP 23 - OCT 01
Typhoon DIDANG	Baguio	605.3	5/25/1976	MAY 12 - MAY 27
Tropical Storm ARING	Masbate	603.5	12/4/1976	DEC 02 - DEC 07
Typhoon REMING	Surigao	564.7	11/18/1968	NOV 12 - NOV 22
Typhoon CORA	Baguio	546.6	11/17/1953	NOV 12 - NOV 19
Typhoon OSANG	Baguio	536.3	7/25/1980	JUL 20 - JUL 26
Tropical Storm MIDING	Baguio	534.2	8/23/1978	AUG 20 - AUG 27

Annex Notes

Technical Description of Econometric and Statistical Methods Employed

In this paper, the link between climate variables (on temperature anomalies and precipitation deviations from normal) and greenhouse gas emission is examined with a variety of statistical methods and econometric tools. For more details, see Baum (2006), Hamilton (1994) or Enders (2004).

a) <u>Statistical Tests on Existence of Unit Roots</u>

There is suspicion that the three sets of monthly time series, namely, the average surface temperature anomalies in Asia-Pacific, the rainfall deviations from normal in Asia-Pacific and the global C02 concentration (from mean in situ samples in Mauna Loa) are cointegrated, i.e. they share a common trend and tend to move together in the long-run. Cointegration presupposes that the time series data are non-stationary. A stationary series fluctuates around a constant long-run mean and, this implies that the series has a finite variance which does not depend on time. On the other hand, non-stationary series have no tendency to return to a long-run deterministic path and the variances of the series are time-dependent. A unit root test establishes if a time series is non-stationary. Since the monthly time series exhibit seasonal behaviour, these data were firstly de-seasonalized using seasonal differencing. Various unit-root tests, e.g., Dickey-Fuller, Augmented Dickey-Fuller and Philipps Perron, were performed on the seasonally-differenced data, suggesting that the time series are stationary.

The Dickey Fuller test involves testing the null hypothesis that a time series y_t contains a unit root, i.e. that ρ =1 for the auto regression:

$$y_t = \alpha + \rho y_{t-1} + \delta t + \varepsilon_t$$

(with specifications on $\alpha = 0, \delta \neq 0$, or including lagged values of the difference of the time series in the regression) and the alternative is that the variable was generated by a stationary process (i.e. $\rho \neq 1$). Since the underlying regression is likely to be plagued by serial correlation, an augmented Dickey Fuller test instead considers an underlying model of the form

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \xi_1 \Delta Y_{t-1} + \xi_2 \Delta Y_{t-2} + \cdots + \xi_k \Delta Y_{t-k} + \varepsilon_t$$

with a testing of the null hypothesis β =0 using some T statistic. The estimation of parameters in these models may done through least-squares or generalized least-squares regression. Another test, The Phillips-Perron procedure can be viewed as Dickey–Fuller statistics that have been made robust to serial correlation by using Newey-West standard errors.

b) <u>Vector Auto-Regression</u>

To explore the linkage among the three sets of seasonally differenced time series, we make use of Vector Auto Regression (VAR) on the time series. A VAR model relates K stationary variables of interest by firstly forming a (K × 1) random vector

$$\mathrm{Y}_t = (\mathrm{y}_{1t}, \mathrm{y}_{2t}, \dots, \mathrm{y}_{kt})^T$$

with the components of the random vector specified as linear functions of p of their own lags, p lags of the other K -1 components, and possibly additional exogenous variables (here, global carbon dioxide emission). Algebraically, a p-order VAR model, written VAR(p), is given by

$$Y_t = \nu + \mathbb{A}_1 Y_{t-1} + \mathbb{A}_2 Y_{t-2} + \cdots + \mathbb{A}_p Y_{t-p} + U_t$$

where

$\mathbb{A}_1$ through $\mathbb{A}_p$ are K x K matrices of parameters,
$\mathbb{B}_0$ through $\mathbb{B}_s$ are K x M matrices of coefficients,
ν is a K x 1 vector of parameters, and
U_t is assumed to be white noise

The VAR model thus treats every stationary variable as endogenous in the system as a function of the lagged values of all endogenous variables in the system. In order to determine the optimal number of lags p for the VAR model, we made use of various Information Criteria, e.g., Akaike, Hannan-Quinn and Schwarz Bayesian Information Criteria and the Sequential likelihood ratio test to find the model that best explains the data parsimoniously.

A VAR model is often difficult to interpret. What we often want to do with a VAR is to evaluate the effects of shocks, or innovations. For instance, will a shock to seasonally differenced C02 stock have a permanent effect on the temperature (or precipitation), or a transitory effect? If the effect is transitory, how long will it take to dissipate? To do such evaluation, we need to compute the impulse response functions (IRFs). These IRFs are derivatives that trace out the response of current and future values of each of the variables to a one-unit increase in the current value of one of the VAR errors under the assumption that this error returns to its expected value of zero in subsequent periods and that all other errors are equal to zero.

c) Granger Causality

A major use of VAR models is forecasting. Granger (1969) developed the notion of forecasting ability through Granger-causality. If a variable, or group of variables, y_1 is found to be helpful for predicting another variable, or group of variables, y_2 then y_1 is said to Granger-cause y_2; otherwise it is said not to Granger-cause y_2.

More formally, y_1 does not Granger-cause y_2 if for all s > 0 the MSE of a forecast of $y_{2,t+s}$ based on ($y_{2,t}$, $y_{2,t-1}$, …) is the same as the MSE of a forecast of $y_{2,t+s}$ based on ($y_{2,t}$, $y_{2,t-1}$, …) and ($y_{1,t}$, $y_{1,t-1}$, …). Note that Granger causality does not imply true causality in the theoretical sense; rather it only implies forecasting ability.

d) Principal Components Analysis

Principal component analysis (PCA) is a statistical tool for reducing a set of indicators into a new set of composite indices, called *principal components* that together explain all or nearly all of the variation in the original set of indicators. Each principal component or PC is a linear function of the original indicators (in standardized scores). The first PC is that linear function of the original indicators that has the maximum variance. That is, no other linear function of the original indicators can explain more of the total variation in the set than the first PC. It takes the form

$$PC_1 = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1p}X_p \quad ,$$

where the a_{1i} are coefficients and the X_i are original indicators (in standard scores). The variance of PC_1 is equal to the largest eigenvalue or characteristic root of the correlation matrix of the indicators.

The second PC is that linear function of the variables that is uncorrelated with the first PC and that has the maximum variance next to the first PC. It takes the form

$$PC_2 = a_{21}X_1 + a_{22}X_2 + \cdots + a_{2p}X_p \quad ,$$

where the a_{2i} are coefficients, usually different from the a_{1i}, and the X_i are the original indicators. The variance of the second PC is equal to the second largest eigenvalue of the correlation matrix.

The third PC is that linear function of the variables that is uncorrelated with the first two PCs and has the maximum variance after the first two PCs. Its variance is equal to the third largest eigenvalue of the correlation matrix, and so on. A researcher usually extracts as many PCs as necessary to explain a specified percentage of the variation in the original set of variables or as many PCs as have eigenvalues that exceed some threshold.

The coefficients, which are also called *loadings*, are directly proportional to the correlations of the respective indicators with the PC. A high loading (in absolute value) suggests that the corresponding indicator is important in determining the given PC. Indicators that do not have high loadings on the PCs can, in practice, be discarded from the pool of indicators to be used in constructing the index. In applications that use PCA in constructing a single composite index, the resulting first PC usually serves as the index. The index may be named by looking at the extent of how factors load into the index.

e) <u>Logistic Regression</u>

Logistic regression is a form of regression analysis that involves explaining a binary outcome (consisting of some event and its non-occurrence) from a set of explanatory variables $X_1, X_2, \dots, X_k$, that may be binary, continuous, or a mix of any of these. The relationship between the binary response variable and the explanatory variables is given by:

$$log\left(\frac{\theta}{1-\theta}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$$

where θ and 1−θ respectively represent the probability of the event occurring and the probability of not occuring. Note that for categorical explanatory variables, a set of binary indicator variables are first generated to represent membership (or non-membership) in each of the categories, with one of the indicator variables serving as base or reference to compare other categories with.

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