PBL Netherlands Environmental
Assessment Agency

A STATISTICAL STUDY OF WEATHER-RELATED DISASTERS

Past, present and future

BACKGROUND STUDIES

A statistical study of weather-related disasters: Past, present and future

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Contents

Abstract

Disasters such as floods, storms and droughts may have serious implications for human health, the environment, and the economic development of countries. Examples of severe disaster impacts are: the 1983 drought in Ethiopia and Sudan, which led to over 400,000 people killed by famine; the 2002 drought in India and floods in China which together affected 450 million people; and the 2005 Hurricane Katrina and subsequent flooding in the United States, which led to economic damages valued at USD 140 billion (in 2010 US dollars). This report places such severe disaster consequences in a statistical context.

The report's main focus is on weather-related disasters, subdivided into three groups: meteorological disasters (tropical and extra-tropical storms, local storms), hydrological disasters (coastal and fluvial floods), and climatological disasters (droughts, temperature extremes (e.g. heatwaves). In addition to this categorisation, statistics were calculated for three regions: the OECD countries (the developed countries), the BRIICS countries (the emerging economies Brazil, Russia, India, Indonesia, China and South Africa) and the RoW countries (rest of the world, developing countries).

A number of conclusions were drawn. First, the global spread of disaster burdens appears to differ as a function of disaster type: (i) economic losses are mainly due to meteorological disasters (52% of global total), (ii) most people are affected by hydrological disasters (63% of global total), and (iii) the number of people killed mainly refers to climatological disasters (56% of global total). Furthermore, disaster burdens appear to depend strongly on region, showing the following characteristic pattern: (i) the highest economic losses occur in OECD countries (63% of global total), the largest number of people affected occurs in the BRIICS countries (84% of global total), and the largest number of people are killed in the rest of the world (77% of global total). These findings are based on averages over the 1980–2010 period.

Second, state-of-the-art estimates for trends in disaster burdens show seemingly contradictory results. On the one hand, the disaster burden increased enormously over the 1980–2010 period (statistically significant in all cases). Economic losses in OECD countries, for example, increased by a factor of 4.4. On the other hand, all but one of the trend patterns show that disaster burdens increased over the first half of the sample period (1980–1995) and stabilised thereafter. The only exceptions are losses in the OECD countries: these show continuous growth over the whole sample period.

Third, the report provides explanations for disaster trend patterns. Generally, such explanations are difficult to give since they depend on four interacting factors: (changes in) wealth, population, climate and vulnerability. It would be misleading to draw simple conclusions, such as stating that recent floods in Pakistan are due to climate change. By normalisation of disaster trends, that is, correcting for changes in wealth and/or population, trend patterns for economic losses and people affected appear stable. These results are consistent with historical drivers of

these disaster burden patterns; the frequency and intensity of storms and floods. No global or regional trends were found for these drivers (although significant trends were found on local scales). Strong trends were found for temperature-related extremes. However, these extremes represent a relatively small contribution to economic losses and people affected.

Fourth, the number of studies on *future* disaster burdens is limited, and mainly focuses on storms and floods. Case studies indicate that economic losses due to disasters may increase over the 2010–2040 period. This increase could largely be explained by a growing world population and increases in wealth, and to a lesser extent by climate change. In general, predictions of disaster burdens are hampered by the complex interactions between changes in wealth and population, in climate drivers of disasters and in vulnerability.

Finally, results are provided from a PBL study with respect to changes in the number of 'people at risk' and the amount of 'value at risk' due to floods. The study covers the 2010–2050 period and assumes stable climate variables. The results show that, for all regions, the number of 'people at risk' is expected to increase between 2010 and 2050: by 9% in OECD countries, 37% in BRIICS countries and 55% in the rest of the world (RoW). If amounts of 'value at risk' are compared between 2010 and 2050, lowest percentages are found for OECD countries: around 130%. Changes for the BRIICS countries and those in RoW are 650% and 430%, respectively. Calculations for cities most vulnerable to floods show that these are located in coastal zones and predominantly in Southeast Asia. Examples are Dhaka, Kolkata, Shanghai, Jakarta, Mumbai, Bangkok, Wuhan, Jakarta, Khulna, Guangzhou, Manila, Patna and Ho Chi Minh City. All calculations have been based on the OECD baseline scenario for 2010 to 2050.

ONE

Introduction

1.1 Weather-related disasters

Floods, storms, heatwaves and droughts are disasters that may have serious implications in terms of health, the environment, and economic development. For example, drought in Ethiopia and Sudan, in 1983, led to a famine that killed 400,000 people. Drought in India, and floods and storms in China, in 2002, affected 450 million people. Hurricane Katrina and subsequent flooding led to economic damages valued at USD[1] 140 billion.

Drivers of such disasters are weather and climate extremes and their implications will be termed here as weather-related disasters or catastrophes. An important report on this topic is the IPCC special report on managing the risks of extreme events and disasters to advance climate change adaptation (IPCC-SREX, 2012). Netherlands Environmental Assessment Agency, or PBL in short, was involved in the review process of this report and parts of the present report have been initiated by analyses and comments made within the IPCC review process.

However, this was not the mean reason for writing this report. The report serves as background report to a PBL contribution to the OECD Environmental Outlook to 2050 (OECD, 2012). For Chapter 5 of this outlook report, PBL analysed both global and regional disaster burdens (OECD countries, BRIICS[2] countries and the Rest of the World). Furthermore, results were divided according to disaster burden into hydrological disasters (floods), climatological disasters (temperature extremes and drought), meteorological disasters (storms) and, to a lesser extent, geophysical disaster events (tsunamis, earthquakes, volcano eruptions). These four types of disasters are illustrated in Figure 1.1, for the year 2010. The figure shows 960 disasters, with a distinction between four types of disaster events and varying in severity.

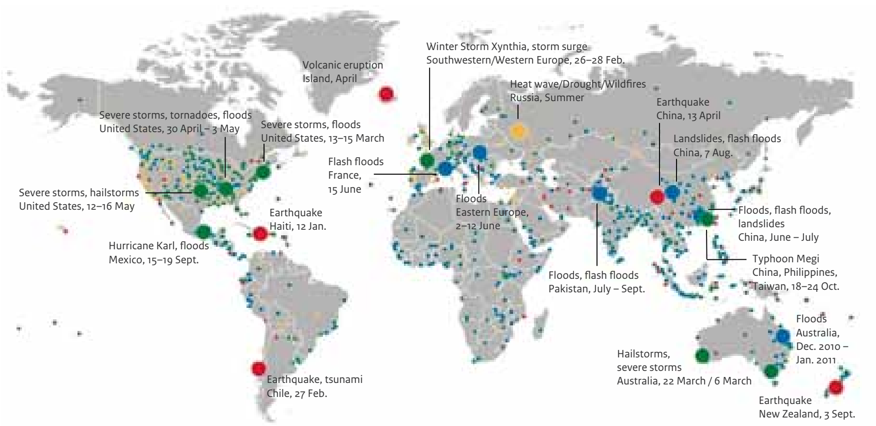
Another part of the PBL contribution to the OECD report (2012) relates to an overview of disaster projections for the future, based on the literature available. For one specific disaster type (fluvial and coastal floods) projections were made up to the year 2050, based on demographic and economic projections (OECD baseline scenario). In doing so, climatic conditions related to floods were assumed to be constant over time (no changes in extreme precipitation and/or coastal storms).

Next to the IPCC-SREX and OECD contributions, the results described here have led to a review article on the statistical treatment of weather extremes and disasters for *Climate of the Past* (Visser and Petersen, 2012).

1.2 The approach followed in this report

The character and severity of impacts depends not only on the extremes themselves but also on exposure and vulnerability (IPCC-SREX, 2012). Here, exposure means the

Figure 1.1
Natural catastrophes, 2010



- Natural catastrophes
- Geophysical events (earthquake, tsunami, volcanic activity)
- Hydrological events (flood, mass movement)
- Selection of significant loss events
- Meteorological events (storm)
- Climatological events (extreme temperature, drought, wildfire)

Source: NatCat database, Munich Re (2011, pages 54-55)

number of people living in disaster-prone regions, as well as the number of economic, social or cultural assets in these regions. Vulnerability stands for the propensity of predisposition of a country or region to be adversely affected by disasters. Therefore, to avoid pitfalls in the attribution of disasters or disaster patterns to factors such as climate change, both historical disaster data and data on explanatory factors were gathered to put patterns of disaster burden into perspective. The role of growing wealth and growing population will be dealt with through a process called normalisation.

The reliability of disaster data, taken from the CRED database EM-DAT, was established beforehand. From this database, historical disaster data were analysed on different time scales (mainly on the 1980–2010 period, and where necessary the 1950–2010 or 1900–2010 period). Three aspects of disaster burden are considered throughout the report: the number of people killed, the number of people affected in some way (injured, homeless or evacuated) and the corresponding economic losses.

As stated above, disaster burden and trends therein are analysed both on a global scale and regionally: developed countries (OECD), emerging economies (the BRIICS countries) and the developing countries (Rest of World). In doing so, the report gives important information on disaster trends and burden, the underlying drivers and the spatial spreading. However, the report is not directed to the *management* of disaster risks. At present, 130 governments are engaged in self-assessments of their progress towards the so-called Hyogo Framework for Action (HFA). This framework contributes to what is now the most complete global overview of national efforts to reduce disaster risk. For the management of disaster risks and progress therein, the reader is referred to the following two reports: UNISDR (2011) and IPCC-SREX (2012).

1.3 This report

The report is organised as follows. In Chapter 2 the background of the three regions used throughout this report is described: OECD, BRIICS and remaining countries (Section 2.1). Furthermore, an overview of the disaster databases is given, along with definitions of disaster terminology (Sections 2.2 and 2.3). In Section 2.4 the statistical treatment of trends in disaster data is shortly exemplified.

Chapter 3 gives on overview of the results for disaster burden (Section 3.1) and trends therein (Section 3.2) on a global scale. Results are split-up as for different disaster types. In Chapters 4 and 5 the same analysis is performed, but now split-up for three regions. In Chapter 4, disaster burdens are quantified, while analyses of trends in disaster burdens are given in Chapter 5. Here, the analyses are confined to weather-related disaster events only. In Chapter 6 the trend patterns found in Chapter 5, are explained as far as possible. Here, changes in wealth, changes in population, the role of climate change and changes due to adaptation are treated in separate sections. Chapter 7 shortly deals with communicational aspects of disasters: the attribution of individual disasters to climate change (Section 7.1) and results in the literature which are contradictory to results presented here (Section 7.2).

Chapters 3 through 7 deal with historical data on disaster burden. In the subsequent Chapters 8 and 9 the future of disaster burden will be dealt with. Chapter 8 gives a short overview of the future of disasters as presented in the literature. In Chapter 9 a PBL case study for flooding on a global scale is given, with predictions for people at risk and economic losses at risk up to the year 2050. Also a summary is given for cities most vulnerable to floods. The report ends with a summary, conclusions and a suggestion for future research items (Chapter 10).

Notes

1 In 2010 US dollars.

2 BRIICS: Brazil, Russia, India, Indonesia, China and South Africa.

TWO

Background and data

2.1 OECD and BRIICS

Disaster data throughout this report are analysed on a global scale and the globe is divided into three regions: the OECD countries, the BRIICS countries and the Rest of World. See Figure 2.1 for the spatial spreading of theses regions. The background of these regions is as follows.

The Organisation for Economic Co-operation and Development (OECD) is an international economic organisation of 34 countries, founded in 1961, to stimulate economic progress and world trade. It is a forum of countries committed to democracy and the market economy, providing a platform to compare policy experiences, seek answers to common problems, identify good practices, and co-ordinate domestic and international policies of its members.

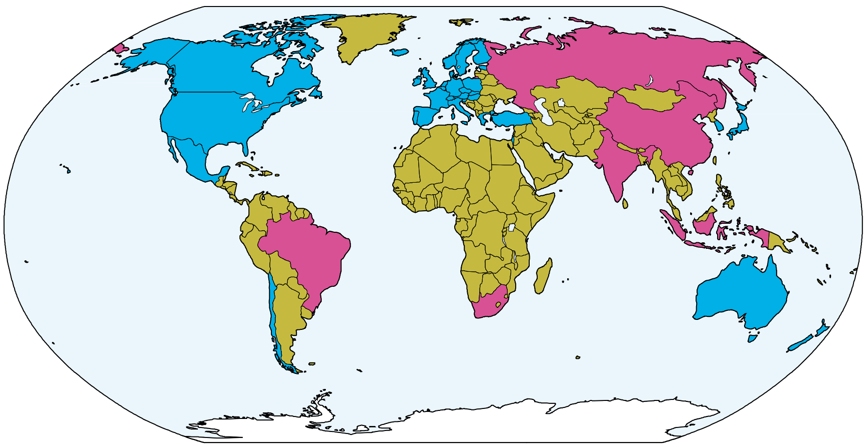
The initial 20 member countries, from 1961 onwards, in alphabetical order, consisted of: Austria, Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States of America. Later, the following 14 countries also became a member: Australia, Chile, Czech Republic, Estonia, Finland, Hungary, Israel, Japan, Mexico, New Zealand, Poland, Slovenia, Slovakia and South Korea[1]. Most OECD member countries are high-income economies with a high Human Development Index (HDI) and are regarded as developed countries.

BRIICS is an acronym for Brazil, Russia, India, Indonesia, China and South Africa. This group of countries is often denoted as the emerging economies; initially this group only consisted of Brazil, Russia, India and China (then called BRIC countries). Later, in 2010, South Africa was added, changing BRIC to BRICS. The term 'emerging economies' was first raised by the investment bank Goldman Sachs and was derived from their GDP projections for the year 2050. They also added Indonesia to the BRICS countries, leading to the acronym BRIICS. In the Goldman Sachs calculations, BRIICS countries are part of the ten largest economies in the world by 2050.

As a characterisation of OECD countries, BRIICS countries and the Rest of World the population and GDP developments is given in Figure 2.2. The left panel shows the GDP for these three regions, expressed as PPP (Purchasing Power Parity). PPP is a presentation of GDP where country data have been corrected for the value goods and services. Not surprisingly, the GDP of OECD countries (blue line) is dominant in the panel. It should be noted that the OECD presents projections of GDP for the 2010–2020 period (see OECD, 2012, Figure 2.6).

The middle panel shows the population growth in the three regions. Here, the BRIICS countries dominate. It should be noted that the OECD presents population growth for the 1970–2050 period (see OECD, 2012, Figure 2.1).

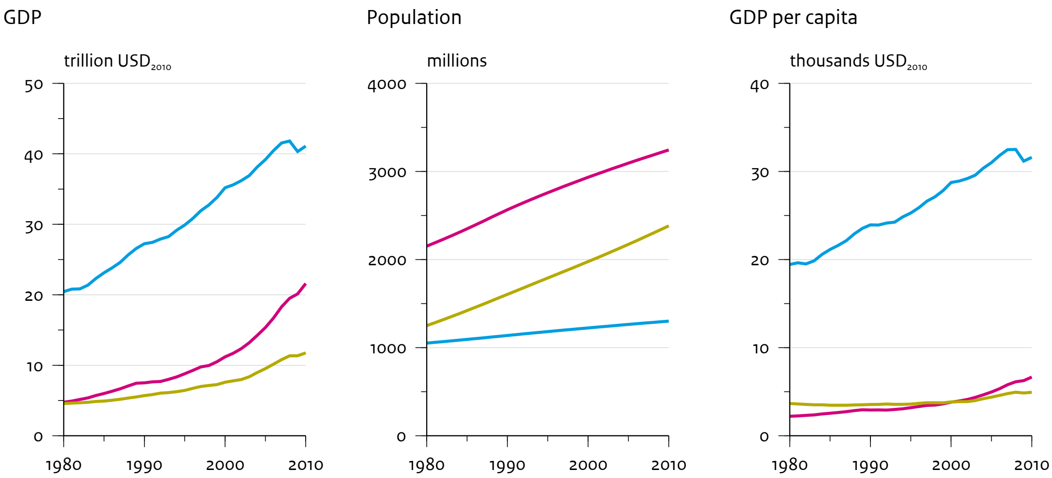
Figure 2.1
OECD and BRIICS countries, 2012



OECD countries
BRIICS countries
Rest of world

Source: PBL

Figure 2.2
GDP and population



OECD countries
BRIICS (Brazil, Russia, India, Indonesia, China, South Africa)
Rest of the world

Source: GISMO (PBL)

The right panel combines the data shown in the other two panels: the GDP-PPP per capita. Now, the dominance of the OECD countries is even stronger than in the presentation of GDP-PPP. Furthermore, it can be seen that the GDP per capita in BRIICS countries start to accelerate only very recently, from 2005 onwards.

For more information the reader is referred to OECD (2012, Chapter 2).

2.2 The CRED database EM-DAT, terminology

For this report the emergency database, EM-DAT, is chosen. EM-Dat is a global database maintained by the World Health Organization (WHO) and the Centre for Research on the Epidemiology of Disasters (CRED) at the KU Leuven University, Belgium. Since 1999, the Office of Foreign Disaster Assistance (OFDA) of the United States Agency for International development (USAID) has also supported CRED in improving the database.

OFDA and CRED have established and maintained the database to improve capacities to cope with disasters and to prevent them from happening. The main objective of the database is to serve the purposes of humanitarian action at national and international levels. It is an initiative aimed at rationalising decision-making for disaster preparedness as well as providing a strong base for vulnerability assessment and priority-setting. EM-DAT regularly validates and updates disaster data from various national and international organisations that specialise in disaster information analysis and dissemination (Adikari and Yoshitani, 2009).

EM-DAT is the selected data source for this report because it is the only database that records all the components of disasters, and on a non-commercial basis. It is widely used by international agencies and thought to be a very reliable data source on disasters throughout the world, although other databases also exist: the Dartmouth Flood Observatory, the NatCat database of Munich Re, and the Sigma database of SwissRe.

EM-DAT and Munich Re apply the following classification of disaster events (cf. Figure 1.1):

- Geophysical events originate from solid earth, i.e., earthquakes, volcano eruptions and mass movements.
- Meteorological events are caused by short-lived/small to mesoscale atmospheric processes (in the spectrum from minutes to days). These events include hurricanes (typhoons), extra-tropical storms and local storms.
- Hydrological events are caused by deviations in the normal water cycle and/or overflow of bodies of water caused by wind set-up. These events include coastal and fluvial floods, flash floods and mass movements.
- Climatological events are caused by long-lived/ mesoscale-to macro-scale processes (in the spectrum from intra-seasonal to multi-decadal climate variability). These events include cold waves, heatwaves, other extreme temperature events, droughts and wildfires.

For each of these four disaster types a typical disaster report has been given in Appendix D, taken from the Munich Re website on disaster statistics.

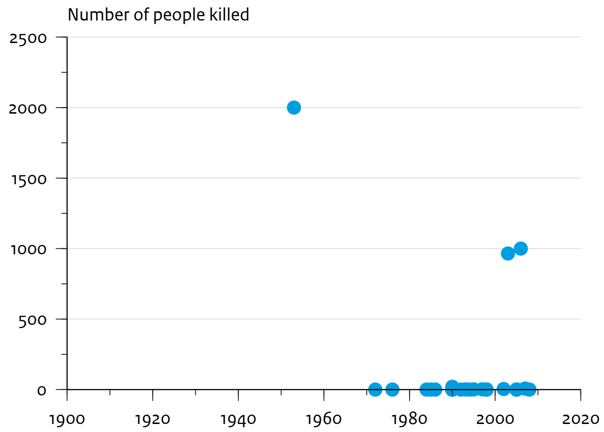
Disaster burden is summarised in three indicators: economic losses, the number of people affected and the number of people killed. Definitions of these terms are provided in the Glossary at the back of this report.
The reliability of the CRED database was verified by PBL using a number of tests, described in Appendix A. One such test is illustrated in Figure 2.3. Here, the disaster records in EM-DAT are validated as for historical disasters in the Netherlands, between 1900 and 2010. This validation was enabled by detailed disaster descriptions taken from the study by Buisman (2011). This study describes of disasters over the past 800 years using a wide range of documentary sources. Figure 2.3 shows that disasters in the Netherlands are absent in EM-DAT before the year 1950. The records after 1950 were found to be complete. In one case a disaster was termed as ‘storm’, while it should have been categorised as ‘fluvial flood’.

From this test case and the general advice of CRED, disaster data will generally be presented throughout this report from 1980 onwards. For more information on EM-DAT in relation to the NatCat and Sigma databases, the reader is referred to Guha-Sapir and Below (2002).

2.3 Maps for flood impact projections

Chapter 9 analyses the impact of floods on the population and assets at risk, for the year 2050, compared to the year 2010. These analyses are on a global scale. For such an assessment three different data sets are required: (i) a global map with flood-prone areas, (ii) a global map with the distribution of population (in 2010 and 2050) and (iii) idem for assets. The combination of these maps yields maps for the population and assets at risk. Ideally data on floods, population and assets would have been available for the current situation and for one or more climate and economic scenarios. However, in the approach taken here it is assumed that the intensity and frequency of floods

Figure 2.3
Disaster records for the Netherlands in the CRED database EM-DAT



Disasters missing from CRED database (Buisman, 2011)
– 1906: coastal flood
– 1916: coastal flood
– 1921: drought
– 1926: river flood
– 1928: storm
– 1929: extreme cold
– 1947: extreme cold / heat

Source: PBL

Example of a reliability check of the CRED database EM-DAT. Disaster records were checked for the Netherlands over the 1900–2010 period. Disasters before the year 1950 appear to be absent in the database. Disaster data were validated using data from Buisman (2011).

are constant over time. The same holds for vulnerability. No changes in vulnerability will be taken into account.

Flood-prone areas

To construct a map that shows flood prone areas, the following three different data sets were used:

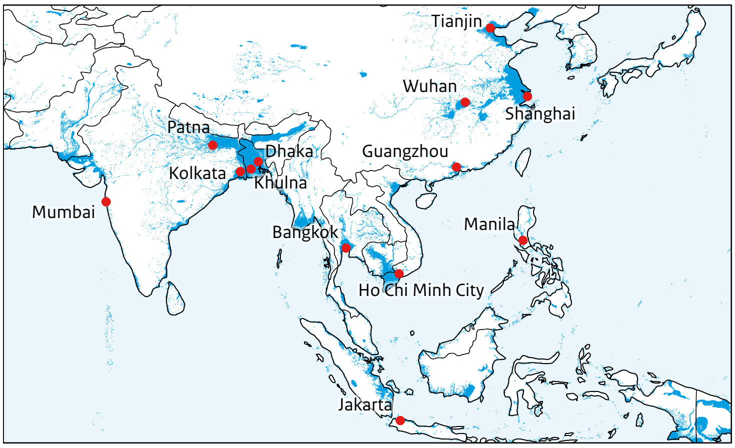
- The Dartmouth flood database. The Dartmouth Flood Observatory[2] translated many floods, imaged by satellite, to detailed maps of inundation extents. These maps were collected by PBL and integrated into one map. Note that this aggregated map does not contain information on water depth or the frequency of flooding. The map contains flood events from 1985 to 2010. One could say the map represents one-in-twenty-five-years events.
- The Global Lakes and Wetlands Database (GLWD) (Lehner and Döll, 2004). From the GLWD, the category of freshwater marshes and floodplains was selected, as these areas could be flooded. The Dartmouth database as well as this GLWD category contain mainly information about fluvial floods.
- Data from the Shuttle Radar Topographic Mission (SRTM)[3] was used to construct a map of coastal flood-prone areas. The SRTM is a highly detailed digital elevation map (DEM) (3 arc seconds ~90 by 90 metres). The SRTM data set was aggregated to a spatial resolution of 30 by 30 arc seconds using the minimum (that is the lowest elevation) value within each 30 arc seconds cell. Following the aggregation, the SRTM was used to derive low-lying areas along the coast which might be flooded by the sea when confronted with a five-metre storm surge. These areas could simply be determined by subtracting five metres from the elevation map. Subsequently, all cells with a value of less than zero were selected and inland sinks were removed. This method, using different limiting elevation values, is often used to select low-elevation coastal zones (LECZ) (Vafeidis, 2011).

The GLWD has a spatial resolution of 30 by 30 arc seconds (~600 by 600 metres). Therefore, the more detailed Dartmouth map and the more detailed SRTM were scaled up to that resolution. Combining these three maps a resulting map was gained with potential flooded areas, on a resolution of 30 by 30 arc seconds. This map has a binary character: the value true (prone to floods) or false (see Figure 2.4). Note that this map does not contain any information on the return period and the water depth of a flood.

Population and GDP in 2010 and 2050

Population and GDP-PPP data were provided by the GISMO model[4]. Regional population projections from GISMO were scaled down first to the national and then to the grid level (0.5 by 0.5 degrees). Here, use was made of (i) the UN World Population prospects which provide data at country level and (ii) CIESIN's Gridded Population of the World. A linear downscaling algorithm was used to scale down to the grid level needed[5]. Next, the urban-rural distinction was made using grid-based estimates of

Figure 2.4
Flood-prone areas in Southeast Asia



Source: PBL

the urban and rural population from GRUMP (CIESIN), in combination with the different national growth figures for rural and urban populations using the UN world urbanisation prospects[6] (UN, 2003). For different IPCC-SRES scenarios, different variants (low, medium, high) of the UN population prospects were chosen. For the 'impact in 2050 in flood prone areas' study the medium population variant was scaled down to the 0.5 degrees grid level.

Unfortunately, there are no global geographical data sets on assets or 'wealth'. Therefore, GDP - PPP per capita was taken as an approximation for 'assets'. The GDP-PPP is based on GDP per capita data per country from the World Bank's world development indicators (WDI). Here, the base year and economic growth rates from the IPCC-SRES scenarios were chosen[7]. Convergence in the income gap in relative terms was taken into account in a dynamic way. That is, for different regions a different convergence year (which is the starting point of convergence) in the time period to 2100 was chosen. Regional economic growth rates combined with the GDP per country in the base year resulted in GDP for the scenarios per country. The result was GDP-PPP per capita on a country level. To calculate 'population at risk' and 'value at risk', data on population and GDP per capita were further scaled down to 30 arc seconds, the resolution of the flood-prone areas (Appendix B).

2.4 Trend estimation methodology

Choosing a specific trend model is not a trivial matter. A scan of the climate literature on trend methods provides a large number of models. To name but a few: low pass filters, ARIMA models, linear trend with OLS, kernel smoothers, splines, trends in rare events by logistic regression, Bayesian trend models, simple moving averages, neural networks, structural time-series models (STMs), smooth transition models, Multiple Regression models with higher order polynomials, Mann-Kendall tests for monotonic trends (with or without correction for serial correlations), robust regression trend lines (MM or LTS regression), LOESS and LOWESS smoothing, Students t-test on sub-periods in time, extreme value theory with a time-varying location parameter, and last not but least, some form of expert judgment (drawing a trend 'by hand'). See Visser and Petersen (2012) for more details.

The trend model almost exclusively applied in the field of disaster management is the OLS straight line. This model has the advantage of being simple and generating uncertainty information for any trend difference [μ_t - μ_s] (indices 't' and 's' are arbitrary time points within the sample period). Disadvantage is the linearity assumption which is not desirable in all cases.

Throughout this report a sub-model from the class of STMs was applied, the so-called Integrated Random Walk (IRW) model. This model is attractive since it relaxes the assumption of a trend being a straight line: the trend pattern may show a flexible behaviour. Its flexibility may be chosen to follow a straight line or in its most flexible mode, to go through all data points. An optimal flexibility can be chosen by maximum likelihood (ML) optimisation. In that case, the sum of squared one-step-ahead prediction errors is minimised. All trend results presented in this report were obtained by ML optimisation.

Two forms of the IRW model were applied:
1. The additive model $y_t = \mu_t + \varepsilon_t$. Here, the series y_t presents the data over a time interval, μ_t is the trend in the data, and ε_t is a white noise process (for all examples in this report the noise was normally (Gaussian) distributed). The IRW algorithm, along with the Kalman filter to estimate unknown parameters, gives uncertainties for the trend estimate μ_t, the trend differences $[\mu_t - \mu_{t-1}]$ and the trend differences $[\mu_{2010} - \mu_t]$. For details see Visser (2004).
2. The multiplicative model $x_t = \mu_t' * \varepsilon_t'$, or $y_t = \log(x_t) = \mu_t + \varepsilon_t$. Explanation as above. Here, the IRW trend model is estimated for the y_t process and estimates are back transformed by taking exponentials. Due to the multiplicative nature uncertainties are found for trend ratio $[\mu_t / \mu_{t-1}]$ and the trend ratio $[\mu_{2010}/\mu_t]$.

For more information the reader is referred to Visser (2004), and Visser and Petersen (2009, 2012).

Notes

1 For information on the OECD, see www.oecd.org or http://en.wikipedia.org/wiki/Oecd.
For BRICS countries, see http://en.wikipedia.org/wiki/BRICS and http://www2.goldmansachs.com/our-thinking/brics/brics-reports-pdfs/brics-remain-in-the-fast-lane.pdf.

2 Http://floodobservatory.colorado.edu/.

3 Http://www2.jpl.nasa.gov/srtm/.

4 Http://themasites.pbl.nl/en/themasites/gismo/index.html.

5 Http://www.mendeley.com/research/downscaling-drivers-global-environmental-change-enabling-global-sres-scenarios-national-grid-levels/.

6 Http://www.mendeley.com/research/downscaling-drivers-global-environmental-change-enabling-global-sres-scenarios-national-grid-levels/.

7 Http://www.mendeley.com/research/downscaling-drivers-global-environmental-change-enabling-global-sres-scenarios-national-grid-levels/.

THREE

Global disaster burden

This chapter shows the varying impacts of global disasters, per type of disaster. The disaster categorisation is described in Section 2.2 (hydrological, climatological, meteorological and geophysical disasters). Geophysical disasters were included to show how the disaster burden from weather-related disasters compares to non-weather-related disasters (earthquakes, volcano eruptions, tsunamis). Disaster burden is given for three impacts: (i) economic losses, (ii) people affected and (iii) people killed.

All data in this chapter are based on the CRED database EM-DAT. Based on uncertainty considerations (Section 2.2 and Appendix A) the analyses are confined to the sample period from 1980 to 2010. Furthermore, major disasters were chosen only (for definition and argumentation, see Section 2.2)

3.1 Disaster burden and disaster types

In calculating the disaster burden all disaster information was integrated over the 1980–2010 period, thus giving a robust estimate for this burden. It is noted that the hydrological type of disasters is dominated completely by floods (landslides and avalanches have only marginal contributions to the total burdens). Such a situation is not the case for the climatological type of disasters. Here, the burden is spread more or less evenly over extreme temperatures on the one hand and droughts on the other hand.

Table 3.1 gives the results for the three disaster types. In addition to disaster impacts, a column was added for the number of major disasters per group. As such this indicator is not a measure for disaster burden. However, it does provide information on how the disasters are spread over the three disaster types. The final column shows the absolute burden, represented by an average annual value.

Table 3.1 shows that the disaster burden is unequally distributed over the disaster types (maximum percentages are highlighted in yellow):

- The highest economic losses are due to meteorological disasters (storms): 52%;
- The highest number of people affected is due to hydrological disasters (floods): 63%;
- The highest number of people killed is due to meteorological disasters (combination of temperature extremes and droughts): 56%.

It is noted here that some disasters have a dual nature. Hurricanes such as Katrina (2005) are categorised in EM-DAT as meteorological disasters. However, the resulting floodings highly contributed to the economic damages. Since the economic losses from Katrina were of a record height (around USD 130 billion), this may partly explain the high percentage in economic losses due to storms (for information on Katrina, see http://en.wikipedia.org/wiki/Effects_of_Hurricane_Katrina_in_New_Orleans).

Table 3.1
Disaster burden statistics for all weather-related disasters, averaged over the 1980–2010 period

	Economic losses	People affected	People killed	Number of major disasters
Meteorological disasters	52%	12%	32%	43%
Hydrological disasters	34%	63%	12%	42%
Climatological disasters	14%	25%	56%	15%
All weather-related disasters	100% or USD **57** billion /year	100% or **140** million/year	100% or **41** thousand/year	100% or **44** disasters/year

NB Green fields show the highest percentages per type of disaster burden.

Table 3.2
Disaster-burden statistics for all types of disasters, averaged over the 1980–2010 period

	Economic losses	People affected	People killed	Number of great disasters
Meteorological disasters	38%	11%	19%	39%
Hydrological disasters	25%	62%	7%	37%
Climatological disasters	10%	24%	33%	14%
Geophysical disasters	27%	3%	40%	10%
All global disasters	100% or USD **78** billion/year	100% or **144** million/year	100% or **69** thousand/year	100% or **49** disasters/year

NB Green fields show the highest percentages per type of disaster burden.

The last column of Table 3.1 shows that the number of major disasters is equal for the types meteorological and hydrological, 43% and 42% of the global total, respectively. The number of climatological disaster is much lower: 15%.

To visualise the integrated disaster burden, the time evolution of burden over time is plotted in Figure 3.1. The results from Table 3.1 can easily recognised: the upper panel for economic losses is dominated by the colour green (storms), the second panel for the number of people affected, is dominated by the colour blue (floods), and the third panel for the number of people killed is dominated by the colour yellow (temperature extremes and drought). Some major disasters are highlighted by catchwords.

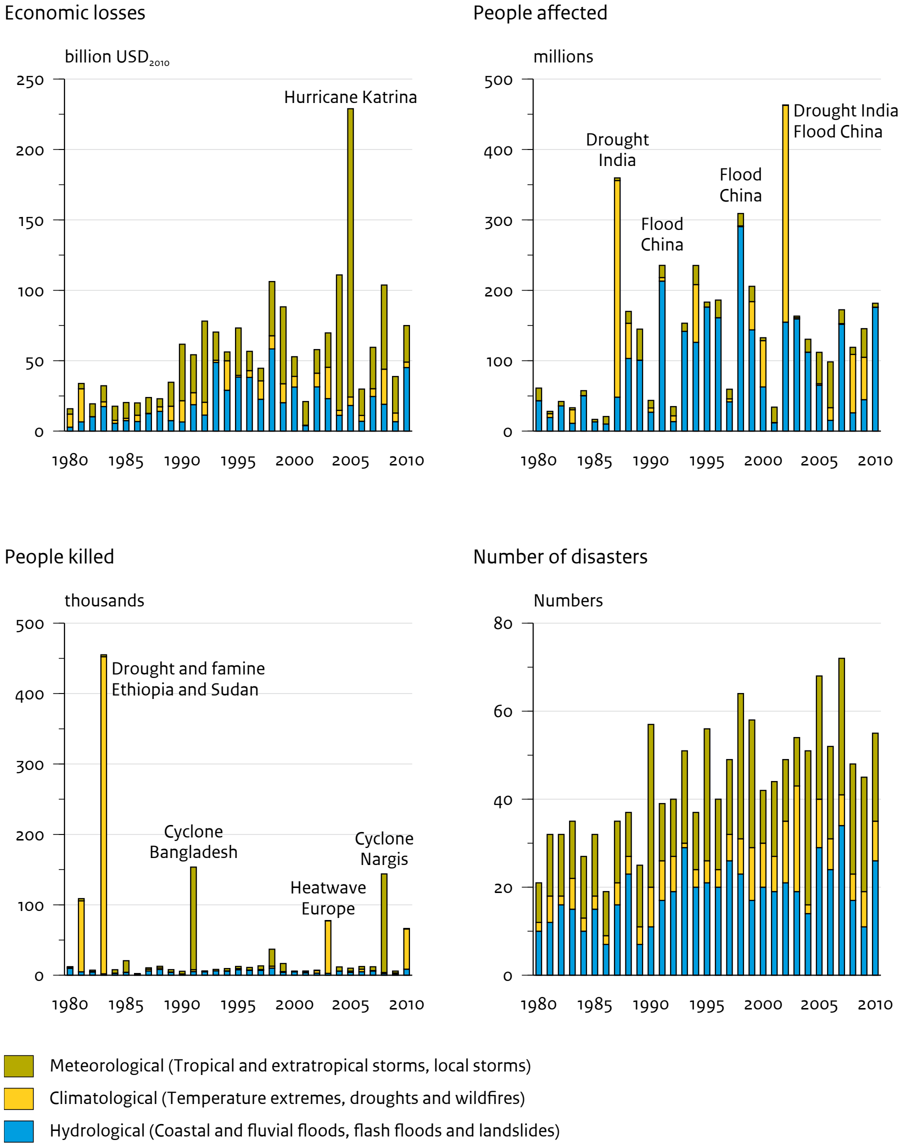
It is illustrative to compare the weather-related disasters shown in Table 3.1, with disasters with a geophysical nature: earthquakes, volcano eruptions and tsunamis. A comparison of disaster burden is given for all four disaster types in Table 3.2.

The table shows that the main impact of geophysical disasters relates to numbers of people killed: 40% of all people killed in natural disasters, is due to these types of disasters. The number of people affected is very low (3%), followed by economic damages from meteorological disasters (27%). The large number of people killed is explained by the fact that earthquakes, tsunamis and volcano eruptions are difficult to predict. Thus, early warning systems, such as those in place for floods, are not available for geophysical hazards.

3.2 Trends in disaster burden

The results, thus far, concerned integrations over the 1980–2010 period. It is also important to see how disaster burden changes over time. To analyse trends in these data, a sample period of 31 years is rather short, especially since the driving forces behind disaster burden are weather or climate extremes. Some of these occurrences can be rare and, for example, have an average return period of once in a century. Possible drawbacks of this relatively short sample period will be dealt with Chapter 6.

Figure 3.1
Global weather-related disaster statistics



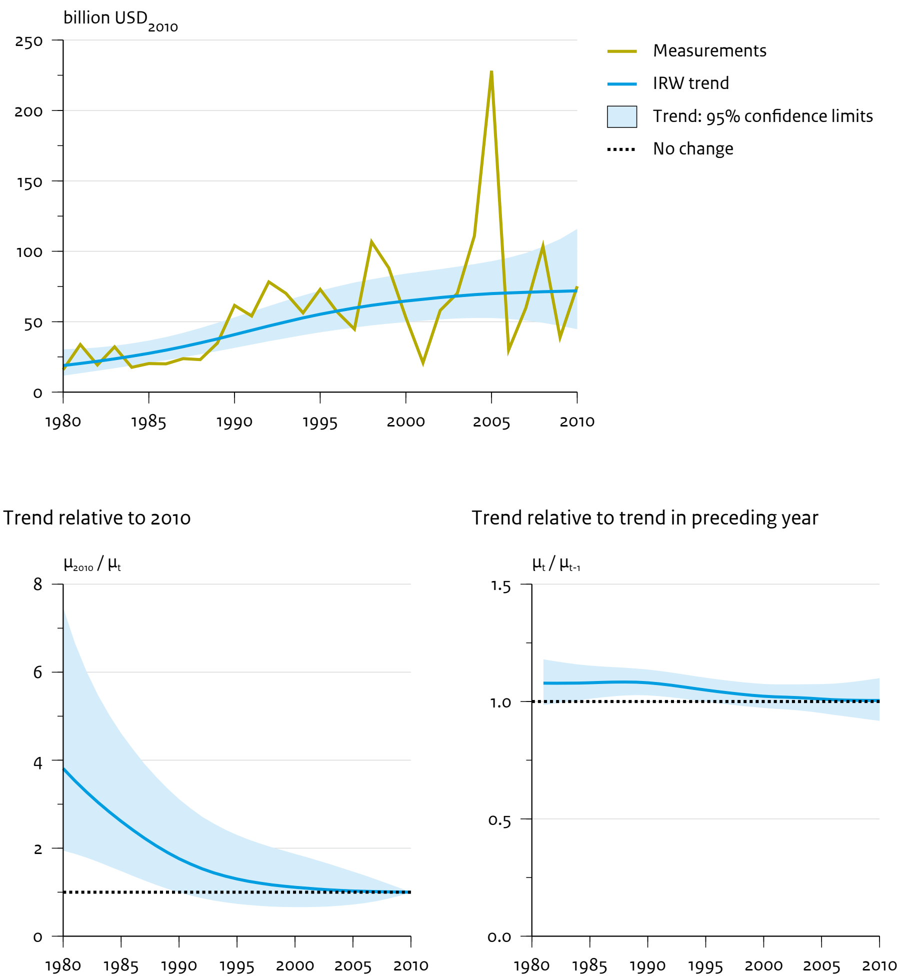
Source: PBL

Extreme events are denoted by catchwords. Only disasters in the severity classes 4 and higher were selected (major, great and devastating disasters, Munich Re categorisation).

The global evolution of economic losses is given in Figure 3.2A. The upper panel shows the data (black curve) along with the estimated IRW trend (green line) and 95% confidence limits for the trend line (green dashed lines). The methodology of estimating trends and maximum uncertainty information has been given in Section 2.4. The main reference for this method is Visser (2004). Note that the high value in 2005 is for a large part due to hurricane Katrina (http://en.wikipedia.org/wiki/Hurricane_Katrina).

It is noticeable that trend estimation has been performed after a logarithmic transformation of the data. Therefore, the upper uncertainty bands are wider than the lower bands, due to the transformation back to the original scale (in USD billions). This transformation also explains why the lower left panel shows the trend ratios [μ_{2010} / μ_t], instead of the trend difference [$\mu_{2010} - \mu_t$] which would have the result without the transformation. The same holds for the ratio in the lower right panel. Clearly, a ratio value of 1.0:1 would mean for both lower panels: no change in trend.

Figure 3.2A
Global economic losses due to weather-related disasters



Source: PBL

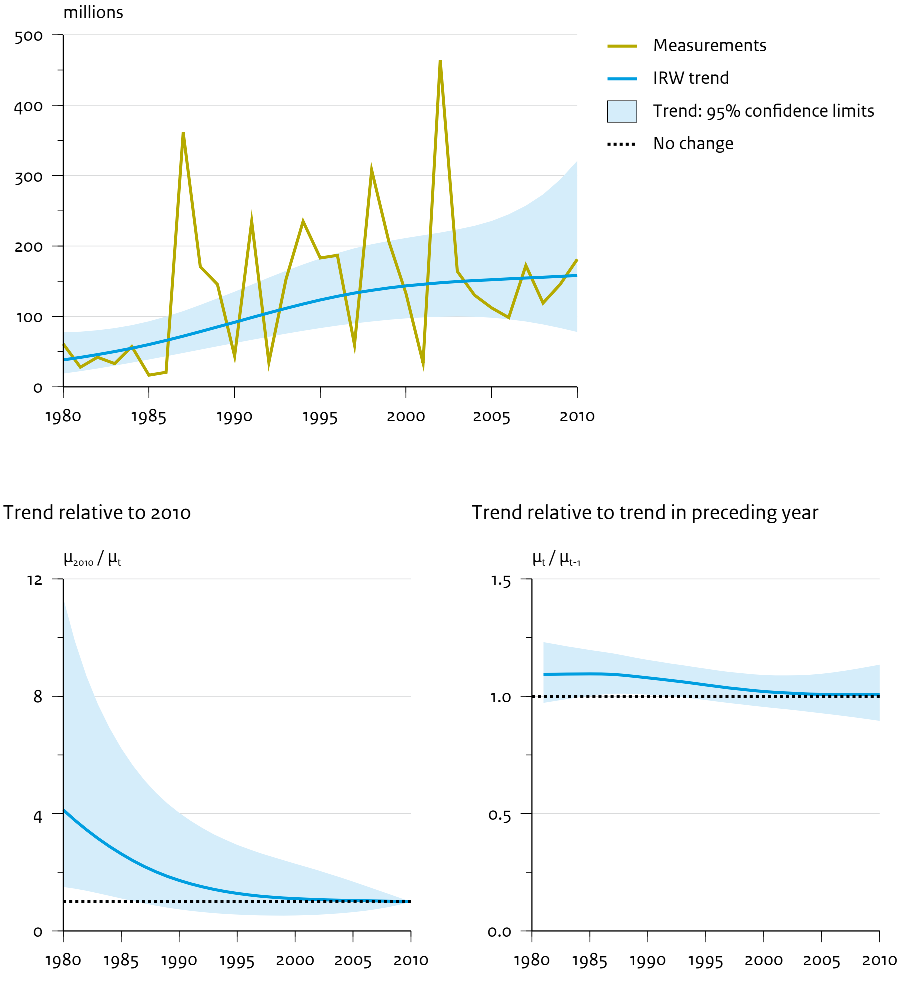
IRW trend estimation for global economic losses due to weather-related disasters. The upper panel shows the data along with the IRW trend and 95% confidence limits. The trend ratio [μ_{2010}/μ_t] is given in the lower left panel and the trend ratio [μ_t/μ_{t-1}] in the lower right panel. Trend estimation was performed on logarithms of the original loss data.

The middle panel shows that the trend ratio [μ_{2010}/μ_t] is statistically different from 1.0 only for the time period between 1980 and 1990. In other words, the trend value for global economic losses in 2010, statistically, was not significantly higher than loss values over the preceding period (1991–2009) = 0.05). However, compared to the 1980–1990 period, the trend value in 2010 rose significantly. The trend ratio [μ_{2010}/μ_{1980}] is estimated to be 3.8:1 (2.0:1 – 7.5:1). Thus, the increase over 31 years was almost fourfold, and statistically significant ($\alpha = 0.05$).

The lower right panel shows that the highest trend acceleration occurred at the beginning of the series, around the ratio 1.08 (or an increment in losses of 8% per year). At the significantly larger than values in the 1980–1986 period ($\alpha = 0.05$). The lower panel shows that the increment ratio is 1.1:1 in 1980 (annual increment in trend value of 10% per year) and ends in 2010 with in increment ratio of 1.0:1 (0% increase). At the end of the series, the annual increment ratio has fallen to 1.0:1 (increment in losses of 0%).

A discussion on the trend pattern in economic losses will be given in Section 7.2.
The trend patterns for people affected are given in Figure 3.2B and show similar patterns to those in Figure 3.2A; a

Figure 3.2B
Number of people affected by weather-related disasters, globally



Source: PBL

IRW trend estimation for the global number of people affected due to weather-related disasters. The upper panel shows the data along with the IRW trend and 95% confidence limits. The trend ratio [μ_{2010}/μ_t] is given in the lower left panel and the trend ratio [μ_t/μ_{t-1}] in the lower right panel. Trend estimation was performed on logarithms of the original numbers.

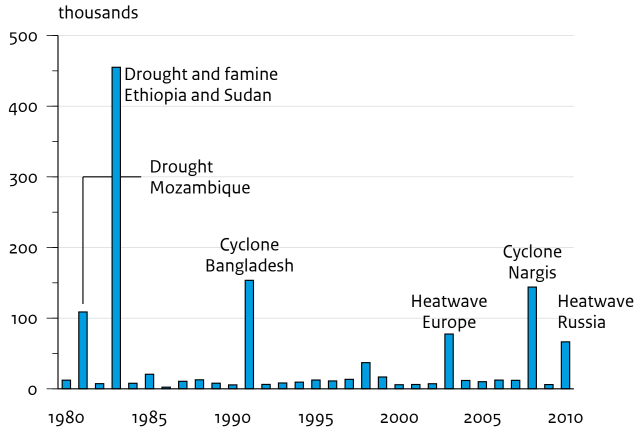
rising trend over the 1980–1995 period and stabilisation thereafter.

The lower left panel shows that the trend value in 2010, μ_{2010}, was statistically significant for the 1980–1986 period. The trend ratio [μ_{2010}/μ_{1980}] was estimated to be 4.1:1 (1.5:1 – 11.4:1). Thus, the increase over 31 years was fourfold and statistically significant ($\alpha = 0.05$). The lower right panel shows a trend increment ratio in 1980 accounts for 1.1:1 in 1980 (increment of 10% per year) which diminished to 1.0:1 in the year 2010 (increment of 0% per year).

The trend estimation process for people killed appeared to lead to unsatisfactory estimates. The reason for that is best explained by showing the data, see Figure 3.2C. The annual data are generally lower than 50,000 people killed. However, there are six extreme values, which can be attributed to single disaster events. These events are highlighted by catchwords in the graph. The highest value is for the year 1983, the famine in Ethiopia and Sudan (a disaster which became known by the Live Aid concerts: http://en.wikipedia.org/wiki/Live_Aid).

For this type of data it can be said that a sample period of 31 years is too short to give trend estimates.

Figure 3.2C
Number of people killed in weather-related disasters, globally



Source: PBL
Extreme disasters are indicated by catchwords. Estimation of a trend for these data was not possible because of these 'outliers', and is therefore not shown.

Finally, Figure 3.2D shows the trend pattern for the annual number of major disasters. For this series a logarithmic transformation is not needed and the fitted trend appears to be a straight line. The trend difference [μ_{2010}–μ_{1980}] is estimated to be 33 (21–44) (lower left panel). Thus, the increase over 31 years is 33 major disasters. The difference is statistically significant (α = 0.05).

3.3 Conclusions

As for the spreading of disaster burden (Section 3.1), it was found that disaster burden indicators differed in disaster origin: economic losses were mainly due to meteorological disasters (52%), the number of people affected mainly referred to hydrological disasters (63%) and the number of people killed mainly referred to climatological disasters (56%). If geophysical disasters are included, these percentages change for the number of people killed: for all people killed due to all types of natural disasters 40% comes from geophysical disasters, followed by 33% due to climatological disasters, 7% due to hydrological disasters and 19% due to meteorological disasters.

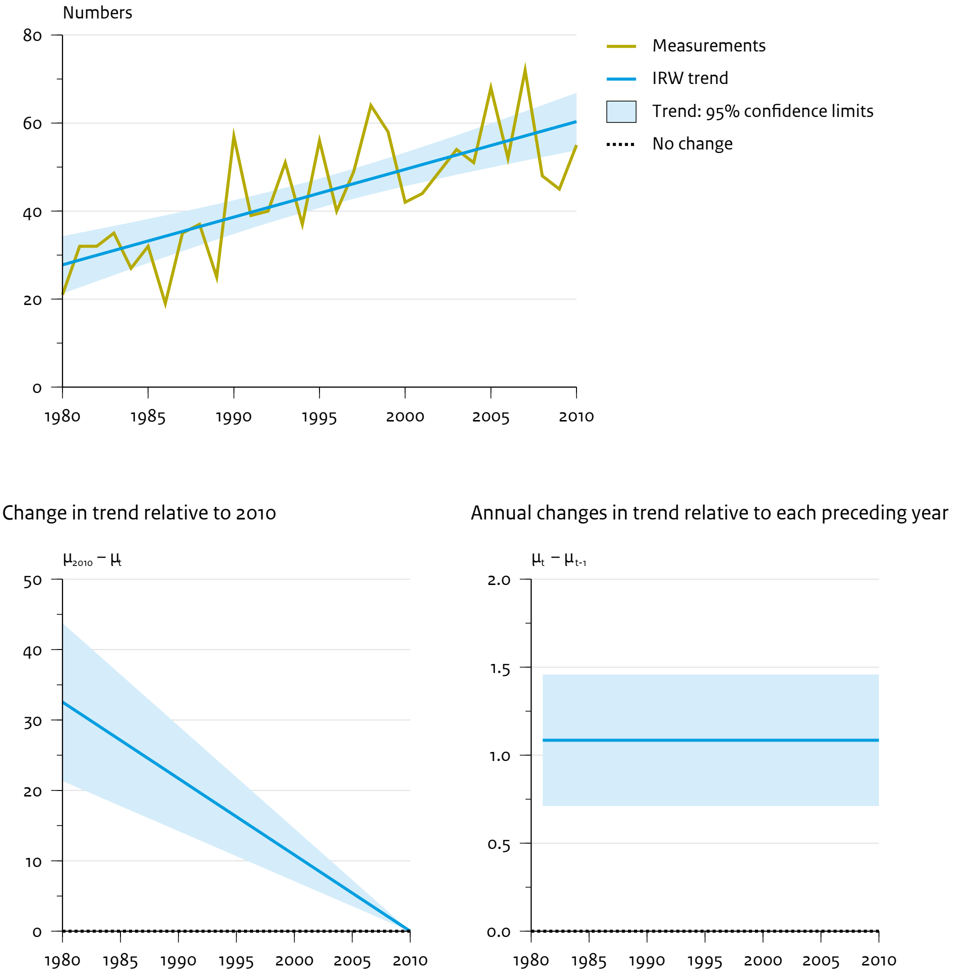
Trend patterns showed that global economic losses increased over the 1980–1995 period and stabilised thereafter. This stabilisation was not influenced by the 'outlier' in 2005: an annual loss of over USD 200 billion, from which USD 130 billion was attributed to hurricane Katrina. Seen over the whole sample period, from 1980 to 2010, economic losses showed a statistically significant fourfold increase. Section 7.2 discusses this trend pattern in relation to trends published by other institutions.

The data on people affected appear to show the same pattern as that for losses; an increase over the 1980–1995 period with a stabilisation thereafter. The data do not show one extreme value but three high values (more than 300 million people affected in one year). These extremes fit in the trend model since logarithms are taken. The influence of this transformation can be illustrated by taking a logarithmic scale on the y-axis instead of a linear scale in Figure 3.3: the upper panel of Figure 3.2B is identical to Figure 3.3, apart from the y-axis scaling. Over the whole 1980–2010 sample period, the number of people affected showed a statistically significant *fourfold increase*.

The data on the number of people killed, globally, were found to be dominated by six extreme values (annual numbers of more than 50,000 people killed); these extremes did not allow an accurate trend estimation. Section 6.3 shows a disaster series which starts in 1900, our analysis and a discussion on the consequences.

Finally, a linear increase was found for the global number of major disasters over the 1980-2010 period. The increment over this period consists of 33 major disasters, and is statistically significant.

Figure 3.2D
Global weather-related disasters

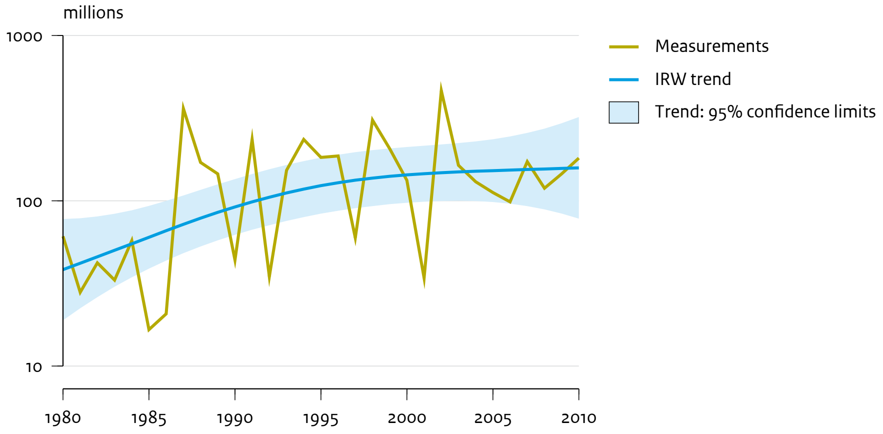


Source: PBL

IRW trend estimation for the global number of weather-related disasters. The upper panel shows the data along with the IRW trend and 95% confidence limits. The trend difference [$\mu_{2010}-\mu_t$] *is given in the lower left panel and the trend difference* [$\mu_t-\mu_{t-1}$] *in the lower right panel.*

Chapter 6 discusses the question of why trends rise or stabilise. Section 7.2 shows that other interpretations of trends in global disaster data exist in the literature, as well.

Figure 3.3
Number of people affected by weather-related disasters, globally



Source: PBL

Same graph as upper panel of Figure 3.2B. The only difference is the logarithmic scale for the y-axis chosen here.

FOUR

Regional spreading of disaster burden

The analyses thus far have been for global data. However, disaster burdens and trends over time may deviate for different parts of the world, for countries with varying levels of wealth and varying number of people. This chapter analyses how the disaster burden, as described in Section 3.1 for global data, changes if the world would be divided into three regions: rich countries (here: OECD countries), emerging economies (here: BRIICS countries), and all other countries (rest of the world (RoW)).

Similar to Section 3.1, calculations have been based on the CRED database EM-DAT, using data over the 1980–2010 period. Section 4.1 presents disaster burdens due to weather-related disasters (the sum of meteorological, climatological and hydrological disasters). Subsequently, Section 4.2 shows a categorisation of disaster burdens according to the three disaster types: hydrological, climatological and meteorological. Finally, Section 4.3 shows disaster burdens due to flood disasters and drought disasters. The chapter ends with conclusions.

4.1 Weather-related disasters

In Table 4.1 integrated disaster burden are summed for the three regions and the three burden indicators: economic losses, people affected and people killed. The table shows a remarkable spreading of disaster burden over the three regions: the highest economic losses are found for the OECD countries (63% of global total losses), the highest number of people affected is found for the BRIICS countries (84% of global total) and the highest number of people killed is found for the Rest of World (77% of global total).

The result from Table 4.1 is visualised in Figure 4.1. The upper panel shows a stacked graph for economic losses. The colour green, the OECD countries clearly dominate the graph. The middle panel shows the number of people affected. The colour orange appears to be the dominating colour: the BRIICS countries. And the lower panel shows that the number of people killed. Here, the colour blue is dominating: the Rest of World.

4.2 Hydrological, meteorological, climatological and geophysical disasters

It is interesting to see how disaster burden is spreading over different disaster types: hydrological, climatological and meteorological disasters. Will the disaster-burden pattern shown in Table 4.1, also show up for other categorisations of disasters?

Results are shown in Table 4.2A. The upper panel shows that the pattern is different for hydrological disasters (floods to a large extent): all three disaster burdens are highest for the BRIICS group of countries (yellow cells in the table). Economic losses, averaged over the 1980–2010

Table 4.1
Disaster burden statistics for weather-related disasters

Weather-related disasters	Economic losses	People affected	People killed	Number of major disasters
OECD countries	63%	2%	8%	37%
BRIICS countries	24%	84%	15%	28%
Rest of World	13%	14%	77%	35%
Globally	100% or USD **57** billion/year	100% or **140** million people /year	100% or **41** thousand people /year	100% or **44** disasters/year

NB The table presents the total of hydrological, climatological and meteorological disasters. All data have been averaged over the 1980–2010 period. Green fields show the highest percentages within the three regions.

Table 4.2A
Disaster-burden statistics for three disaster types

Hydrological disasters	Economic losses	People affected	People killed	Number of major disasters
OECD countries	38%	1%	4%	23%
BRIICS countries	45%	86%	55%	38%
Rest of World	17%	13%	41%	39%
Globally	100% or USD **20** billion/year	100% or **89** million/year	100% or **5** thousand/year	100% or **18** disasters/year

Climatological disasters	Economic losses	People affected	People killed	Number of major disasters
OECD countries	58%	1%	11%	45%
BRIICS countries	32%	90%	10%	29%
Rest of World	10%	9%	79%	26%
Globally	100% or USD **8** billion/year	100% or **34** million/year	100% or **23** thousand/year	100% or **7** disasters/year

Meteorological disasters	Economic losses	People affected	People killed	Number of major disasters
OECD countries	80%	5%	2%	48%
BRIICS countries	8%	60%	8%	18%
Rest of World	12%	35%	90%	34%
Globally	100% or USD **29** billion/year	100% or **17** million/year	100% or **13** thousand/year	100% or **19** disasters/year

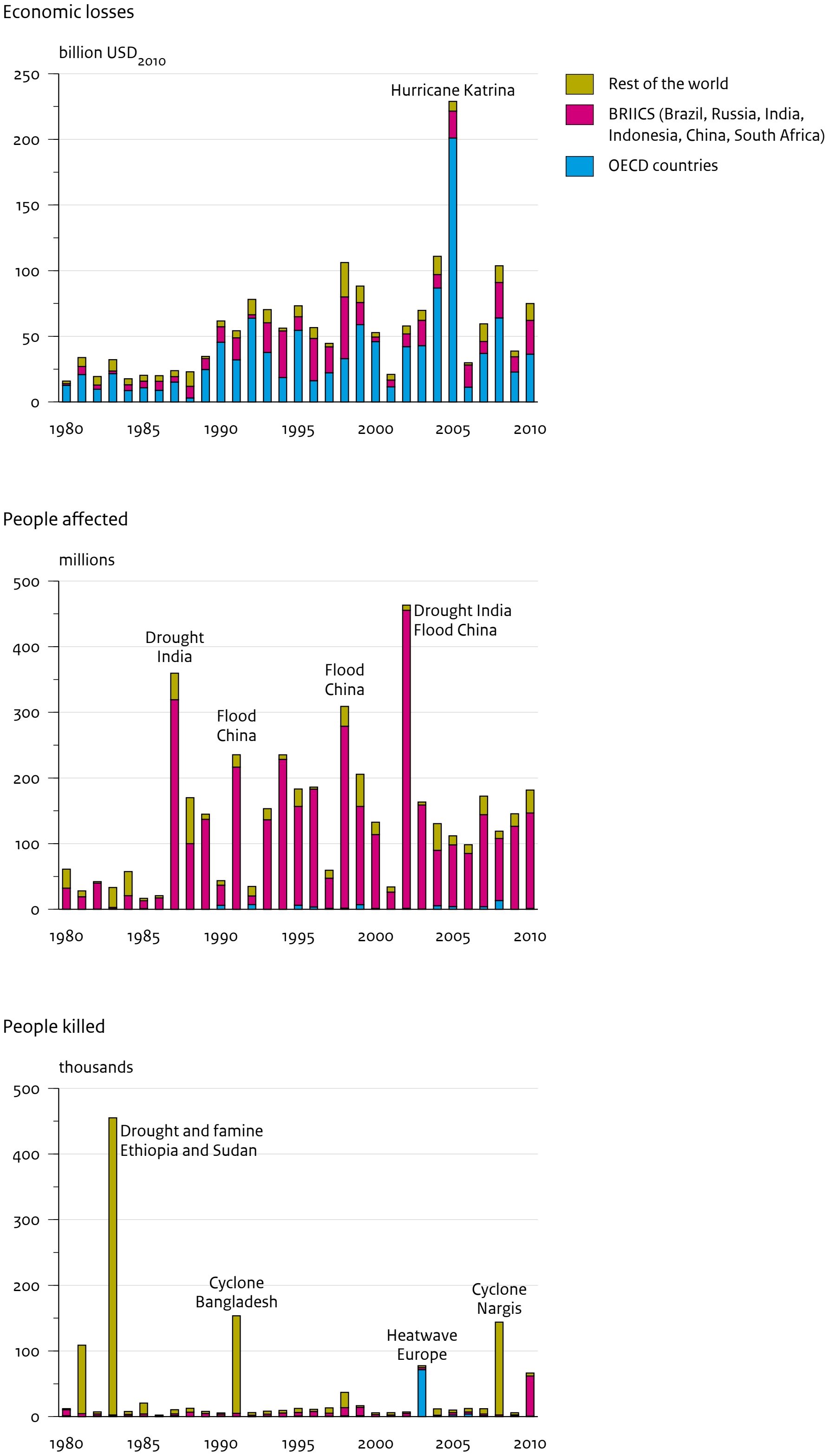
NB Green fields show the highest percentages within the three regions. The upper panel contains hydrological disasters (coastal and fluvial floods, flash floods, landslides), the middle panel contains climatological disasters (heatwaves, droughts, forest fires), and the lower panel contains meteorological disasters (hurricanes, extra-tropical storms, local storms, tornados, hail storms). All data have been averaged over the 1980-2000 period.

period, originate for 45% from the BRIICS countries and idem 86% of the people affected and 55% of the people killed. Remarkable is that the number of major hydrological disasters for the BRIICS equals that for the Rest of World (38% of the global total).

The middle and lower panel of Table 4.2A show the pattern as found in Table 4.1: highest percentages for economic losses in the OECD countries, highest number of people affected in the BRIICS countries and highest percentages for people killed in the Rest of World.

It is also interesting to compare the absolute differences in disaster burden compared over the three disaster types. Global economic losses due to hydrological disasters is USD 20 billion/year; for climatological

Figure 4.1
Global weather-related disaster statistics, per region



Source: PBL

Weather-related disaster burdens, stacked for the OECD, BRIICS and RoW countries (the upper line of each panel equals the global burden for each impact). The upper panel shows disaster losses (in billion USD[1]), the middle panel shows the number of people affected (in millions), and the lower panel shows the number op people killed (in thousands). Main disaster events are indicated by catchwords.

FOUR

Table 4.2B
Disaster-burden statistics for geophysical disasters (earthquakes, volcano eruptions, tsunamis)

Geophysicaldisasters	Economic losses	People affected	People killed	Number of major disasters
OECD countries	63%	10%	5%	31%
BRIICS countries	22%	72%	40%	31%
Rest of World	15%	18%	55%	38%
Globally	100% or USD **21** billion /year	100% or **4** million/year	100% or **28** thousand/year	100% or **5** disasters/year

NB All data are averages over the 1980–2010 period. Green fields show the highest percentages within the three regions.

Table 4.3
Disaster-burden statistics for floods (upper panel) and droughts (lower panel)

Flood disasters	Economic losses	People affected	People killed	Number of great disasters
OECD countries	38%	1%	4%	24%
BRIICS countries	45%	86%	56%	38%
Rest of World	17%	13%	40%	38%
Globally	100% or USD **19** billion/ year	100% or **89** million/year	100% or **5** thousand/ year	100% or **18** disasters/ year

Drought disasters	Economic losses	People affected	People killed	Number of great disasters
OECD countries	52%	1%	0%	35%
BRIICS countries	33%	90%	1%	27%
Rest of World	15%	9%	99%	38%
Globally	100% or USD **4** billion/year	100% or **32** million/year	100% or **18** thousand/year	100% or **2** disasters/year

NB All data are averages over the 1980–2010 period. Yellow fields show the highest percentages within the three regions.

disasters USD 8 billion/year is found, and for meteorological disasters USD 29 billion/year. Thus, highest global losses are found for meteorological disasters (damage due to storms). As for people affected the highest numbers are found for people affected: on average 89 million/year. This is for climatological and meteorological disasters 34 and 17 million/year, respectively. Finally, the highest number of people killed appears to be due to climatological disasters: on average 13,000 people per year. This is for hydrological and meteorological disasters 18,000 and 19,000 people per year, respectively.

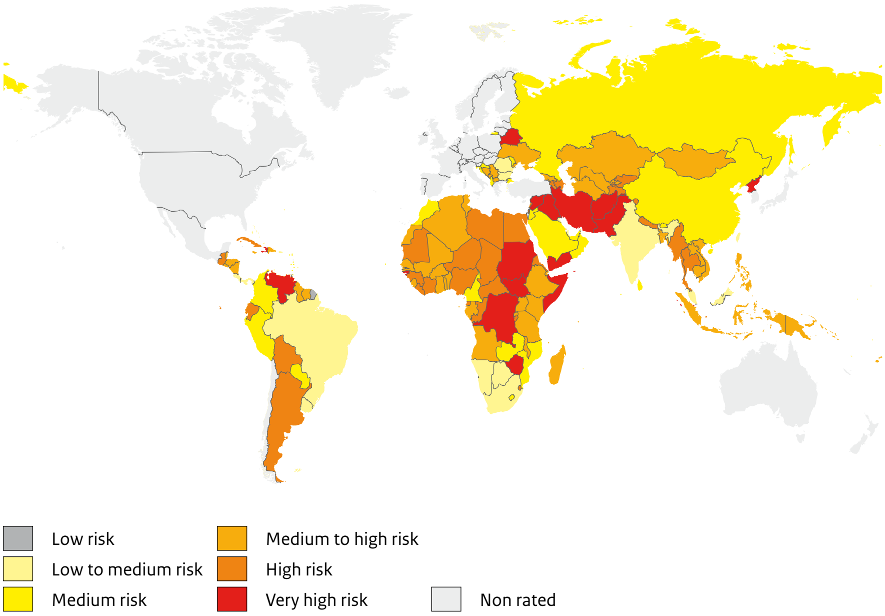
How do these disaster-burden numbers compare to other natural disasters: earthquakes, volcano eruptions and tsunamis? The disaster burden for this category is summarised in Table 4.2B. Remarkable is that distribution of disaster burden is identical to that shown for weather-related disasters, summarised in Table 4.1: highest damages fro the OECD countries (63% of global total), highest number of people affected for the BRIICS countries (72% of global total) and highest number people killed for the Rest of World (55% of global total).

If the absolute disaster burden from Table 4.2B is compared with that in Table 4.2A, it can be seen that the number of people killed by geophysical disasters is highest: 28,000 people per year on average (climatological disasters account for 23,000 people per year).

4.3 Flood and drought disasters

For some studies it is of interest to know the disaster burden due to water-related disasters, rather than due to weather-related disasters. To this end a selection in EM-DAT was made for flood disasters and drought disasters. The disaster burdens have been summarised in Table 4.3.

Figure 4.2
Political risk map, 2012



Source: AON, 2012
Political risk is defined by combining risks, such as those of (civil) war, strikes, riots and civil unrest, non-payments, supply-chain disruptions, and legal and regulatory risks.

It appears to statistics for floods are almost equal to that for hydrological disasters (upper panel of Table 4.2A). This is not the case for droughts, compared to climatological disasters (middle panel of Table 4.2A) since the disaster burden due to extreme high or low temperatures is substantial. Therefore, the pattern of yellow cells for floods equals that for hydrological disasters. The pattern of yellow cells for drought disasters has the well-known pattern: highest losses for the OECD countries (52% of global total), highest number of people affected for the BRIICS countries (90% of global total) and highest number of people killed in the rest of World (99% of global total).

4.4 Discussion

The main result found in this chapter is the typical spreading over disaster burden over the three regions: highest losses in the OECD countries, highest number of people affected in the BRIICS countries and the highest number of people killed in the Rest of World. The only exception to this rule is for the group of hydrological disasters. Here, all highest disaster-burden percentages are found for the BRIICS countries.

The result for economic losses is not surprising. The GDP data in the left panel of Figure 2.2 show that the total wealth in OECD countries was four times that in the RoW countries and double that of the BRIICS countries (between 2005 and 2010). For GDP per capita the differences are even more pregnant: the GDP per capita is six fold that of both BRIICS and RoW countries. Given a more or less even distribution of number of major disasters over the regions (last column Table 4.1), it is logical that the largest losses will occur in the OECD countries. Furthermore, it is logical that OECD countries do not show the highest numbers for people affected or people killed: they have more financial abilities to adapt to disasters (e.g., evacuation schemes, early warning systems, irrigation systems).

The finding that largest numbers of people affected fall are found in the BRIICS region is also logical. Table 3.1 shows that the largest number of people affected are found for hydrological disasters (63% of disasters on a global scale). And the upper panel of Table 4.2A shows that 86% of these numbers occur in the BRIICS countries. Within this group the largest numbers are found for China

The reason why the BRIICS countries do not show the highest number of people killed, may be explained by adaptation measures. As for China, Dr. Y. Hu (UNESCO-IHE, private communication) has stated that this may have three explanations: (i) flood warning and forecasting systems were improved in recent decades (34,000 new hydrological or precipitation stations were built, as well as over 8.600 flood reporting stations, all over the country), (ii) each year, before the rainy season, flood control agencies at all levels draw up plans for flood prevention and regulation, for the major rivers and lakes, and (iii) during the rainy season, the flood control and drought relief headquarters follow a strict 24-hour-duty system as well as a system of daily consultations. In case of flooding and drought, emergency response is initiated according to the emergency plan, to avoid casualties and minimise economic losses (cf. Nie et al., 2011).

Finally, the explanation for finding the highest number of people killed in the RoW countries is logical too. First, poverty in many of these countries is high and governments do not have the means for adapting to potential disasters. Moreover, the political risks in many of the RoW countries are high. Political risk includes (civil) wars, riots, corruption, and non-payments. Clearly, countries with high political risks will be more vulnerable to impacts of extreme weather events. See Figure 4.2 for a world map of political risks, published by Oxford Analytica and Aon (a global provider of risk management services).

The map shows low risks for the OECD countries (not rated in 2012, but low risk in 2011), medium-low and medium risks for BRIICS countries, and low risks up to very high risks in the RoW countries. Most countries in Africa fall in the categories medium-high up to very high risk[2]. In Section 6.3 more details will be given as for political risks and vulnerability.

4.5 Conclusion

The main result found in this chapter is a characteristic spreading of disaster burden over the three regions: highest losses in the OECD countries, highest number of people affected in the BRIICS countries and the highest number of people killed in the Rest of World. The only exception to this rule found here, is for the group of hydrological disasters. Here, all highest disaster-burden percentages are found for the BRIICS countries. Explanations for differences in wealth and vulnerability between the three regions were given. As part of that the case of floods in China was discussed.

Notes

1 In 2010 US dollars.

2 Similar maps are known as country risk maps. See http://en.wikipedia.org/wiki/Country_risk, for examples. Maps with similar background and spatial patterns were published by BEH (2011) as world maps for vulnerability, coping capacity, susceptibility and a combination of these maps, the WorldRiskIndex.

Trends in regional disaster burden

This chapter describes trends in regional disaster burdens (global trends are discussed in Section 3.2). Section 5.1 provides trends in economic losses, trends in people affected are described in Section 5.2, trends in people killed in Section 5.3, and Section 5.4 discusses trends in major disasters. All analyses have been based on the CRED database EM-DAT, for the 1980–2010 period. In all cases, only major disasters were selected (see argumentation in Section 2.2).

The analyses in this chapter have all been based on disaster data, extracted directly from EM-DAT. Chapter 6 presents analyses based on data and trend patterns relative to changes in wealth and population in the respective regions.

5.1 Trends in losses

The trend in global economic losses appeared to increase over the 1980–1995 period and showed a stabilisation over the 1995–2010 period. The global data show one outlier in losses: the year 2005 (with huge losses due to hurricane Katrina). In Figure 5.1 the trends for the OECD region are shown (upper panel), idem the BRIICS countries (middle panel) and idem RoW countries (lower panel). Note that the trend ratio information ([μ_{2010} / μ_t] and [μ_{2010} / μ_t]) is not shown here.

The upper panel (OECD) shows a slightly increasing exponential trend with the 2005 outlier being more pregnant than that shown in Figure 3.2A for global losses. The trend shows a fourfold increase over the 1980–2010 period: from around USD 13 billion in 1980 to around USD 52 billion in 2010. For the trend ratio [μ_{2010}/μ_{1980}] the following estimates were found: 4.4:1 (1.8:1 – 10.9:1). The 95% confidence limits appear to be very wide, due to the large inter-annual variability.

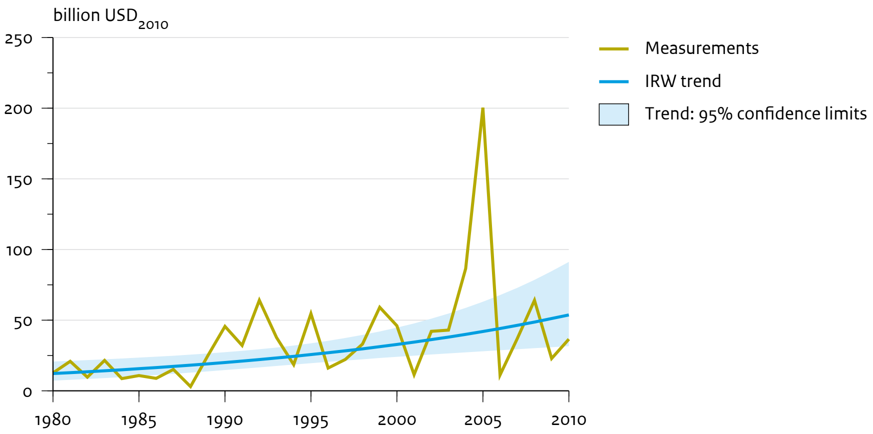
The middle panel (BRIICS) shows a slightly increasing pattern up to the year 1995 and a stabilisation thereafter. This is the pattern found in Figure 3.1 for global losses. Note the difference in scale of the y-axis: the upper panel ranges up to USD 200 billion, while the middle panel ranges up to USD 50 billion. The trend shows a sevenfold increase over the 1980–2010 period: from around USD 2.4 billion in 1980 to USD 17.1 billion in 2010. For the trend ratio [μ_{2010}/μ_{1980}] the following estimate is found: 7.1:1 (2.7:1 – 19:1). The 95% confidence limits appear to be very wide, again due to the large inter-annual variability. Furthermore the trend ratio [μ_{2010}/μ_t] is non significant over the 1987–2009 period ($\alpha = 0.05$).

Finally, the lower panel (RoW) shows a very small rising trend. Note the difference in scale of the y-axis: the upper panel ranges up to USD 200 billion, the middle panel ranges up to USD 50 billion and the lower panel ranges up to USD 30. The trend in the loss data appears to be a straight line and is not significant for the whole 1980–2010 period ($\alpha = 0.05$). The mean losses account for USD 6.2 billion.

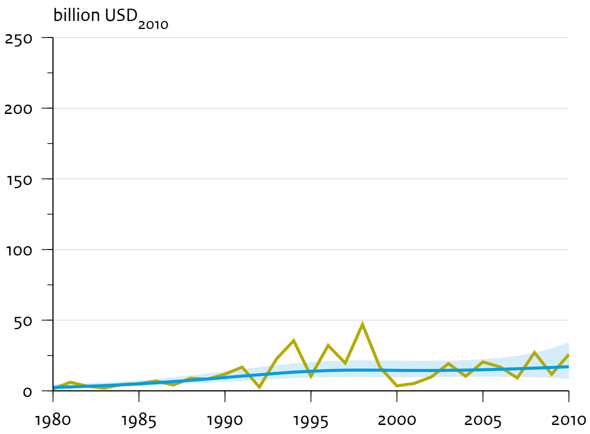
Figure 5.1

Economic losses due to weather-related disasters, per region

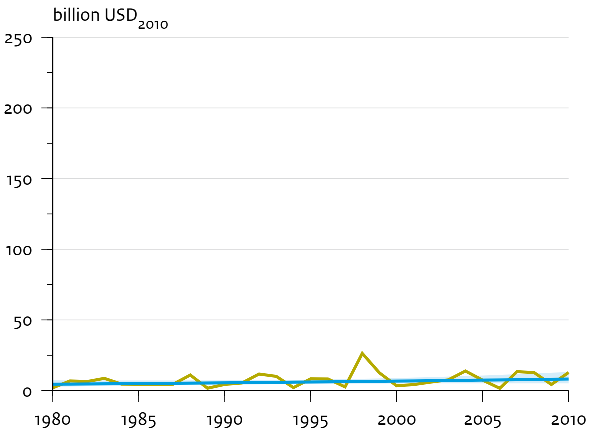
OECD countries



BRIICS (Brazil, Russia, India, Indonesia, China, South Africa)



Rest of the world

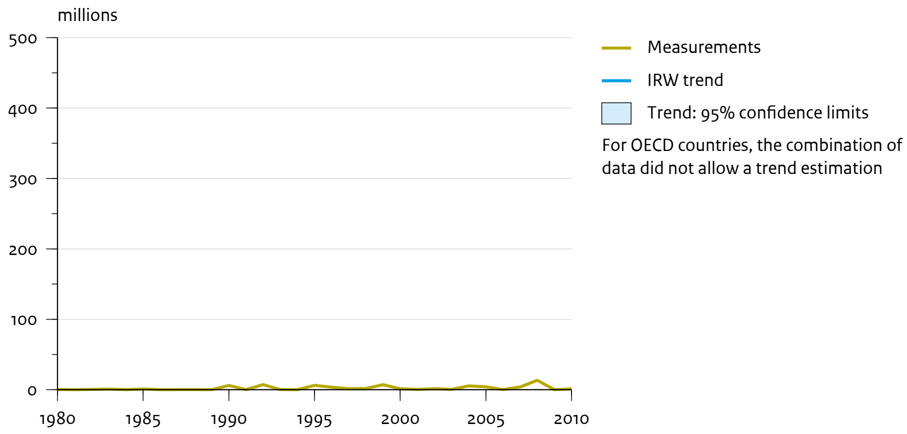


Source: PBL

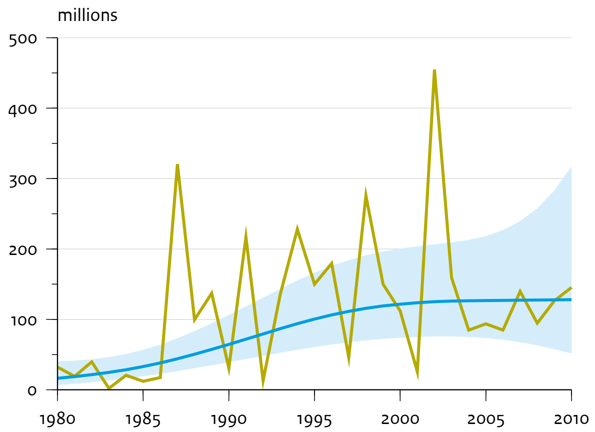
Figure 5.2

People affected by weather-related disasters, per region

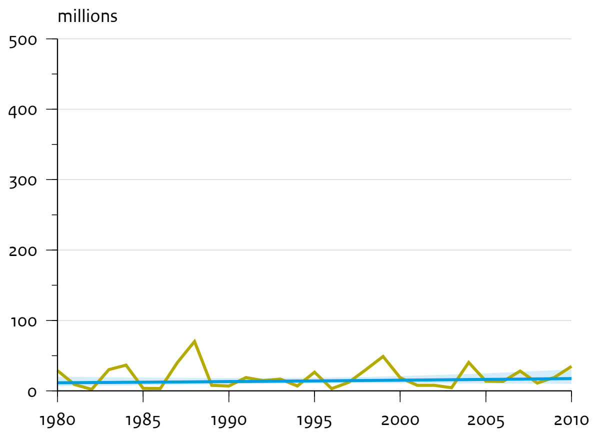
OECD countries



BRIICS (Brazil, Russia, India, Indonesia, China, South Africa)



Rest of the world



Source: PBL

5.2 Trends in people affected

The trends in people affected are shown in Figure 5.2. That is to say, it was not possible to estimate a feasible trend model for the OECD countries, data shown in the upper panel of Figure 5.2. Variability, or at the beginning of the series, the lack of variability, yields model residuals which do not pass the statistical requirements for residuals. For some consecutive years, such as 1989 and 1990, the number of people affected changes enormously: from 50,000 to 6,100,000 people affected.

One can fit other trend models through the data, such as a flexible spline function. However, it is chosen here to give a visual judgment of the data only. Although variability is large from year to year, the judgment taken here is that the number of people affected stabilises from 1990 onwards at a value of around 3.5 million people.

For the BRIICS countries (middle panel) an IRW trend could be estimated. The trend pattern shown equals that of economic losses in the BRIICS countries (middle panel Figure 5.1): an increasing trend over the 1980–1995 period, and stabilisation thereafter. Note the difference in scale of the y-axis: the upper panel ranges up to 14 million people affected, while the middle panel ranges up to 5 million people affected. The trend shows an eightfold increase over the 1980–2010 period: from around 16 million people affected in 1980 to 128 million people affected in 2010. For the trend ratio [μ_{2010}/μ_{1980}] the following estimate is found: 7.7:1 (2.2:1 – 28.2:1). The 95% confidence limits appear to be very wide, again due to the large inter-annual variability. Furthermore, the trend ratio [μ_{2010} / μ_t] is non-significant over the 1987–2009 period ($\alpha = 0.05$).

Similar to the BRIICS countries, for the RoW countries, the trend in people affected equals the trend pattern estimated for economic losses: a straight line which shows a small statistically non-significant increase over the sample period between 1980 and 2010. The mean annual value of people affected was around 14 million.

5.3 Trends in people killed

The situation for the number of people killed equals that shown in Figure 3.2C: the data are governed by large outliers where data between these outliers are relatively very small. Therefore, no trend estimates are shown for these data.

The data shown in Figure 5.3 can be interpreted as follows. Weather-related disasters lead to people killed in a complex non-linear, threshold-like manor: for many major disasters the number of people killed in individual disasters is rather low. However, some extreme weather and/or societal conditions may lead to extreme numbers of people killed. To draw conclusions on trends, one would need longer sample periods. This point will be addressed in Section 6.3 where a discussion is given as for the number of people killed over the 1900–2010 period.

5.4 Trends in the number of disasters

The regional results for the number of major weather-related disasters equal that found for the global number of weather-related disasters, shown in Figure 3.2D: all trends appear to be linear and rising. See Figure 5.4. For OECD countries, an annual increase in disasters of 0.64 ± 0.24 was found, for BRIICS countries this increase was 0.22 ± 0.12, and for Rest of the World 0.22 ± 0.19 (2-σ limits given).

It might be surprising that trend patterns found here, deviate from those found in Sections 5.1, 5.2 and 5.3. There might be two explanations. First, for a hazard to become a disaster, thresholds are used, depending on economic losses and the number op people killed (cf. the definition of disaster severity classes, given in Section 2.2). Therefore, the number of disasters depends in a non-linear way on changes in population and GDP, as shown in Figure 2.2. Second, Figure 5.4 shows the increase for the number of major disasters to be linear. However, Visser and Petersen (2012, Figure 7B) show that the number of great disasters stabilised around 1990 and decreased thereafter. It is to be expected that the largest part of the disaster burden was due to these great disasters.

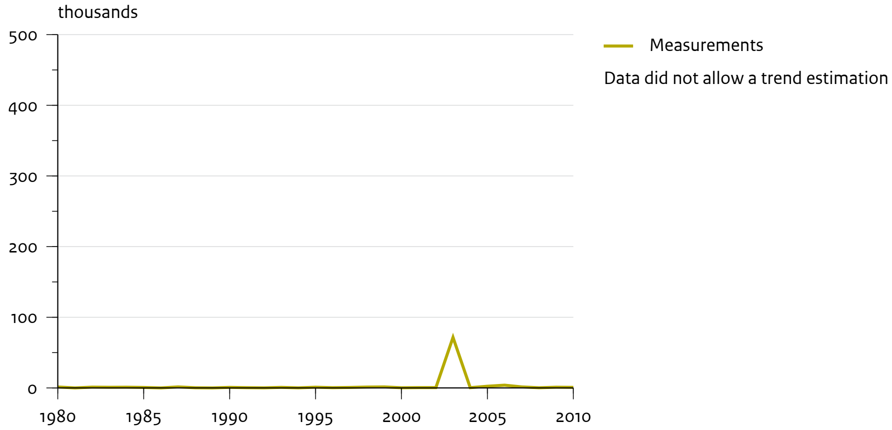
5.5 Conclusions

Regional disaster data were analysed according to the approach used for global data (Section 3.2). The results have been summarised in Figures 5.1 to 5.4.

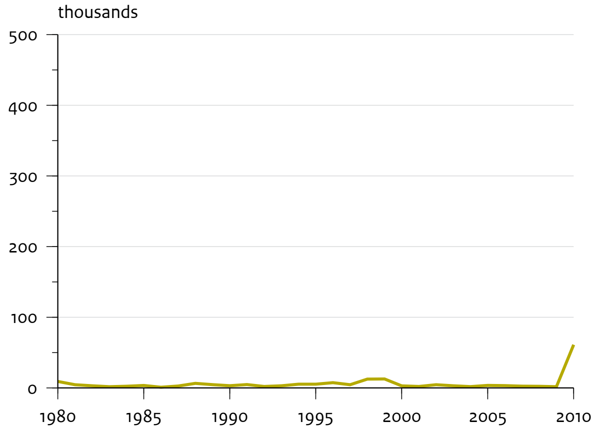
The regional trends for economic losses deviate from those found for global losses:
- The OECD countries show an exponential increasing trend over the 1980–2010 period. The increase over the 1980–2010 period was considerable: a factor 4.4 (1.8 – 10.9). The 95% confidence limits appear to be very wide, due to the large inter-annual variability.
- The BRIICS countries show a rise over the 1980–1995 period and stabilise thereafter. The increase by a factor of 7.1 (2.7–19) over the 1980–2010 period was considerable. Again, the 95% confidence limits are very wide, due to the large inter-annual variability.

Figure 5.3
People killed in weather-related disasters, per region

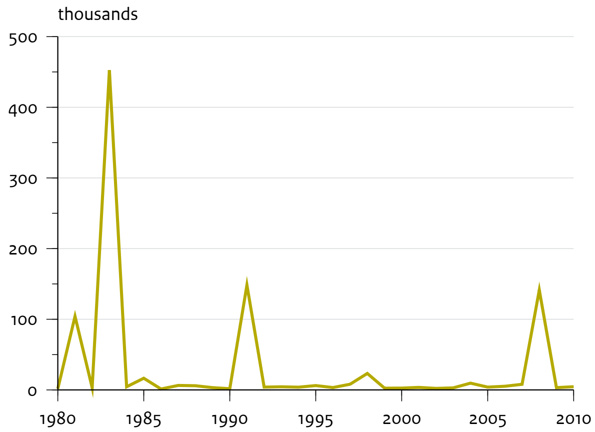
OECD countries



BRIICS (Brazil, Russia, India, Indonesia, China, South Africa)



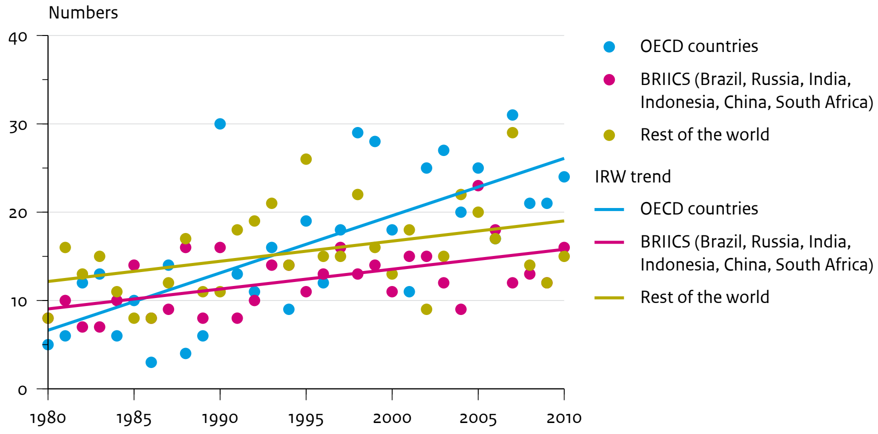
Rest of the world



Source: PBL

As patterns are dominated by extreme outliers, a trend could not be estimated.

Figure 5.4
Major weather-related disasters



Source: PBL

Trends in the number of major disasters are linear for all three regions. The annual increment for OECD countries was 0.64 ± 0.24, for BRIICS countries 0.22 ± 0.12, and for RoW countries 0.22 ± 0.19 (2-σ limits).

- The RoW countries show a stable trend pattern over time (no significant increase or decrease).

For the number of people affected, we found that:
- No IRW trend could be estimated by using the annual OECD data, due to a number of outliers. Visual inspection of the data suggests an increase over the 1980–1990 period and stabilisation thereafter, at an annual level of around 3.5 million people.
- The trend pattern for BRIICS countries equals the pattern for losses, and it equals the trend pattern found for the global number of people affected. This is logical since the absolute numbers of people affected in BRIICS countries are close to the numbers for the globe as a whole.
- The RoW countries show a stable trend pattern over time (no significant increase or decrease).

As for the number of people killed the findings equal those found for global data: the data are governed by a small number of outliers. Therefore, a trend is difficult to estimate.

The trends in the number of major disasters are all linear and increasing. Two qualitative explanations for the deviating patterns have been given.

How can trend patterns be explained?

6.1 Factors that shape disaster risks

Generally, disaster data, and more specifically the trends in disaster data, are influenced by four factors (Figure 6.1):
- changes in wealth of countries and regions;
- changes in the population of countries and regions;
- changes in the frequency and severity of weather and climate extremes (the drivers for weather-related disaster burdens);
- changes in vulnerability and coping capacity of countries and regions.

These four factors will interact in many cases. Thus, it is generally not easy to attribute trend patterns to one of these factors individually. For example, if trends in economic losses are rising, it is too simple to attribute this pattern directly to climate change. To make such an inference, other factors, such as an increase in wealth over the sample period, should have been ruled out. Or vice versa, if losses are stable or even decreasing over time, climate change can still be a factor of importance. One way of correcting for the factor 'wealth' is known as normalisation (Neumayer and Barthel, 2011; Bouwer, 2011). The process of normalisation is explained in Appendix B and will be employed in Sections 6.2 and 6.3.

6.2 Changes in wealth

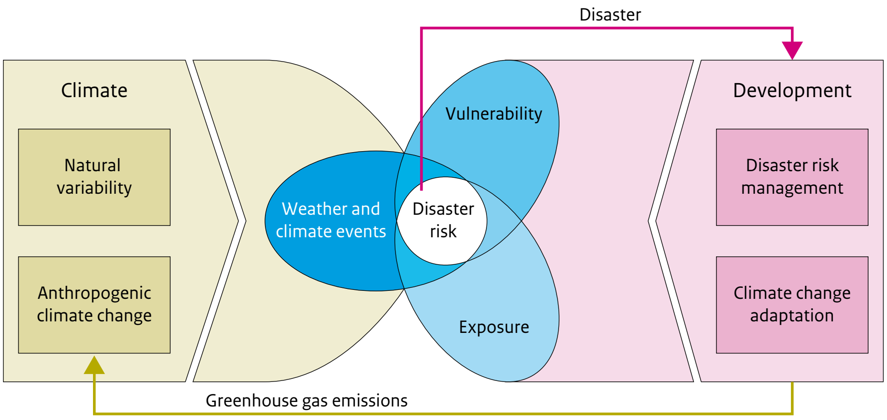
Economic losses and trends therein are shown in Figure 3.2A, upper panel, and in Figure 5.1. Losses are expressed in absolute values per region. However, it could be argued that the impact of losses due to one or more disasters would depends on a region's wealth. In Appendix B two ways of correction, normalisation, are explained. The first method corrects for changes in wealth of a particular country or region, over time. This approach corrects for the fact that disaster losses have a larger impact in times of poverty.

The second method corrects all disaster losses relative to the wealth of the country or region in that particular year. In this way disaster losses can be spatially compared. For details the reader is referred to Appendix B. The unity of losses is dimensionless and denoted as Actual-to-Potential-Loss Ratio (APLR).

Losses calculated accrosing to three methods (non-normalised, normalised and APLR) are shown in Table 6.1 (averages over 1980 to 2010). The table shows that disaster losses were highest for the OECD countries according to the non-normalised method. However, if losses are expressed relative to a region's wealth (GDP), BRIICS countries suffered the highest losses. Patterns over time are shown in Figure 6.2 in stacked format (the upper line of each panel equals the global total).

The graphs in Figure 6.1 illustrate the findings in Table 6.1:
- The largest losses were suffered in OECD countries, if uncorrected.
- If losses are corrected for GDP, the largest losses were suffered in the BRIICS countries.

Figure 6.1
Factors influencing disaster risks



Source: IPCC-SREX (2012)

Table 6.1
Regional economic losses according to three calculation methods[1]

	Non-normalised losses (USD billion /year)	Normalised losses (USD billion/year)	APLR data (/year)
OECD countries	36	46	0.0011
BRIICS countries	14	29	0.0014
Rest of World	8	13	0.0011

NB All data are averages over the 1980–2010 period. Non-normalised figures equal those presented in Chapter 4. Normalised data equal non-normalised data, except that they were corrected for increases in wealth per region (with respect to the 2010 values). The last column shows the data on losses as a ratio which corrects for varying wealth over time and space (Actual-to-Potential-Loss Ratio (APLR)). Highest values in each column are highlighted.

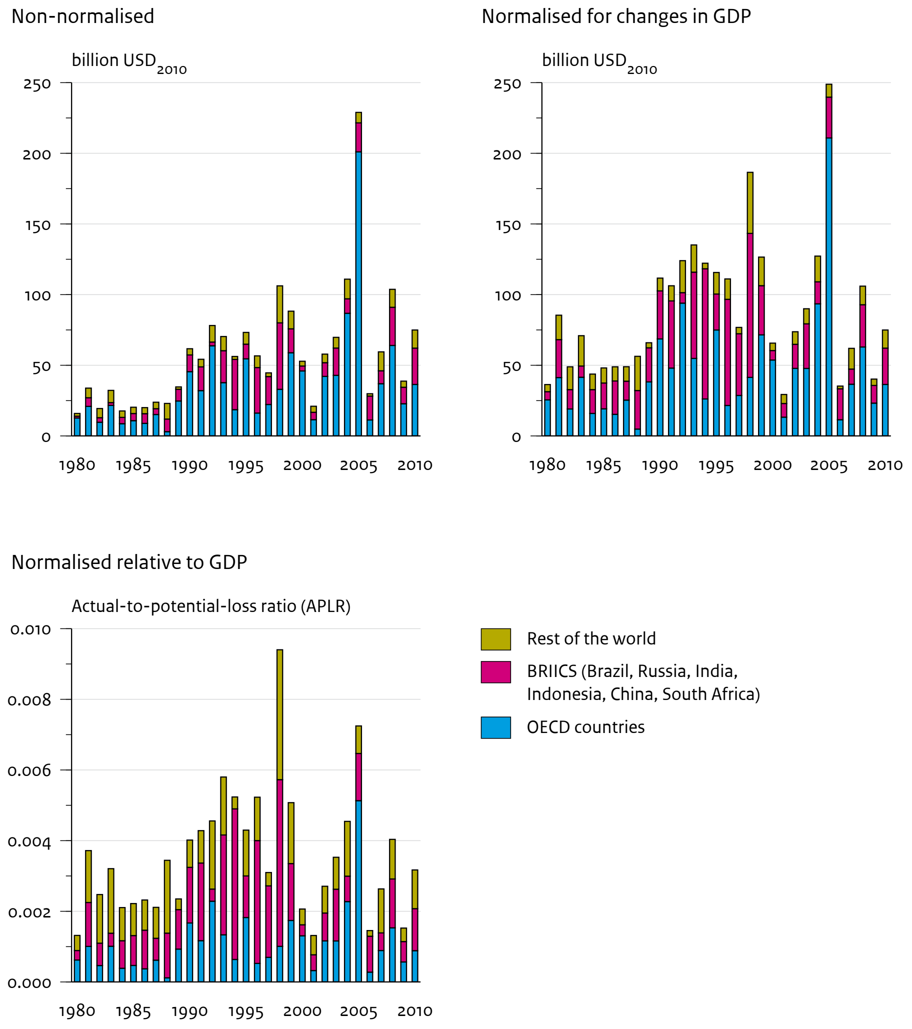
Another observation is that the Katrina peak in the upper and middle panel of Figure 6.1 has become the second highest in the lower panel (Katrina occurred in the richest region).

As for trend patterns in individual regions it was found that all trends in losses stabilise or slightly decrease. It should be noted that trends in individual regions are equal for the middle and lower panel (see equations in Appendix B). Furthermore, a change in trend pattern is logical since GDP curves, shown in the upper panel of Figure 2.2, show rising patterns for all regions. Thus, the rising trend for OECD countries (upper panel of Figure 5.1) stabilises due to the correction for rising GDP.

To illustrate the change in trend patterns the APLR data shown in the lower panel of Figure 6.2 have been plotted in Figure 6.3, along with a LOESS trend estimates for individual regions and the world. The graph shows the stabilised trend patterns for all regions and for the world as a whole. Another interesting observation is that APLRs in the final year (2010) were the same in all regions.

The results found here are consistent with those presented by Neumayer and Barthel (2010). They normalised global and regional data in the same way as shown in the upper right and lower panel of Figure 6.2 (their method of normalisation was more refined, as they used GDP data on a much finer grid). In all cases, stable or slightly decreasing trends were found (Neumayer and Barthel, 2010, Graphs 3 to 7).

Figure 6.2
Global economic losses due to weather-related disasters, per region



Source: PBL

Weather-related economic losses without normalisation (original loss data, upper left panel), with GDP correction per region (upper right panel) and with APLR (Actual-to-Potential-Loss Ratio) indexation following Neumayer and Barthel (2011). The upper two panels are expressed in billion USD (2010), the lower panel is a dimensionless loss ratio.

6.3 Changes in population

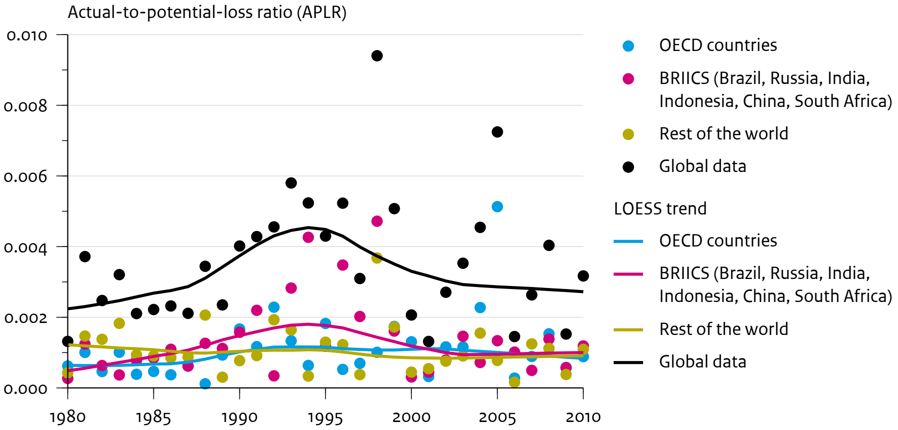
It is logical to assume that trends in the number of people affected or people killed will increase if population increasing, assuming all other factors to be constant. Therefore, it is interesting to correct these two variables for population growth over the 1980–2010 period (Equations 6 and 7 in Appendix B). Table 6.2 present results for averages over the whole sample period.

The upper panel shows that nothing changes in the region ordering of people affected. In all three cases the BRIICS countries experience the highest number of people affected. As for people killed there is no change in the region with highest numbers: the RoW countries. However, the differences between OECD and BRIICS countries vanish if corrections are made for the growing population in the 1980–2010 period (APKR).

Figure 6.4 shows the patterns for the three people affected series described in Appendix B (upper panel the $A_{1,t}$ variable, middle panel the $A_{2,t}$ variable and lower panel the $A_{3,t}$ variable). The panels show that no change in burden or trend pattern occurs, compared to the non-normalised series in the upper panel (which are identical to those shown in Figure 5.2).

Figure 6.3
Economic losses due to weather-related disasters

Normalised relative to GDP



Source: PBL

Table 6.2
Numbers of people affected (upper panel) and killed (lower panel) per region, according to three calculation methods

	Non-normalised people affected (million people/year)	Normalised people affected (million people/year)	APAR people affected (/year)
OECD countries	2	2	0.002
BRIICS countries	118	136	0.042
Rest of World	20	27	0.012

	Non-normalised people killed (thousand people/year)	Normalised people killed (thousand people/year)	APKR people killed (/year)
OECD countries	3	3	0.000003
BRIICS countries	6	7	0.000002
Rest of World	32	50	0.000021

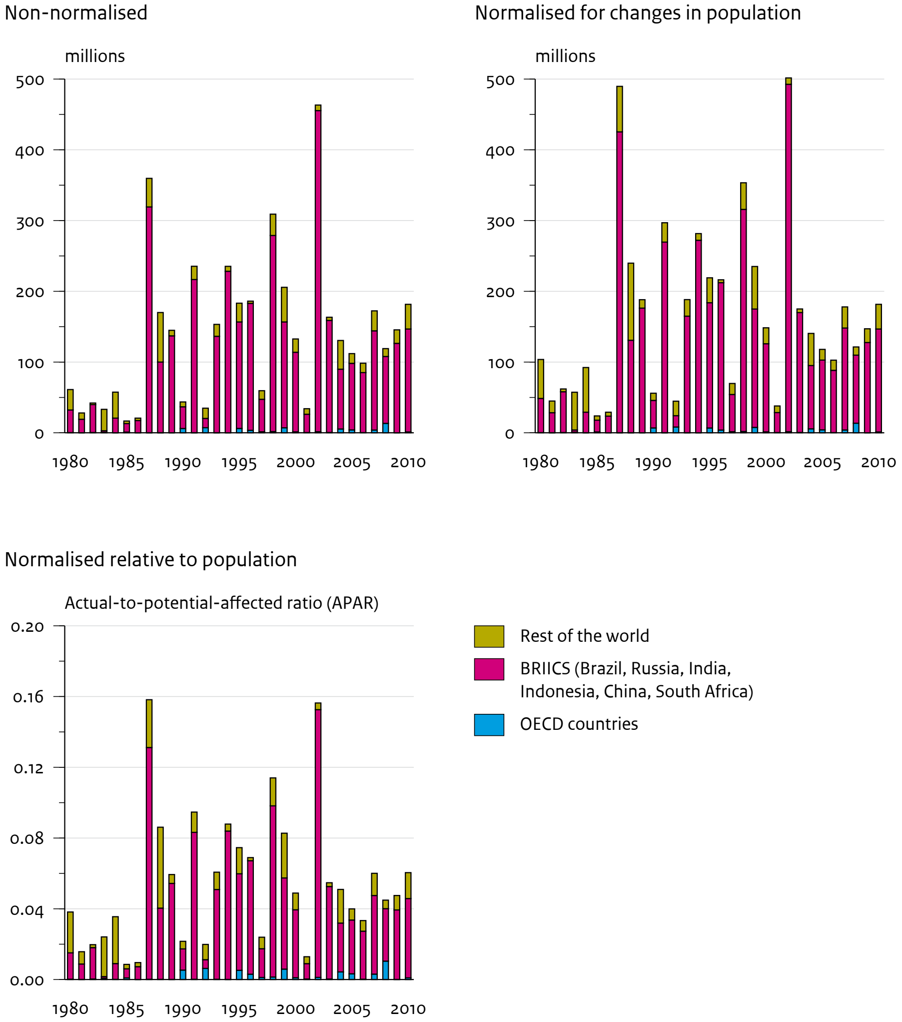
NB See Appendix B for an explanation. APAR stands for Actual-to-Potential-Affected Ratio; APKR stands for Actual-to-Potential-Killed Ratio. Shifts in the loss ordering of regions are highlighted by the yellow cells in the table. Highest values in each column are highlighted.

6.4 The role of climate change

All weather-related disasters are driven by weather and climate extreme events. In Sections 6.3 and 6.4 it was found that normalised disaster burdens show stabilised or even slightly decreasing patterns. This finding suggests that extreme weather or climate events, being the drivers for disaster burden, do not increase either. How does that observation fit with trends in the intensity or frequency of extreme temperatures, droughts, extreme rain events, storms or floods?

Table 6.3 gives an overview of historical trends over the period from 1950 to 2012, provided by IPCC-SREX (2012). Weather and climate variables are clustered according to their impact on the different types of disaster. The table shows that rising trend patterns for temperature extremes are ‘very likely’. However, the results for drought are less clear. Both rising and decreasing trends have been found. Historical trends in storms, the main driver of meteorological disasters, appear to be very uncertain. There are no clear signs for increasing frequencies or intensities. Historical trends in floods, the

Figure 6.4
People affected by weather-related disasters, per region



Source: PBL

Number of people affected by weather-related disasters, without normalisation (original data, upper left panel), with population corrections per region (upper right panel) and with APAR indexation following Equation (7) in Appendix B. The upper two panels express millions of people, the lower panel is a dimensionless loss ratio. APAR stands for Actual-to-Potential-Affected Ratio.

main driver for hydrological disasters, appear to be (very) uncertain. On the one hand, there are indications of a rise in heavy precipitation events; on the other hand, there are no clear signs of more frequent or more intense floods.

If these findings are combined with those in Table 3.1, the following qualitative view develops. Economic losses are dominated by meteorological disasters and to a lesser extent by hydrological disasters (52% and 34% of global losses, respectively). And since it is unclear whether the drivers of these two types of disasters show increasing patterns, it would not be unlikely that normalised economic losses also would show a stabilised pattern .

The same holds for the number of people affected. Table 3.1 shows that these numbers are dominated by hydrological disasters (63% of global numbers). Since the trends in the drivers of hydrological disasters are more or less stable over time, it is not illogical that trends in people affected stabilise over time (with or without normalisation).

Increasing trends could be expected for the number of people killed since these numbers have the strongest

Table 6.3
Summary of historical trend patterns in weather and climate extremes, 1950–2010

Weather/hazard variable	Driver of	Historical patterns (since 1950)
Temperature extremes	Climatological disasters	*Very likely* decrease in the number of unusually cold days and nights, on the global scale. *Very likely* increase in the number of unusually warm days and nights, on the global scale. *Medium confidence* in the increase in the length or number of warm spells, including heatwaves, in many (but not all) regions. *Low or medium confidence* in trends in temperature extremes in some sub-regions, due to a lack of observations or to varying signals within sub-regions.
Droughts	Climatological disasters	*Medium confidence* that some regions of the world have experienced more intense and longer droughts, in particular in southern Europe and west Africa, but opposite trends also exist.
Monsoons	Meteorological disasters	*Low confidence* in trends because of insufficient evidence.
Tropical cyclones	Meteorological disasters	*Low confidence* that any observed long-term (40 years or more) increases in tropical cyclone activity are robust, when accounting for past developments in observational capabilities.
Extra-tropical cyclones	Meteorological disasters	*Likely* poleward shift in extra-tropical cyclones. *Low confidence* in regional changes in intensity.
Storms	Meteorological disasters	*Low confidence* in trends due to insufficient evidence.
Precipitation extremes	Hydrological disasters	*Likely* statistically significant increases in the number of heavy precipitation events (e.g., 95th percentile) in more regions than in those with statistically significant decreases, but strong regional and sub-regional trend variations.
Fluvial and flash floods	Hydrological disasters	Limited to medium evidence available to assess climate-driven observed changes in the magnitude and frequency of floods, at regional scales. Furthermore, there is low agreement regarding this evidence, and thus overall *low confidence* at the global scale regarding even the sign of such changes. *High confidence* in the trend towards an earlier occurrence of spring peak river flows in snowmelt- and glacier-fed rivers.
Extreme sea levels, coastal floods	Hydrological disasters	*Likely* increase in extremely high water levels worldwide related to trends in mean sea level in the late 20th century.

Terms such as 'low confidence' and 'medium evidence' are explained in IPCC-SREX (2012). Source: IPCC-SREX (2012)

relation to climatological disasters (56% of global numbers). However, trends in the number of people killed are difficult to estimates due to large 'outliers' in the data (Figure 5.3). Therefore, the results for people killed are inconclusive given the data at hand.

The over-all conclusion from the analysis of extreme weather and climate events seems to be consistent with those found in Sections 6.2 and 6.3, with the exception of the number of people killed. For this indicator results are inconclusive. The word 'seems' has been used this one factor has not been addressed, that of vulnerability to disaster risk over time.

6.5 Vulnerability, a function of adaptation and political stability

The final factor influencing trends in disaster burden is the time-varying vulnerability of countries and regions. This section describes two sides of vulnerability adaptation and political stability. The first factor has a positive effect on disaster burden; the second factor may have both positive and negative implications for countries.

Adaptation

IPCC (2007b, Chapter 17) concludes that adaptation to climate change is already taking place, but on a limited basis (with very high confidence): societies have a long

Table 6.4
Examples of countries with adaptation initiatives

Country	Hazard	Measures
Sudan	Drought	Expanded use of traditional rainwater harvesting and water conserving techniques; building of shelter-belts and wind-breaks to improve resilience of rangelands; monitoring of the number of grazing animals and cut trees; set-up of revolving credit funds.
Botswana	Drought	National government programs to re-create employment options after drought; capacity building of local authorities; assistance to small subsistence farmers to increase crop production.
Bangladesh	Sea-level rise and salt-water intrusion	Consideration of climate change in the National Water Management Plan; building of flow regulators in coastal embankments; use of alternative crops and low-technology water filters.
Philippines	Drought and floods	Adjustment of silvicultural treatment schedules to suit climate variations; shift to drought-resistant crops; use of shallow tube wells; rotation method of irrigation during water shortage; construction of water impounding basins; construction of fire lines and controlled burning; adoption of soil and water conservation measures for upland farming.
Canada	Extreme temperatures	Implementation of heat health alert plans in Toronto, which include measures such as: opening of designated cooling centres at public locations; information to the public through local media; distribution of bottled water through the Red Cross to vulnerable people; operation of a heat information line to answer heat-related questions; availability of an emergency medical service vehicle with specially trained staff and medical equipment.
United States	Sea-level rise	Land acquisition programs taking account of climate change (e.g., New Jersey Coastal Blue Acres land acquisition program to acquire coastal lands damaged/prone to damages by storms or buffering other lands; the acquired lands are being used for recreation and conservation); establishment of a 'rolling easement' in Texas, an entitlement to public ownership of property that 'rolls' inland with the coastline as sea-level rises; other coastal policies that encourage coastal landowners to act in ways that anticipate sea-level rise.
The Netherlands	Sea-level rise	Adoption of Flooding Defence Act and Coastal Defence Policy as precautionary approaches allowing for the incorporation of emerging trends in climate; building of a storm surge barrier taking a 50 cm sea-level rise into account; use of sand supplements added to coastal areas; improved management of water levels through dredging, widening of river banks, allowing rivers to expand into side channels and wetland areas; deployment of water storage and retention areas; conduct of regular (every 5 years) reviews of safety characteristics of all protecting infrastructure (e.g., dykes); preparation of risk assessments of flooding and coastal damage influencing spatial planning and engineering projects in the coastal zone, identifying areas for potential (land inward) reinforcement of dunes.

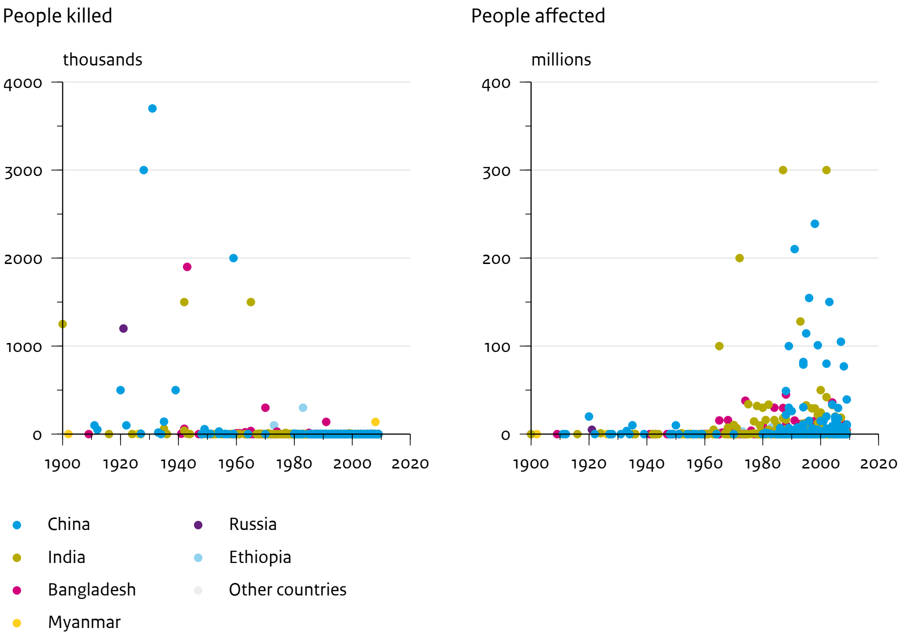
Source: IPCC (2007b, Table 17.1)

record of adapting to the impacts of weather and climate through a range of practices that include crop diversification, irrigation, water management, disaster risk management, and insurance. But climate change poses novel risks often outside the range of experience, such as impacts related to drought, heatwaves, accelerated glacier retreat and hurricane intensity Adaptation measures that also consider climate change are being implemented, on a limited basis, in both developed and developing countries. These measures are undertaken by a range of public and private actors through policies, investments in infrastructure and technologies, and behavioural change. Examples of adaptations to observed changes in climate are given in Table 6.4.

Although adaptation has taken place and not necessarily for reasons of climate change alone, it is difficult to quantify the influence of adaptation for aggregated regions such as the OECD, BRIICS or RoW. In the literature on disaster management no quantitative information can be found (e.g., IPCC-SREX, 2012). Indications for adaptation can be found from the CRED database EM-DAT by plotting all individual major disasters over the 1900–2010 period.

Figure 6.5 shows the results for people affected (left panel) and people killed (right panel). As stated in Section 2.2, the data over the 1900–1980 period are not complete since a (great) number of disasters are missing. However, if disaster burden would decrease over the full 1900–2010

Figure 6.5
Major weather-related disasters



Source: PBL
The sample period is from 1900 to 2010.

sample period despite the missing data, this would give an indication of adaptation.

The results for people killed indeed show a sharp drop in the number of people killed if numbers for the period from 1900 to 1980 and 1980 to 2010 are compared. Numbers of people killed of one million or more do not occur anymore in recent decades. This is remarkable since the population in countries such as China and India has increased enormously: China's population grew from 400 million people in 1900 to around 1300 million people in 2010; for India these numbers are 234 million in 1900 and around 1150 million people in 2010. This example shows a clear indication of adaptation. The right panel of Figure 6.5, however, shows an increase in the number of people affected, certainly coupled to the sharp increase in population in countries such as China and India.

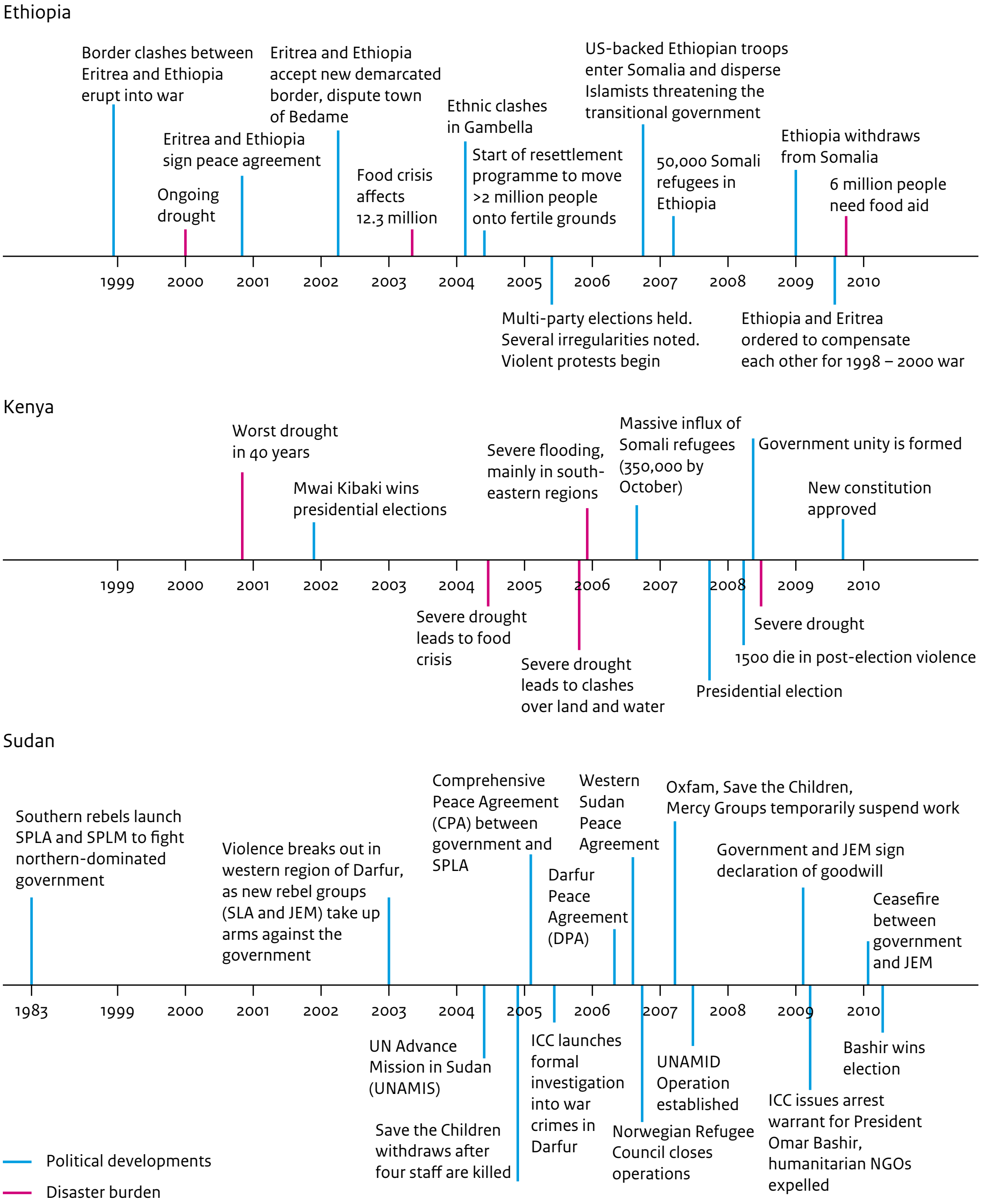
Political stability
Adaptation measures will improve the vulnerability of countries and regions to disasters. However, there are also factors with adverse impacts. These factors are poverty and governmental instability (cf. the political risk map shown in Figure 4.2). Typical countries where the severity of disaster impacts is entangled with political instabilities (civil conflicts), are countries lying in the horn of Africa as described in detail in CRED (2011b). This report shows timelines for eight African countries, along with detailed information on malnutrition, displacement, mortality and humanitarian aid.

Three of such timelines are shown in Figure 6.6: Ethiopia (upper panel), Kenya (middle panel) and Sudan (lower panel). For these countries disaster burden is interwoven with concurrent ethnic clashes, intense influx of refugees, election violence and continuous violence by rebel groups. A recent reference for the relation between civil conflicts and global climate has been given by Hsiang et al. (2011).

6.6 Conclusions

Trend patterns in disaster burden are not easy to explain since these patterns are governed by four factors: (i) changes in wealth, (ii) changes in population numbers, (iii) changes in intensity or frequency of extreme weather events and (iv) changes in vulnerability. Since these factors are interwoven, it is not easy to pinpoint changes to one specific factor.

Figure 6.6
Time-line for African countries for which political developments and disaster burden are largely interwoven



Source: PBL

Timelines are taken from CRED (2011b). This report shows timelines for eight African countries, along with detailed information on malnutrition, displacement, mortality and humanitarian aid.

It has been shown how disaster burden indicators can be filtered for changes in wealth or population through the method of normalisation. It was found that none of the trends in economic losses or the number of people affected is rising after normalisation (between 1980 and 2010). These findings are in line with those published by Neumayer and Barthel (2011).

Results for the number of people killed were inconclusive (due to large 'outliers' in the data). As for the third factor, changes in intensity or frequency of extreme weather events, it was found that trends in the drivers of disasters which led to the highest disaster burdens (storms and floods) are unclear. Finally, the role of changes in vulnerability is difficult to quantify. Here, two counteracting factors play a role: positive influences from adaptation, negative influences from poverty and/or political instability.

Note

1 Normalised and non-normalised losses in 2010 US dollars.

SEVEN

Disasters and disaster trends in the media

7.1 Individual disasters and climate change

The message from Chapter 6 is that patterns in disaster burden are difficult to explain due to interacting factors. However, numerous explanations for disasters and disaster burden can be found in the media. Mostly, disasters are directly coupled to climate change. As an example, the case of the Pakistan floods in 2010 is given here.

A Google search for 'Pakistan floods 2010 climate change' delivers over 13 million hits. If the word 'Facebook' is added there are fewer hits, but they still amount to 2 million. An example, taken from the website of Scientific American, is given in Figure 7.1. This text shows that the Pakistan floods are seen as 'a foreshadow of extreme weather to come'. However, the text also states that scientists at the WMO have no doubts that higher ocean temperatures had contributed to this disaster.
As a consequence of the discussion in Chapter 6, it is difficult to make such statements. The same holds for the enumeration of a series of disasters, as done in a number of reports, websites and press releases. Two examples are the following[1]:

Munich Re, 3 January 2011- Press release. Overall picture of natural catastrophes in 2010 – very severe earthquakes and many severe weather events
Several major catastrophes in 2010 resulted in substantial losses and an exceptionally high number of fatalities. The overall picture last year was dominated by an accumulation of severe earthquakes to an extent seldom experienced in recent decades. The high number of weather-related natural catastrophes and record temperatures both globally and in different regions of the world provide further indications of advancing climate change.[...]

WHO brochure 2011: 'Weather extremes in a changing climate':
Devastating climate and weather-related events recorded in recent years have captured the interest of the general public, governments, and media. This brochure provides a sample of extreme events for the past decade (2001-2010). Some of these events compare with – or exceeded in intensity, duration or geographical extent – the most significant historical events.[...]

However, an enumeration of severe disasters does not imply or proof any specific disaster trend behaviour. Nor does it imply or proof a specific cause of disaster burden and trends therein, such as climate change. It is true that the basis of water- and weather-related disasters is formed by extreme weather or climate events. But the burden of disasters is also influenced by other factors: growing population in endangered areas, the increase of wealth in these areas and the vulnerability of people to disaster risk (Bouwer, 2011; IPCC-SREX, 2012).

Figure 7.1

Example of climate change coupled to one particular disaster

Is the Flooding in Pakistan a Climate Change Disaster?

Devastating flooding in Pakistan may foreshadow extreme weather to come as a result of global warming

By Nathanial Gronewold and Climatewire | August 18, 2010 | 21

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UNITED NATIONS -- Devastating flooding that has swamped one-fifth of Pakistan and left millions homeless is likely the worst natural disaster to date attributable to climate change, U.N. officials and climatologists are now openly saying.

Image: IMAGE COURTESY OF WIKIMEDIA COMMONS

Most experts are still cautioning against tying any specific event directly to emissions of greenhouse gases. But scientists at the World Meteorological Organization (WMO) in Geneva say there's no doubt that higher Atlantic Ocean temperatures contributed to the disaster begun late last month.

Source: Scientific American (http://www.scientificamerican.com/article.cfm?id=is-the-flooding-in-pakist)

Example of coupling climate change to one particular disaster: the 2010 flooding in Pakistan.

For more discussions on communicational aspects of disasters and disaster burden, the reader is referred to IPCC-SREX (2012, Chapter 3 - FAQ 3.2). In their press release, the IPCC showed a slide given in Figure 7.2, showing the Pakistan floods in 2010. As for changes in disaster losses exposure of people and assets are named as the major cause, not climate change. Note that the role of vulnerability is not addressed here. Other discussions can be found in Visser and Petersen (2012, Section 6).

7.2 Contradictory trends presented in the literature

The upper panel of Figure 3.2A shows the trend pattern in global weather-related losses, for the 1980–2010 period: a rising pattern up to 1995 and stabilisation thereafter. However, also other trend shapes can be found in the literature. Figure 7.3 shows an alternative trend pattern for (almost) identical loss data: an exponential rising trend (the red dashed line). The figure is taken from Munich Re (2010a). Both trend patterns yield different suggestions as for the long-range evolution of losses. Also, the projection for the coming decades would be different for both trend models (stable losses versus exponential growth of losses in the near future). Another example of contradictory trend presentations is given in Visser and Petersen (2012, Figure 7B), where trends are estimated for the number of great natural disasters, as published by Munich Re (2010b) and reprinted in Pielke (2010, p. 167). Again, the result is an exponential increasing trend. When an IRW trend is estimated (Section 2.4), a different trend pattern arises; showing an increase up to 1992 and a decrease thereafter.

These examples illustrate that the interpretation of trend patterns in disaster data might be influenced by the trend method chosen. Now, the logical question is: which trend pattern is correct, or are both correct? Visser and

Figure 7.2
Result of IPCC research concerning increase in disaster losses

Source: IPCC-SREX press release, November 2011

Petersen (2012) show that, in principle, there is no 'best' trend model. The choice of a specific trend model depends on the specific 'demands' or 'wishes' of the researcher. For example, the IRW trend model gives full uncertainty information on estimates, while the Munich Re analysis does not give any of such clues.

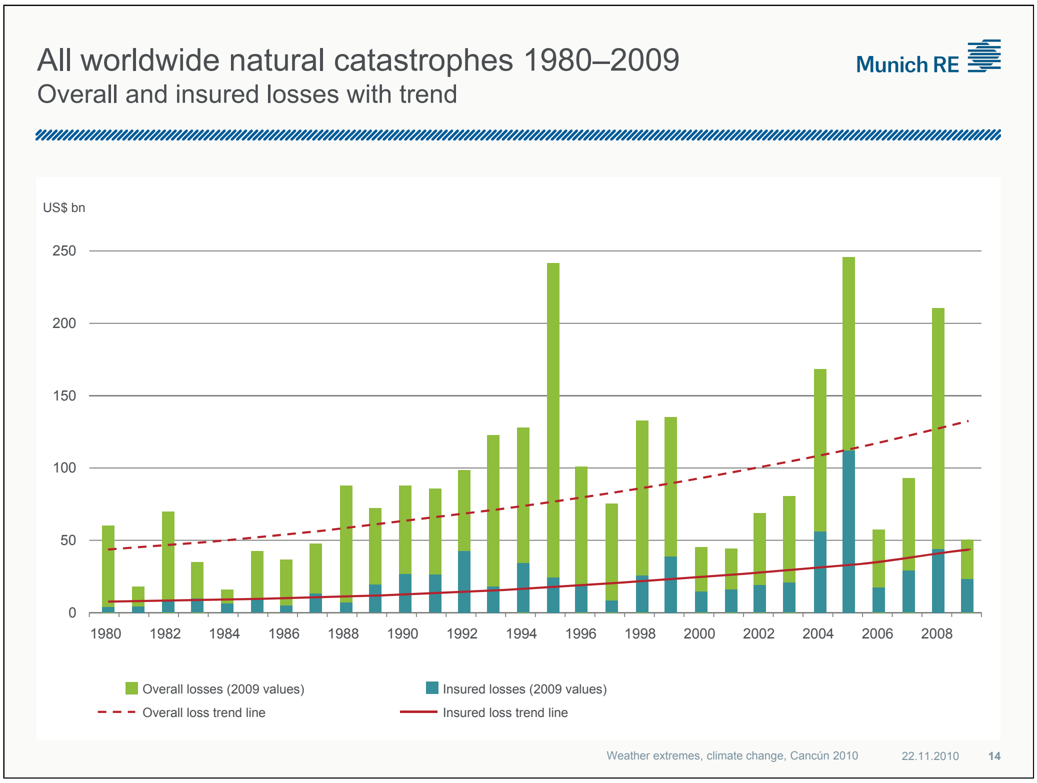
As a check, an OLS straight line was estimated through the loss data after taking logarithms. This was most likely also the approach followed by Munich Re, and did reproduce the pattern from Figure 7.3. However, the residuals of the trend model (i.e., the deviations from the trend estimate) did not meet the basic statistical requirements for being white noise. Thus, from a statistical point of view, the exponential model is not a correct trend model for the data at hand. The residuals for the IRW trend did meet all statistical requirements.

7.3 Presenting data on disasters over extended periods of time

Some reports present disaster statistics as illustrated in Figure 7.4. Here, it is not the choice of a specific trend model, as in Section 7.2, but the choice of different sample lengths. The examples in Figure 7.4 show patterns for the number of disasters over the 1900–2010 period. These patterns show strong exponential increases and could be used in connection with suggestive implications as for climate change. As shown in Section 2.2 and Appendix A, disaster databases do not give reliable estimates for the 1900–1980 period. The true number of disasters is highly underestimated, leading to the exponential patterns in Figure 7.4.

Furthermore, it should be noted that disasters are counted based on threshold definitions for people killed and economic losses. Thus, as population and wealth grow over time, the number of disasters will grow accordingly. Therefore, a causal relation between the

Figure 7.3
Example of a trend estimate of weather-related disasters, according to Munich RE



Source: PBL

The data and trend (red dashed line) are taken from Munich Re (2010a). The trend was estimated by an OLS straight line fit after taking logarithms.

number of disasters and climate change is not obvious without a careful analysis.

7.4 Conclusion

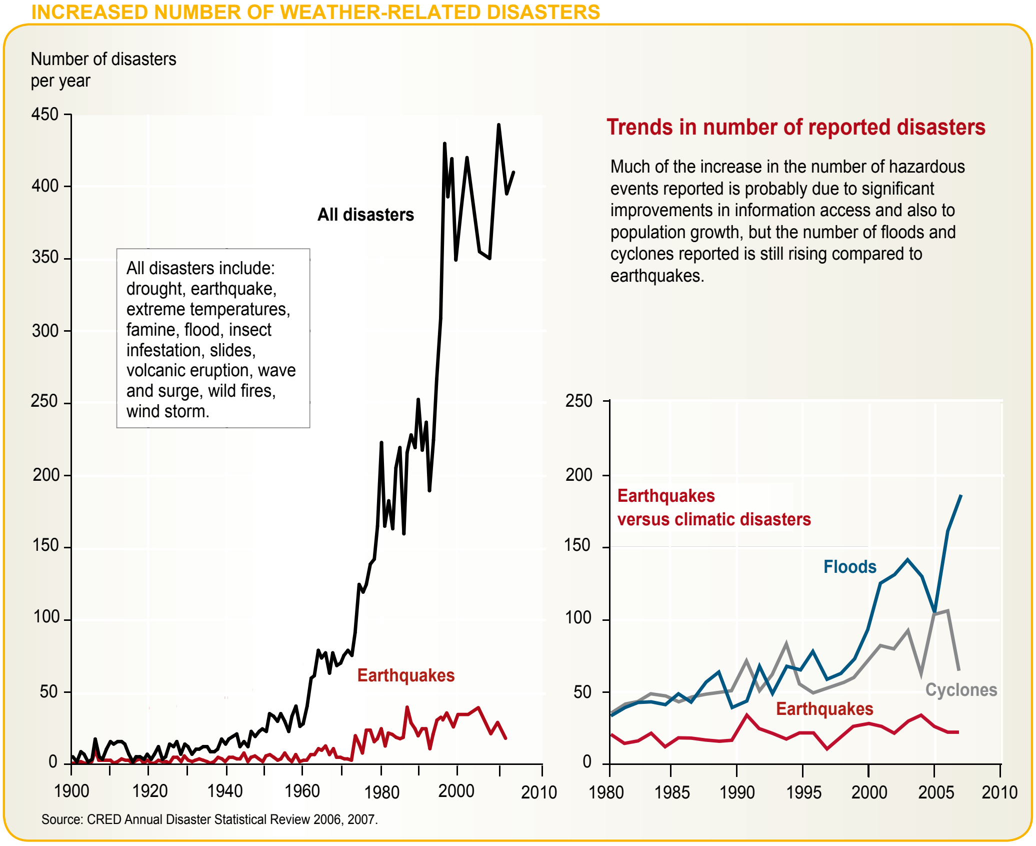
From a communicational point of view, disasters, disaster burden and their causes could be presented in suggestive or even misleading ways. The main example often found in the media, is the direct coupling of disasters and climate change. The inferences given in Chapter 6 and in Visser and Petersen (2012, Section 6) make clear that such conclusions should be drawn with care. Furthermore, the way trends in data are estimated, may influence conclusions. Finally, the sample period should be chosen with corresponding uncertainty in these data in mind.

Note

1 Text taken from the following websites: http://www.munichre.com/en/media_relations/press_releases/2011/2011_01_03_press_release_en.pdf and http://www.wmo.int/pages/mediacentre/news/documents/1075_en.pdf.

Figure 7.4

Example of doubt about reliability of data on weather-related disasters



Source: UNESCO, 2011

EIGHT

Future of water- and weather-related disasters

Prediction is very difficult, especially about the future
(quote generally believed to be by Niels Bohr, 1885–1962)

Projections of disaster burden on a global scale are available only on a limited scale. Articles in the literature are sparse. Some examples can be found for economic losses due to future storms and future floods. These examples will be described in this chapter shortly. First, a simple approach will be followed in Section 8.1, along the lines of Chapter 6. Here, future trends in the individual drivers of disaster burden will be described one by one (wealth, population, climate change and vulnerability). On a smaller spatial scale a larger variety of case studies can be found in the literature. A concise overview is given Section 8.2. An example of flood research from PBL will be given in Chapter 9.

8.1 Drivers of disaster burden

The first driver of disaster burden is the change in wealth. In this report, historical and future data on GPD-PPP were used from the OECD baseline scenarios (OECD, 2012, Figures 2.1 and 2.6). Here, the following projections for GDP-PPP over the 2010–2050 period are given: an increase in GPD-PPP of 138% for the OECD countries, an increase of 520% for the BRIICS countries and an increase of 409% for the RoW countries. These data strongly suggest that the impact of disasters will increase with respect to economic losses (all other factors being constant over the 2010–2050 period). The smallest change is foreseen for the OECD countries.

The same result holds for changes in population, be it on a more moderate scale. Here, the following projections for the 2010–2050 period are given: an increase in population of 11% for the OECD countries, an increase of 19% for the BRIICS countries and an increase of 67% for the RoW countries. These data suggest that the impact of disasters will increase with respect to people affected and people killed (all other factors being constant over the 2010–2050 period). Again, the smallest changes are foreseen for the OECD countries.

As for weather and climate extremes, projections are given by IPCC-SREX (2012). Their results are summarised in Table 8.1. In fact, future projections for weather and climate extremes resemble those found for historical trends:

- Temperature extremes will increase in frequency and magnitude. Droughts will become more severe in some regions: the Mediterranean region, central Europe, southern North America, north-east Brazil, and southern Africa. These projections indicate an increase in climatological disasters, all other factors being constant
- Less clear is the situation for meteorological disasters. Likely decreases or no change in frequency of tropical cyclones are expected. Decreases are projected in mid-latitude storms. Thus, disaster burden due to storms ('meteorological disasters') might expected to be more or less stable over time, all other factors being constant.

Table 8.1

Summary of future weather and climate extremes up to the year 2100

Weather variable	Driver of	Future projections (up to 2100)
Temperature extremes	Climatological disasters	*Virtually certain* decrease in frequency and magnitude of unusually cold days and nights on global scale. *Virtually certain* increase in frequency and magnitude of unusually warm days and nights on global scale. *Very likely* increase in length, frequency, and/or intensity of warm spells, including heatwaves, over most land areas.
Droughts	Climatological disasters	*Medium confidence* in projected increase of duration and intensity of soil moisture and hydrological drought in some regions of the world, in particular in the Mediterranean region, central Europe, southern North America, north-east Brazil, and southern Africa. Overall *low confidence* elsewhere because of insufficient agreement of projections.
Monsoons	Meteorological disasters	*Low confidence* in projected changes of monsoons, because of insufficient agreement between climate models.
Tropical cyclones	Meteorological disasters	*Likely* decrease or no change in frequency of tropical cyclones. *Likely* increase in mean maximum wind speed, but possibly not in all basins. *Likely* increase in heavy rainfall associated with tropical cyclones.
Extra-tropical cyclones	Meteorological disasters	*Likely* impacts on regional cyclone activity but *low confidence* in detailed regional projections due to only partial representation of relevant processes in current models. *Medium confidence* in a reduction in the numbers of mid-latitude storms. *Medium confidence* in projected poleward shift of mid-latitude storm tracks.
Storms	Meteorological disasters	*Low confidence* in projections of extreme winds (with the exception of wind extremes associated with tropical cyclones).
Precipitation extremes	Hydrological disasters	*Likely* increase in frequency of heavy precipitation events or increase in proportion of total rainfall from heavy falls over many areas of the globe, in particular in the high latitudes and tropical regions, and in winter in the northern mid-latitudes.
Fluvial and flash floods	Hydrological disasters	*Low confidence* in global projections of changes in flood magnitude and frequency because of insufficient evidence. *Medium confidence* (based on physical reasoning) that projected increases in heavy precipitation would contribute to rain-generated local flooding in some catchments or regions. *Very likely* earlier spring peak flows in snowmelt and glacier-fed rivers.
Extreme sea levels and coastal floods	Hydrological disasters	*Very likely* that mean sea level rise will contribute to upward trends in extreme sea levels. *High confidence* that locations currently experiencing coastal erosion and inundation will continue to do so due to increasing sea level, in the absence of changes in other contributing factors.

Source: IPCC-SREX (2012)

Terms such as 'very likely' or 'high confidence' are explained in IPCC-SREX (2012).

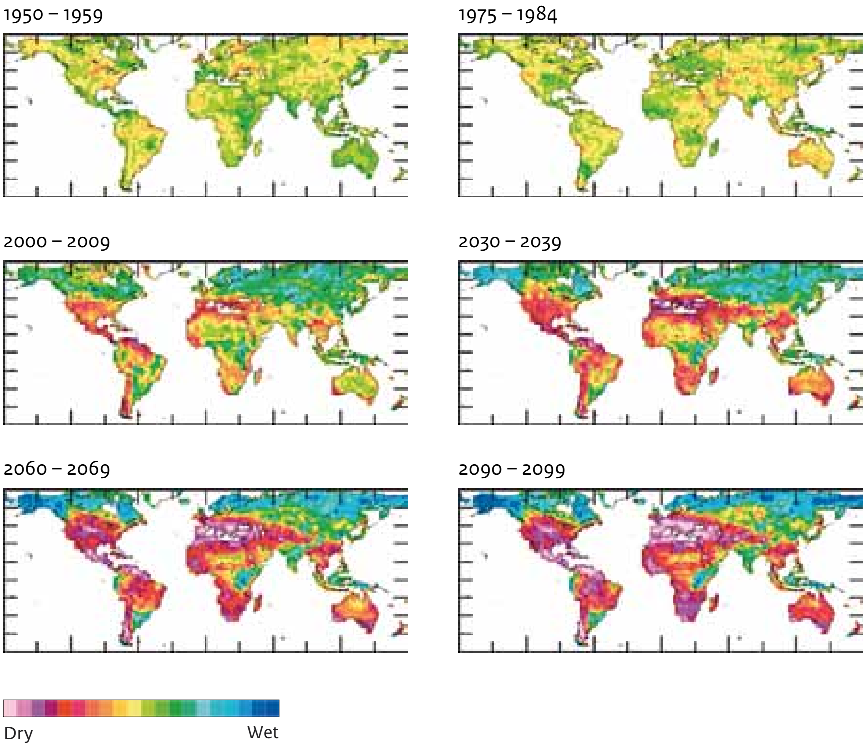
- Future developments in floods show a clearer sign of aggravation, especially extreme sea levels and coastal floods. Thus, disaster burden due to floods will be rising where more confidence is given to coastal floods than to fluvial floods, all other factors being constant.

As for droughts Dai (2011) shows detailed global maps for historical periods and future periods up to the year 2100. See Figure 8.1 for an example. These graphs are consistent with the IPCC-SREX projections given in Table 6.3 and Table 8.1: increasing drought severity in the Mediterranean region, central Europe, southern North America, north-east Brazil, and southern Africa. Additionally, drought severity is projected to aggravate for Australia and eastern China. Global maps for temperature and precipitation changes for the 1990–2050 period are given in OECD (2012; Figures 3.10 and 3.11).

The fourth factor, vulnerability, is difficult to predict and literature is sparse. PBL (2012) analyses food security issues for sub-Saharan Africa up to the year 2050, where food availability can been seen as an important determinant of vulnerability. From this report the following conclusion is taken:

Population growth in sub-Saharan Africa, in combination with a relatively high income growth, is expected to result in a more than fourfold increase in total food demand by 2050, compared to

Figure 8.1
Drought hazards based on climate model data, 1950 – 2099



Source: Dai, 2011 (Figure 11)

Global spatial patterns of drought hazards (the SC-PDSI indicator) over the historical periods from 1950 to 1959 and 1975 to 1984. The present situation comes closest to the 2000–2009 period. Future developments are given for the periods between 2030 and 2039, 2060 and 2069 and 2090 and 2099. Red to pink areas are extremely dry (severe drought) conditions while blue colors indicate wet areas relative to the 1950–1959 period.

2000. With such an increase in food consumption, malnutrition is expected to be eradicated almost entirely, but not until 2050. In west Africa, such an increase in agricultural production is achieved through the expansion of agricultural land, while in east Africa, where the potential for agricultural expansion is smaller, productivity is projected to increase. The projection is based on the OECD baseline scenario for their Environmental Outlook to 2050, and assumes that sub-Saharan Africa will benefit from their so-called demographic window of opportunity: the ratio of active to non-active people is likely to increase over the next two decades.

8.2 Disasters - regional case studies

There are only a limited number of studies available which address future disaster burden. And existing studies only cover projected economic losses. Bouwer (2010) summarises a number of these studies in his Ph.D. thesis, Chapter 7. The literature is divided as for articles on windstorms and flood hazards. Changes in losses are presented as a difference between present and the year 2040. The case studies concerned countries (the United States, Japan, China, the United Kingdom, Germany, Spain, Australia and the Netherlands) as well as regions (Europe and the Atlantic) and the global scale. From Bouwer's study the following conclusions were taken:

All projections of future weather risks show on average increases in disaster losses
due to climate change. Flood losses are projected to increase more rapidly under
climate change, compared to projected changes in losses from tropical and extra-tropical windstorms, until the year 2040. However, the contribution from increasing exposure and value of capital at risk to increasing losses is estimated to be substantially larger than changes in the incidence of floods, and in the case of storms between five and ten times larger, than the impact of projected anthropogenic climate change on tropical and extra-tropical storms.

Since loss events are stochastic, and their occurrence varies over time due to natural climatic variations, the relatively small signal from anthropogenic climate change up until the year 2040 is therefore likely to be lost among other causes for increasing and varying losses. Still, the comparison between the contribution to change in risk from anthropogenic climate change and socio-economic change is quite uncertain, given the limited number of studies included here, different methods and assumptions underlying these studies, the large spread in estimates, and the rather crude assumptions about the relation between changes in socio-economics and changes in exposure to hazards. Also, the estimates given here are based on average, or annual expected values. More frequent very large loss events may have severe economic consequences.

Finally, risks are moderated by the complicated interaction of the hazard with risk reduction and adaptation measures, that can influence hazard probability, and exposure and vulnerability of people and capital, human behavior, and thereby the losses that can possibly occur. At the same time, adaptation aimed at reducing risk will come at a cost. And it remains uncertain if sufficient and timely adaptation will be achieved, given the long planning horizon of infrastructure projects, as well as behavioral changes, and the need to show the present benefits of investments in risk reduction.

A recent case study on economic losses in the Rhine catchment area was conducted by Linde et al. (2011). They presented projected losses up to the year 2030. The following summary was taken from their study:

In Europe, water management is moving from flood defence to a risk management approach, which takes both the probability and the potential consequences of flooding into account. It is expected that climate change and socio-economic development will lead to an increase in flood risk in the Rhine basin. To optimize spatial planning and flood management measures, studies are needed that quantify future flood risks and estimate their uncertainties. In this paper, the current and future fluvial flood risk in 2030 is estimated for the entire Rhine basin in a scenario study. The change in value at risk is based on two land-use projections derived from a land-use model representing two different socio-economic scenarios. Potential damage was calculated by a damage model, and changes in flood probabilities were derived from two climate scenarios and hydrological modeling. The results were aggregated into seven sections along the Rhine.

It was found that the annual expected damage in the Rhine basin may increase by between 54% and 230%, of which the major part (three-quarters) can be accounted for by climate change. The highest current potential damage can be found in the Netherlands (110 billion €), compared to the second (80 billion €) and third (62 billion €) highest values in two areas in Germany. Results further show that the area with the highest fluvial flood risk is located in the Lower Rhine in Nordrhein-Westfalen in Germany, and not in the Netherlands, as is often perceived. This is mainly due to the higher flood protection standards in the Netherlands as compared to Germany.

8.3 Conclusion

Studies on disaster burden for the (near) future are limited thus far. A simple approach was given based on projected trends in the four factors which steer disaster burden: wealth, population growth, climate change and changes in vulnerability. Projections show a strong increase in GDP for many regions in the world. The same holds for a growing world population. Both factors will aggravate disaster burden, other factors being constant. For climate change it was found that climatological disasters are expected to increase (heatwaves, droughts), while such changes are unclear for meteorological disasters (storms). Model projections show a likely increase in hydrological disasters (floods), with more specific increases in coastal floods than in river floods. Finally, no studies were found containing projections of changes in vulnerability. Thus, this fourth factor could be seen as 'the great unknown'.

Case studies for economic losses show prevailing influences of increasing wealth and population. Climate change will influence economic losses too, but the first two factors are likely to prevail on the short-term (i.e., coming decades).

NINE

Population and value at risk from floods

For this chapter, data on future population and value at risk in flood-prone areas were derived. These data resulted from a combination of the flood- prone areas with population and assets, represented by GDP. In doing so, two assumptions were made: (i) climate change as a driver of floods and impacts were taken to be constant over time, and (ii) future adaptation to floods was ignored. In fact, the exercise followed the reasoning given in Section 8.1 on wealth and population, but now directed to floods and using detailed maps for GDP and population.

The first assumption seems to be reasonable in the light of the literature discussed in Section 8.2, according to which changes in wealth and population are expected to be the main drivers of disaster burden in the decades to come. This assumption is also consistent with one of the conclusions from IPCC-SREX (2012) on future projections of fluvial and flash floods (up to the year 2100), which reads '*Low confidence in global projections of changes in flood magnitude and frequency because of insufficient literature and poor agreement between models. Increase in magnitude and/or frequency anticipated in regions where rainfall extremes are projected to increase*'. However, for extreme sea levels and coastal impacts the assumption might be too simple: '*It is very likely that mean sea level rise will contribute to upward trends in extreme sea levels. High confidence that locations currently experiencing coastal erosion and inundation will continue to do so due to increasing sea levels, all other factors being equal*' (cf. Table 8.1). See also further research in Section 10.2. As for the assumption on future adaptation: no adaptation estimates can be found in the literature thus far, both on a regional and a global scale.

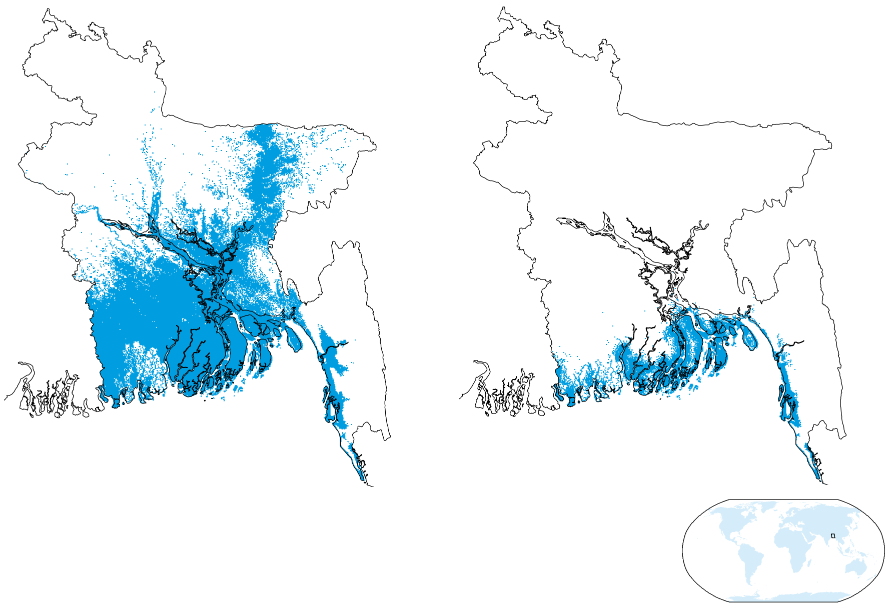
In Section 9.1 two variants for coastal floods are introduced. These variants show the difference between the exposure on a low elevation coastal zone and the exposure of a storm surge which diminishes in height and power as it moves land inward. Section 9.2 is about population at risk and Section 9.3 is about value at risk, expressed in terms of GDP-PPP. Finally, the cities most vulnerable to floods are presented in Section 9.4. The calculation for these cities is based on the same data as used in Sections 9.2 and 9.3. In order to calculate the vulnerability the national GDP was used as an indicator for adaptive capacity of these cities (Section 9.4). All calculations are based on the data sets described in Section 2.3. In Appendix C the preparation of these data is described in detail.

9.1 Two models for coastal flooding calculations

The spatial extent of a coastal flood highly depends on the methodology used and its definition. McGranahan et al. (2007) define a Low Elevation Coastal Zone (LECZ) as 'the contiguous area along the coast that is less than 10 metres above sea level'. But this is about a Low Elevation Coastal Zone. For the present study, the coastal zone that is potentially at risk of flooding from the sea was defined

Figure 9.1
Coastal flood-prone areas Bangladesh

Without distance-decay factor | With distance-decay factor



Source: PBL
For both cases a 5-metre storm surge was assumed. The difference in flooded area appears to be enormous.

as the area that would be under threat from a storm surge of 5 metres. A 5-metre storm surge was chosen because it represents an extreme surge. For this calculation, the Shuttle Radar Topographic Mission DEM map (SRTM) was used (Section 2.3).

The coastal flood map based on SRTM is based on the assumption that a storm surge moves horizontally across the surface until it encounters an obstacle that has a higher elevation than the storm surge itself. However, this method does not represent a storm surge realistically: it assumes that a LECZ is filled with water like in 'a bath tube', which is not the case in practice.

Dasgupta et al. (2009) states: '*As a wave moves inland, its height will diminish. The rate of decay depends largely on terrain and surface features, as well as factors specific to the storm generating the wave. In a case study on storm surges, Nicholls (2006) refers to a distance decay factor of 0.2- 0.4 m per 1 km that can be applied to correct wave heights in relatively flat coastal plains. In this study 30 cm per 1 km distance from coastline was used to estimate the reduction in wave height applied to each inland cell*'. Thus, not only the height of the storm surge is important, also the distance to coast matters. Using a storm surge of 5 metres and the SRTM for the elevation in relation to the storm surge, Figure 9.1 shows the results for waves *without distance decay* and *with a distance decay of 30 cm/km* in Bangladesh. The panels show a considerable difference in flooded area. It should be noted that both methodologies assume there to be no defences (dykes). Both approaches, with and without decay, are presented in the next sections.

9.2 Population at risk

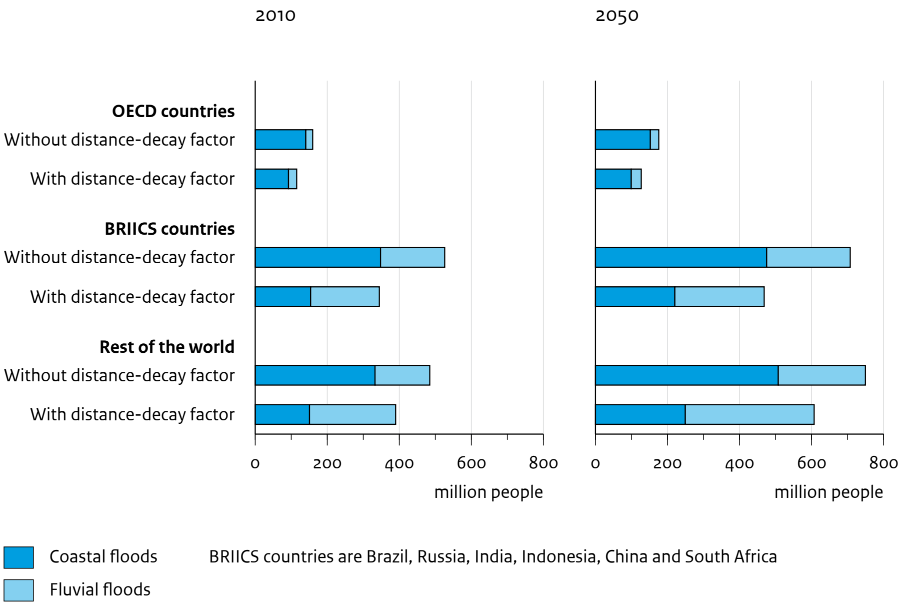
The population maps for 2010 and 2050 were combined with the raster maps of flood-prone areas. To distinguish between the two different methods of calculating, several overlays were made for coastal flooding by a storm surge of 5 metres (without decay (nd) and with a decay (d) of 30 cm/km). Calculations were made using coastal floods only as well as using the combined flood map (Coastal flood, Dartmouth and GLWD) (Table 9.1). The overlays result in four different figures for the population at risk per year.

For each country the total population (True or False in the flood prone map) and the population at risk (True in the flood prone map) as well as the total value (based on

Table 9.1
Eight different overlays

	Population 2010	Population 2050
Coastal floods 5m, without distance decay	X	X
Coastal floods 5m, with distance decay	X	X
All floods 5m, without distance decay	X	X
All floods 5m, with distance decay	X	X

Figure 9.2
Population at risk of flooding



Source: PBL

Figure 9.2 also shows that the decay methodology seriously influences the ratio between people at risk due to coastal floods and people at risk due to fluvial floods. For example, for RoW countries, in 2050, coastal floods dominate for no decay factor, while fluvial floods dominate for decay factor included.

GDP-PPP) and value at risk was calculated using the eight data sets from Table 9.1.
All calculations are for individual countries. As a final step the results of individual countries was aggregated to the OECD group of countries, the BRIICS countries and RoW countries.

In Figure 9.2 the results for coastal and fluvial flood-prone areas are shown for the years 2010 and 2050. Due to the smaller spatial extent of the coastal flood-prone area, the methodology that assumes a certain rate of decay for the storm surge shows significantly fewer people at risk, for all three regions (OECD, BRIICS and RoW). The total population at risk ranges between 0.8 billion (13% of the total world population) and 1.2 billion (17% of the total world population). It is interesting to note that for the 5-metre storm surge without decay the absolute population at risk is larger in the BRIICS countries than in the RoW countries. In contrast, in situations of coastal flooding with a certain rate of decay, a larger part of the population would be at risk in the RoW than in the BRIICS countries. This is caused by a larger overlap of the three data sets in the composed flood map (Dartmouth, GLWD and coastal floods based on low elevation; without decay) for the RoW countries.

Table 9.2 shows changes in population at risk over the 2010–2050 period, directly derived from Figure 9.2. The

Table 9.2
Change in population at risk of coastal floods, and all floods (fluvial plus coastal)

Countries	Changes in population at risk of coastal floods, 2010–2050		Changes in population at risk of fluvial and coastal floods, 2010–2050	
	Without distance decay	With distance decay	Without distance decay	With distance decay
OECD	8%	8%	10%	10%
BRIICS	37%	43%	34%	36%
RoW	53%	66%	55%	56%
Globally	38%	43%	39%	42%

Table 9.3
Share of population at risk of coastal floods (people at risk as a percentage of the population for similar areas)

Region	Without distance decay		With distance decay	
	Part of total in 2010	Part of total in 2050	Part of total in 2010	Part of total in 2050
OECD	12%	12%	8%	8%
BRIICS	11%	13%	5%	6%
RoW	14%	12%	6%	6%
Globally	12%	12%	6%	6%

Table 9.4
Eight different overlays

	GDP-PPP 2010	GDP-PPP 2050
Coastal floods 5m, without distance decay	X	X
Coastal floods 5m, with distance decay	X	X
All floods 5m, without distance decay	X	X
All floods 5m, with distance decay	X	X

table shows that changes over time will be similar for the 'without decay' and 'with decay' variants. Furthermore, the smallest changes relate to the OECD countries; from 8% to 10%. Changes for BRIICS and RoW countries will be around 37% and 55%, respectively.

Thus far, all calculations were for absolute numbers (Figure 9.2). These results can also be expressed relative to the total population of each region (OECD, BRIICS or RoW) in 2010 and projected for 2050. See Table 9.3 for coastal floods. The table shows that percentages for different years and for different regions are close. The use of a distance decay halves the percentages. The finding that percentages in Table 9.3 are very alike for the years 2010 and 2050, is not unexpected; the changes in people at risk, calculated on a fine grid first and aggregated afterwards, resemble the changes in population, all other factors being constant.

9.3 Value at risk

The analyses of the value at risk are based on the GDP-PPP per capita. The growth of 'assets' at risk depends basically on population growth and increasing wealth. Just like the calculations for population at risk eight different overlays for flood-prone areas were made (Table 9.4).

As for population at risk, a considerable difference was found between the results for coastal floods with and without a decay of 0.3 metres per kilometre (Figure 9.3). For value at risk, the risk of coastal floods exceeds that of fluvial floods, in all cases. Furthermore, the largest GDP values in 2010 were found for the OECD countries, whereas, by 2050, this will apply to the BRIICS countries.

Changes over time are summarised in Table 9.5. The table shows the large differences between regions: an increase of around 125% for OECD countries, an increase of around 650% for BRIICS countries and an increase of 430% for RoW countries.

Table 9.5
Change in value at risk of coastal floods, and all floods (fluvial plus coastal)

Countries	Changes in value at risk due to coastal floods, 2010-2050		Changes in value at risk due to fluvial and coastal floods, 2010-2050	
	Without distance decay	With distance decay	Without distance decay	With distance decay
OECD	124%	123%	128%	129%
BRIICS	626%	648%	643%	661%
RoW	416%	403%	437%	447%
Globally	317%	286%	343%	338%

Table 9.6
Share of value at risk of coastal floods (value at risk as a percentage of GDP for identical areas)

Region	Without distance decay		With distance decay	
	Part of total in 2010	Part of total in 2050	Part of total in 2010	Part of total in 2050
OECD	13%	12%	8%	8%
BRIICS	11%	13%	5%	6%
RoW	17%	18%	10%	10%
Globally	13%	14%	8%	7%

Thus far, all calculations were for absolute numbers (Figure 9.3). These results can also be expressed relative to the total population of each region (OECD, BRIICS or RoW) in 2010 and projected for 2050. See Table 9.6 for coastal floods. The table shows that percentages for different years and for different regions are close. The use of a distance decay function halves the percentages.

The finding that the percentages in Table 9.6 are very alike for the years 2010 and 2050, is not unexpected: the changes in value at risk, first calculated on a fine grid and aggregated afterwards, resemble the changes in GDP, all other factors being constant.

9.4 Cities most vulnerable to floods

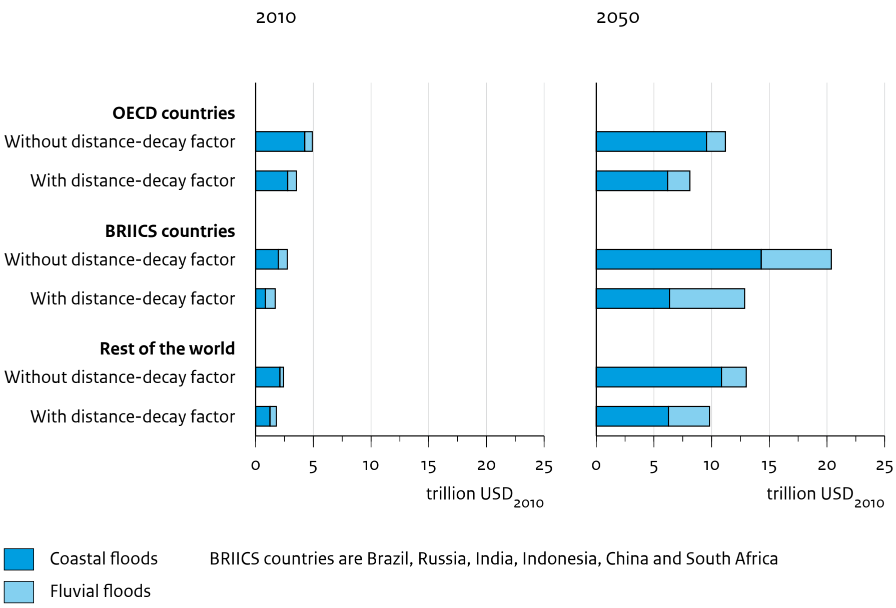
Cities most vulnerable to floods are defined as cities for which the impact of a flood is high and which have a low adaptive capacity. The same data sets as mentioned in Sections 9.2 and 9.3 were used. As a consequence, the vulnerability is based on two indicators only: population at risk and GDP per capita. For a more robust vulnerability analysis, more indicators, such as government effectiveness and education, should be included. Here, vulnerability is defined as the sensitivity to floods in combination with the possibility to be able to cope with the thread of floods now and in the future (coping - adaptive capacity). Given the data one can state that the higher the people at risk, the higher the sensitivity and the lower the GDP, the lower the adaptive capacity, hence the higher the vulnerability.

To calculate the sensitivity, the results for the population at risk, on the 30 arc second spatial level, were aggregated to the 0.5 degree level, for technical reasons. All cells were then ranked from 0 to 1 using the absolute value of people at risk by a maximum–minimum ranking method. The highest value for people at risk was ranked as 1.

For the adaptive capacity GDP per capita was used for individual countries. These data were available at the 0.5 degree spatial scale. Countries were ranked using the same ranking method as the population at risk with one difference: the lowest GDP per capita is ranked 1. Cities 'inherit' the GDP rank of the country. Both ranking results were summed. Then, the result was combined with a world city map given as point data. Cities most vulnerable to floods have a high score on the combination of the rankings. Finally, cities with a population of more than 1 million inhabitants were selected. This selection was made because, by combining the city point data, cities inherit the population at risk of a 0.5 by 0.5 degree cell, which represents the urban area more than point data do.

Again two different model runs for flood-prone areas were applied for the years 2010 and 2050 (with and without decay for coastal flood spreading). This resulted in four ranking lists for each year (Table 9.7).

Figure 9.3
GDP at risk, due to floods



Source: PBL

Table 9.7
Eight different overlays

	Vulnerable cities 2010	Vulnerable cities 2050
Coastal floods 5m, without distance decay	X	X
Coastal floods 5m, with distance decay	X	X
All floods 5m, without distance decay	X	X
All floods 5m, with distance decay	X	X

The ranking lists for 2010 and 2050 are given in Table 9.8 and are calculated for fluvial and coastal floods combined. The table shows that all of the most vulnerable cities at risk in the top 10 are located in Southeast Asia, despite the enormous economic growth in this region. Most of them are coastal cities (Figure 2.4).

9.5 Conclusions

In this chapter, an analysis is given of ‘people at risk’ and ‘value at risk’ for the near future. The analysis relates to fluvial and coastal flooding on a global scale. For the impact of coastal floods, two variants were introduced: with and without a distance-decay function of 30 centimetres per kilometre from the coast. Two important assumptions were made; climate change as well as changes in vulnerability (adaptation, political stability) were taken to be stable over the 2010–2050 period. Furthermore, GDP-PPP per capita was used as an approximation for assets at risk (denoted as ‘value at risk’).

For ‘people at risk’, the lowest numbers were found for the OECD countries, where most of the risk would be from coastal floods. This conclusion holds for 2010 as well as 2050.
The numbers of people at risk in BRIICS and RoW countries are comparable and the ratio between the influence of fluvial floods and coastal floods is around 50%. Not surprisingly, the number of people at risk are

Table 9.8
Top 10 of vulnerable cities in 2010, ordered from most to least vulnerable

Top 10 of vulnerable cities in 2010		Top 10 of vulnerable cities in 2050	
Without distance decay	**With distance decay**	**Without distance decay**	**With distance decay**
Dhaka	Dhaka	Kolkata	Dhaka
Kolkata	Mumbai	Mumbai	Mumbai
Shanghai	Bangkok	Dhaka	Bangkok
Guangzhou	Wuhan	Shanghai	Wuhan
Mumbai	Guangzhou	Guangzhou	Jakarta
Jakarta	Jakarta	Jakarta	Khulna
Bangkok	Khulna	Bangkok	Guangzhou
Wuhan	Manila	Ho Chi Minh City	Manila
Tianjin	Ho Chi Minh City	Manila	Patna
Ho Chi Minh City	Patna	Wuhan	Ho Chi Minh City

higher if no distance-decay function is assumed since inundated areas are larger. If people at risk numbers are compared between the years 2010 and 2050, it was found the lowest percentages are for OECD countries: around 9%. Changes for BRIICS and RoW countries lie much higher: around 37% and 55%, respectively (these percentages depend only slightly on the decay function chosen).

As for 'value at risk' it was found that highest numbers are for the OECD countries in 2010. However, by the year 2050 numbers have switched: OECD countries show the lowest numbers. Value at risk in BRIICS and RoW countries is comparable, although for BRIICS countries it is somewhat higher. For all regions 'value at risk' is dominated by coastal flooding. Again not surprisingly, the value at risk numbers are higher if no distance-decay function is assumed since inundated areas are larger. If value at risk numbers are compared between the years 2010 and 2050, it is found the lowest percentages are found for OECD countries: around 125%. Changes for BRIICS and RoW countries lie again much higher: around 650% and 430%, respectively (percentages depend only slightly on the decay function chosen).

Calculations for cities most vulnerable to floods, show that ranking lists are reasonable insensitive for the distance decay function chosen or the specific year (2010 to 2050). Most vulnerable cities were located in coastal zones and predominantly in Southeast Asia. The top-10 list for 2050 is (from most vulnerable to least vulnerable): Dhaka, Mumbai, Bangkok, Wuhan, Jakarta, Khulna, Guangzhou, Manila, Patna and Ho Chi Minh City. If 'distance decay' is ignored, the cities Kokata and Shanghai should be added.

TEN

Conclusions and outlook

10.1 Summary and conclusions

As part of the OECD Environmental Outlook to 2050 (2012), weather-related disasters and their impacts were analysed, based on disaster statistics from the CRED database EM-DAT. This database allows multiple analyses to be made:

- Analyses can be made for countries or regions. For this report, three regions were chosen, in addition to a global analysis: OECD, BRIICS and RoW countries (Figure 10.1).
- Three indicators of disaster burden can be chosen: direct economic losses, number of people killed and number of people affected.
- Four disaster types can be chosen: meteorological disasters (tropical and extra-tropical storms, local storms), hydrological disasters (coastal and fluvial floods), climatological disasters (droughts, temperature extremes, such as heatwaves), and geophysical disasters (earthquakes, volcano eruptions and tsunamis). The first three types are referred to as 'weather-related disasters', all four are also 'natural disasters'.

Four items have been addressed related to regional and global disaster burden. First, global and regional disaster burden has been derived, computed as averages over the historical period from 1980 to 2010 (Chapter 4 and Section 3.1). Second, trends in disaster burden have derived over the same period (economic losses, number of people affected and number of people killed (Chapter 5 and Section 3.2). Third, explanations for trend patterns have been discussed given in Chapter 6. Explaining factors are: (changes in) wealth, population, climate and vulnerability. Next to that, pitfalls in explaining disasters and disasters patterns have been described in Chapter 7. Finally, a summary has been given of the available literature as for future disaster burden (Chapter 8). A PBL study for global floods and their impacts has been described in Chapter 9. The study covers the range 2010-2050.

The following conclusions have been drawn:

Disaster burden (1980-2010):

- For the global spreading of disaster burden it is found that disaster burden indicators appear to differ as for their disaster origin: (i) economic losses are mainly due to meteorological disasters (52% of global total), (ii) the number of people affected are mainly due hydrological disasters (63% of global total), and (iii) the number of people killed are mainly due to climatological disasters (56% of global total).
- If geophysical disasters are included, these percentages change for the number of people killed. If the total number people killed due to all natural disasters is set to 100%, 40% comes from geophysical disasters, followed by 33% due to climatological disasters, 7% due to hydrological disasters and 19% due to meteorological disasters.
- Weather-related disaster burden strongly depends on the region chosen. The following characteristic pattern

Figure 10.1

Source: Economic Cooperation Administration

The OECD was founded in 1948 as the Organisation for European Economic Co-operation (OEEC). The OEEC helped to administer the Marshall Plan for the reconstruction of Europe after World War II. This poster was distributed to promote the Marshall plan. The OECD was founded in 1961 and at that time consisted of 20 member countries (Canada, France, Germany, the Netherlands and the United States, to name a few). The OECD in its present form consists of 34 member countries.

is found: (i) highest economic losses occur in the OECD countries (63% of global total), highest numbers of people affected occur in the BRIICS countries (84% of global total), and highest numbers of people killed occur in the Rest of World (77% of global total). This characteristic pattern is also found for meteorological and climatological disasters. The only exception is found for the group of hydrological disasters. Here, all highest disaster-burden percentages are found for the BRIICS countries.

- Explanations for these findings have been discussed. OECD countries are among the richest countries. Hydrological disasters lead to the highest number of people affected and these disasters occur

Table 10.1
Summary of disaster trends, 1980–2010, estimated for the OECD, BRIICS and RoW countries

Region	Economic losses		Number of people killed		Number of people affected		Number of disasters
	μ_{2010}/μ_{1980}	pattern	μ_{2010}/μ_{1980}	pattern	μ_{2010}/μ_{1980}	pattern	pattern
OECD	4.4 [1.8 – 10.9]	increase	NA	NA	NA	NA	linear increase
BRIICS	7.1 [2.7 – 18.9]	increase and stabilisation	NA	NA	7.7 [2.2 – 28.2]	increase and stabili-sation	linear increase
RoW	1.0	stable	NA	NA	1.0	stable	linear increase
Globally	3.8 [2.0 – 7.5]	increase and stabili-sation	NA	NA	4.1 [1.5 – 11.4]	increase and stabili-sation	linear increase

NB Also global trend characteristics are given. 'NA' stands for 'not available' (i.e., no satisfactory IRW trend could be estimated).

predominantly in the BRIICS countries. RoW countries are among the poorest countries. Also political instabilities are highest for this group of countries (e.g., the horn of Africa).

Trends in disaster burden (1980-2010):

- Results for trends in disaster burden show seemingly contradictory results. On the one hand burden has increased enormously over the 1980–2010 period (statistically significant in all cases). For example, economic losses in the OECD countries increased by a factor of 4.4. On the other hand, all but one trend pattern shows that the disaster burden increased over the first half of the sample period (1980–1995) and stabilised thereafter. The only indicator with an increasing pattern over the whole sample period is that of economic losses in the OECD countries. Details are given in Table 10.1.
- The analysis of the number of people killed showed that these data are dominated by a small number of extreme number of people killed. Trend analysis yielded unsatisfactory results for these data ('NA' in Table 10.1 and Figure 5.3). The data suggest a stabilisation for all regions (indicative).
- The pattern of the number of weather-related disasters appears to be linear increasing for all cases. This pattern deviates from those found for disaster burden. An explanation may be that that the number of all disasters indeed increases linearly. However, the number of most *severe* disasters stabilises around 1990 and decrease thereafter (Visser and Petersen, 2012, Figure 7B). It is to be expected that the largest proportion of disaster burden will be due to these severest disasters.

Explaining trends in disaster burden:

- Trend patterns in disaster burden are not easy to explain since these patterns are governed by four factors: (i) changes in wealth, (ii) changes in population numbers, (iii) changes in intensity or frequency of extreme weather events and (iv) changes in vulnerability. Since these factors are interwoven, changes cannot be pinpointed to one specific factor. For example, a direct coupling of severe disasters to climate change should be avoided.
- Disaster burden indicators have been filtered for changes in wealth or population through the method of normalisation. All trends in economic losses and in the number of people affected were found to stabilise after normalisation (between 1980 and 2010). These findings are in line with those published by Neumayer and Barthel (2011).
- Changes in intensity or frequency of extreme weather events are the drivers for weather-related disaster burden. Historical patterns are summarised in IPCC-SREX (2012). Results show that trends in the drivers which lead to the highest disaster burden numbers (storms and floods) show patterns which tend to be more or less stable over time (no or weak indications for increasing trends). These findings are consistent with the normalisation conclusion given above.
- The role of (changes in) vulnerability is difficult to quantify. Two counteracting factors play a role: positive influences by adaptation, negative influences by poverty and/or political instabilities.
- Disasters, disaster burden and their causes are sometimes presented suggestively in the media. Examples often encountered, are the direct coupling of disasters to climate change. Other examples deal with the way trends are estimated in data, or the choice of longer sample periods which might suggest enormous increments in disaster burden. Disaster data before the year 1980 should be handled with care.

Future disaster burden

- Studies on disaster burden for the (near) future are limited thus far. A simple approach has been given based on projected trends in the four factors which steer disaster burden: wealth, population growth, climate change and changes in vulnerability. Projections for the first factor, GDP, show a strong increase for many regions in the world. The same holds for a growing world population. Both factors will aggravate disaster burden, other factors being constant. These projections are based on the OECD baseline scenario.
- For climate change it has been found that climatological disasters are expected to increase (heatwaves, droughts), while such changes are unclear for meteorological disasters (storms). Model projections show a likely increase for hydrological disasters (floods). These increases are more likely for coastal floods than for river floods (due to projected sea level rise). These projections are taken from IPCC-SREX (2012).
- No studies have been found which give projections for changes in vulnerability. That holds for the two components of vulnerability: adaptation and political stability.
- Results from a PBL study were given for 'people at risk' and 'value at risk' in the near future. This study was directed to fluvial and coastal flooding on a global scale. For the impact of coastal floods, two variants were introduced: with and without a distance-decay function of 30 cm per km from the coast. As for 'people at risk' it is found that lowest numbers are found for the OECD countries where numbers are dominated by coastal floods. This conclusion holds for 2010 and 2050. Numbers of people at risk in BRIICS and RoW countries are comparable and the ratio between the influence of fluvial floods and coastal floods is around 50%. If 'people at risk' numbers are compared between 2010 and 2050 it is found the lowest percentages are found for OECD countries: around 9%. Changes for BRIICS and RoW countries lie around 37% and 55%, respectively.
- As for 'value at risk' it was found that highest numbers are for the OECD countries in 2010. However, by the year 2050 numbers have switched: OECD countries show the lowest numbers Value at risk in BRIICS and RoW countries is comparable, although for BRIICS countries it is somewhat higher. For all regions value at risk is dominated by coastal flooding. If 'value at risk' numbers are compared between 2010 and 2050 it is found the lowest percentages are for OECD countries: around 125%. Changes for BRIICS and RoW countries lie around 650% and 430%.
- Calculations for cities most vulnerable to floods, show that most vulnerable cities were located in coastal zones and predominantly in Southeast Asia. The top-10 list for 2050 is: Dhaka, Mumbai, Bangkok, Wuhan, Jakarta, Khulna, Guangzhou, Manila, Patna and Ho Chi Minh City. If the so-called 'distance decay function' is ignored, the cities Kokata and Shanghai should be added to this list.

10.2 Future research

Disaster statistics for countries and regions

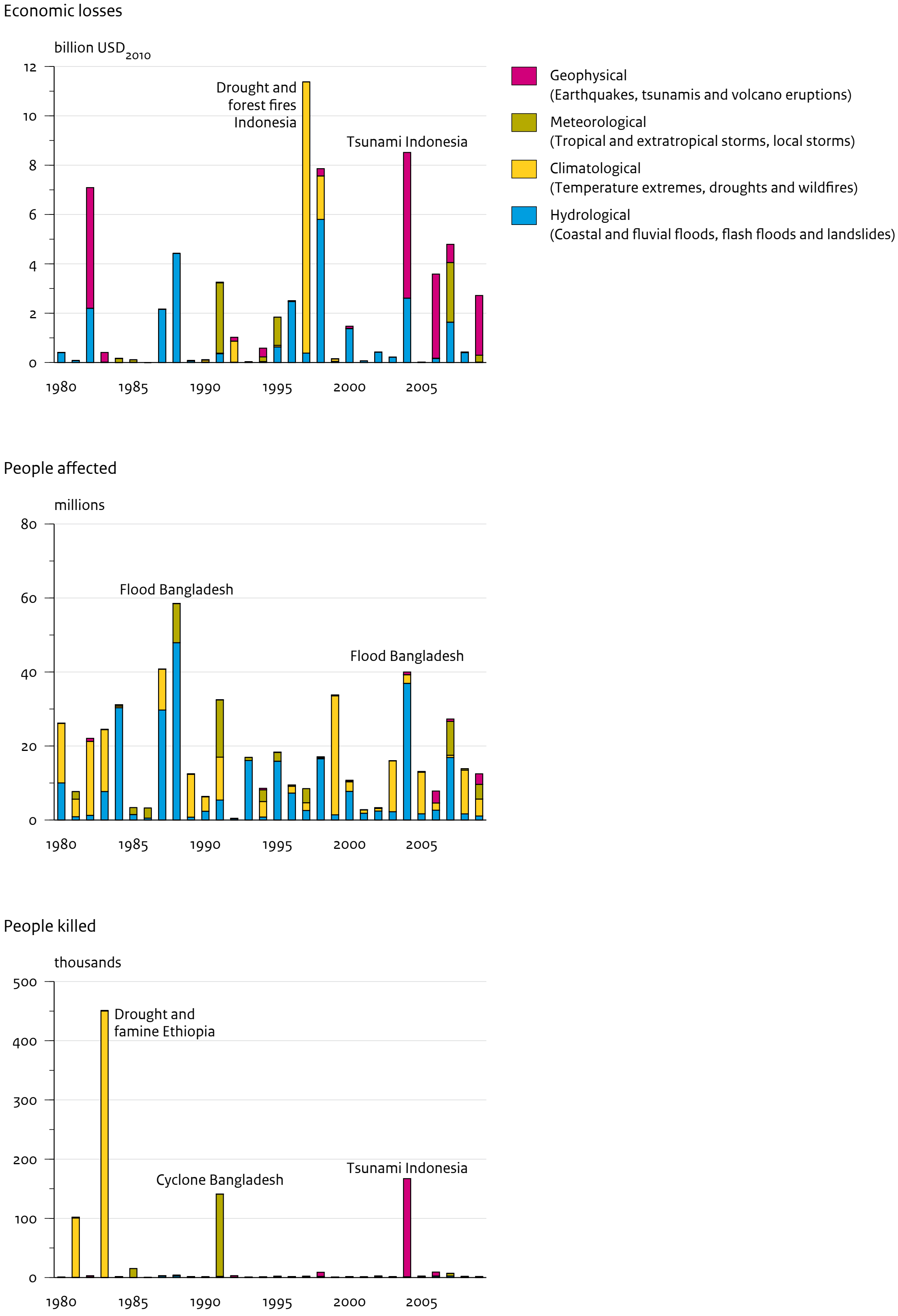
Disaster statistics in this report were calculated on a regional and global scale. However, the CRED database EM-DAT allows analyses to be made on either country scale or for any region derived for any group of countries. Therefore, the CRED database could be used for many other projects and studies (CRED, 2011a). For example, disaster-burden calculations can be performed for EU countries (EEA, 2011) or any individual countries, such as India or China. For countries where extreme emergencies occur, such as in a number of African countries, the CRED database CE-DAT can be of great value (CRED, 2011b).

One potential study could deal with so-called partner countries of the Dutch Directorate General for International Cooperation (DGIS). Partner countries are countries with which the Netherlands has a bilateral development relationship. Since 2011, the Dutch Government has reduced the number of partner countries from 33 to 15. In the process of selecting such partner countries, the government considers five factors: the prospects for achieving the best results, income and poverty levels, the possibilities of progress in the priority areas, the opportunities and interests of the ministries most closely involved, and the quality of governance.

The 15 current partner countries are: Afghanistan, Bangladesh, Benin, Burundi, Ethiopia, Ghana, Indonesia, Kenya, Mali, Mozambique, the Palestinian Territories, Rwanda, Sudan, Uganda and Yemen. Temporary assistance for a transition from development cooperation towards economic cooperation will go to three countries: Colombia, Vietnam, and South Africa. See http://www.minbuza.nl/en/key-topics/development-cooperation/partner-countries/partner-countries.html for more information.

Knowledge about disaster threats for these selected countries could help to set priorities for individual countries. As an example, the CRED database EM-DAT was analysed for the 15 DGIS countries. Results are shown in Figure 10.2. Three types of disaster burden are indicated: number of people affected (upper panel), number of people killed (middle panel) and economic losses (lower panel). Disasters with large impacts are indicated by catchwords in these graphs. In addition,

Figure 10.2
Natural disaster statistics for 15 DGIS partner countries



Source: PBL

Severe disasters are highlighted by catchwords.

statistical information from the CRED emergency database CE-DAT could be informative.

A new global model on floods; the road ahead

The change in population and value at risk as well as the change in ranking in vulnerable cities between 2010 and 2050, given in Chapter 9, was only a function of changes in population and GDP. Climate change, resulting in a change in the frequency and/or intensity of floods, was not taken into account. The flood map was static, and more importantly, the flood map used did not take into account the actual risk of floods as it had no return period and no water depth in it. However, people living at flooded areas may get 'wet feet' only, or they might drown due enormous amounts of water. In Chapter 9 no distinction was made between the two situations, while there will be a huge difference in consequences. Furthermore, 'wet feet' may be a problem, but it can be an advantage too. A regular moderate flood keeps the soil fertile.

PBL collaborates with Deltares (Dutch institute for applied research in the fields of water, subsurface and infrastructure) and Utrecht University in developing a new model for flood risks at a global level, based on the hydrological model PCRaster-Global Water Balance (PCR-GLOBWB) (Van Beek and Bierkens, 2008) and data from the Dynamic Interactive Vulnerability Assessment tool (DIVA)[1] for coastal floods. This new model is linking PCR-GLOBWB to the Integrated Model to Assess the Global Environment (IMAGE) (MNP, 2006). PCR-GLOBWB is a global distributed hydrological model running at a 0.5 × 0.5 degree, daily resolution. PCR-GLOBWB has been designed with particular attention to modelling of groundwater, base flow, (sub)surface runoff processes and river discharge. The outputs of a dynamic routing module are used to estimate flood exposure. IMAGE is an ecological-environmental framework that simulates the environmental consequences of human activities worldwide on a 0.5 × 0.5 degree scale. It represents interactions between society, the biosphere and the climate system to assess sustainability issues , such as climate change, biodiversity and human well-being. See Winsemius (2011) for more information.

By combining the two models, scenario information on change of flood exposure as well as population and GDP will generate flood impact indicators at a global scale. The model will be able to translate floods to potential victims and damage. Victim and damage functions that make use of return periods and water depths of floods, will be part of the model. Thus, the effects of climate change and adaptation measures on victims and damage caused by floods can be analysed more realistically.

Note

1 DIVA covers all 180+ coastal nations in 12,148 coastal segments at national, regional, and global scales including storm surges with a S1, S10, S100 and S1000 return period.

Glossary

Adaptation: In human systems, this refers to the process of adjustment to actual or expected climate and its effects, in order to reduce harm or exploit beneficial opportunities. In natural systems, the process of adjustment to actual climate and its effects; human intervention may facilitate adjustment to expected climate.

Climate change: A change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, which persist for an extended period of time, typically for decades or more. Climate change may be due to natural internal processes or external forcings, or to persistent anthropogenic changes in the composition of the atmosphere or type of land use.

Disaster: Severe alterations in the normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic, or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery. CRED registers a disaster in EM-DAT if one or more of the following criteria are met: (i) 10 or more people are reported killed, (ii) 100 people or more are reported to be affected, (iii) a declaration of a state of emergency has been declared, (iv) a call for international support has been send out.

Disaster risk: The likelihood over a specified time period of severe alterations in the normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic, or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery.

Disaster risk management: Processes for designing, implementing, and evaluating strategies, policies, and measures to improve the understanding of disaster risk, foster disaster risk reduction, and transfer and promote continuous improvement in disaster preparedness, response, and recovery practices, with the explicit purpose of increasing human security, well-being, quality of life, resilience, and sustainable development.

Disaster burden: The CRED database EM-DAT discerns three types of disaster burdens: economic losses, people killed and people affected.

Disaster severity classes: The severity of disasters has been classified by Munich Re into seven categories: '0' (natural event)= no damage, no fatalities; '1' (small-scale loss event)= small-scale damage and/or 0-9 fatalities; '2' (moderate loss event)= moderate damage and/or >10 fatalities; '3' (severe disaster)= damage > USD[1] 60 and/or >20 fatalities; '4' (major disaster)= damage >USD[16] 250 and/or >100 fatalities; '5' (devastating disaster)= damage > USD[16] 650 and/or >500 fatalities; '6' (great disaster) region's ability to help itself clearly overtaxed, interregional/international assistance necessary, thousands of fatalities and/or hundreds of thousands of people homeless, substantial economic losses.

Economic losses: Losses throughout this report refer to the immediate costs of damage and are the direct consequence of weather or climate events. Costs consist of the costing of all physical impacts: on the lives and health of people directly affected, on all types of tangible assets including private dwellings, agriculture, commercial and industrial stocks and facilities, on infrastructure (roads, bridges, ports, water supply, telecommunication), and natural resources. Secondary or consequential impacts are not included. Note that impacts such as loss of lives, cultural heritage and ecosystem services are not included in economic losses, since they are difficult to quantify in terms of monetary value.

Exposure: the presence of people, livelihoods, environmental services and resources, infrastructure, and economic, social and cultural assets in areas or places that are subject to the occurrence of physical events. They are thereby subject to potential future loss and damage.

Hazard or hazard probability: A hazard refers to the possible (future) occurrence of a natural or human-induced physical event that may have adverse effects on vulnerable and exposed elements. Note that a hazard is only one part of disaster risk: vulnerability and exposure are also important factors.

People affected: Sum of people injured, people needing immediate assistance by way of shelter, and people requiring immediate assistance during a period of emergency (this may include displaced or evacuated people).

People killed: Number of people confirmed dead and/or missing and/or presumed dead.

Vulnerability: the susceptibility or predisposition for loss and damage to human beings and their livelihoods, as well as their physical, social, and economic support systems when affected by hazardous physical events. Vulnerability includes the characteristics of a person or group of people and their situation that influences their capacity to anticipate, cope with, resist, respond to, and recover from the impact of a physical event.

Weather extremes: The occurrence of a value of a variable related to weather or climate which is above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable. For the sake of simplicity, extreme weather events and extreme climate events are referred to in this report, collectively, as 'weather extremes'.

Source definitions: CRED (2011), Munich Re (their website), and IPCC-SREX (2012).

Note

1 In 2010 US dollars (x million).

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Appendices

Appendix A Disaster databases and uncertainties

As described in Section 2.2, the CRED database EM-DAT is the main source of data in this report. Since the quality of the analyses is as good as the quality of the underlying data, below a number of uncertainties attached to the use of EM-DAT (and other databases) is briefly addressed. These uncertainties relate to three issues: (i) the role of 'reporting bias', (ii) disaster data compared across differing databases, and (iii) definition issues.

Reporting bias
Reporting bias is an important source of uncertainty. Reporting bias is the phenomenon that the number of disasters that are coded in a database increases over time. This phenomenon is not only due to an increasing population, increasing wealth or climate change (cf. Figure 6.1), but is also influenced by the effect that sources of disaster reporting become sparse further back in time. An illustration of reporting bias is given in Figure 2.3. We checked the disasters reported for the Netherlands in EM-DAT and compared these data to a detailed overview of disasters in Buisman (2011). This showed that data on all disasters before 1950 were absent, while all disasters after 1950 were correctly reported.

Figure A.1 shows a graphic representation of reporting sources as a function of time (1974–2002), redrawn from Guha-Sapir et al. (2004). The graph shows some abrupt changes in the sources used. For example, the use of special agencies strongly rises after the year 1997. The total number of disasters (all severity classes, black curve) suggests an exponential increase in the number of disasters. CRED advises to use data from their database from 1980 onwards, although the database was started as early as in 1901 (cf. Figure 7.3).

We followed the CRED advice for this report. However, we also took a second measure to rule out reporting bias, as much as possible. We only selected major disasters, that is, disasters in the severity classes 4, 5 and 6, following the definitions of Munich Re (see Glossary). The idea is that the more severe disasters would have been reported by many sources, even in the 1970s and 1980s.

Nevertheless, we cannot be perfectly sure that reporting bias is absent from our analyses. However, we have diminished its influence considerately. For our study, any effect of reporting bias on disaster burdens is considered minimal: the contribution of disasters of the classes 1, 2 and 3 to economic losses, people killed and people affected was relatively small.

It should be noted that the rising trend in Figure A.1 is partly explained by increases in population and wealth over the same period. Since the definition of disasters includes a threshold for damage and number of fatalities, the number of disasters in the severity classes 1 and higher will increase due to these two factors.

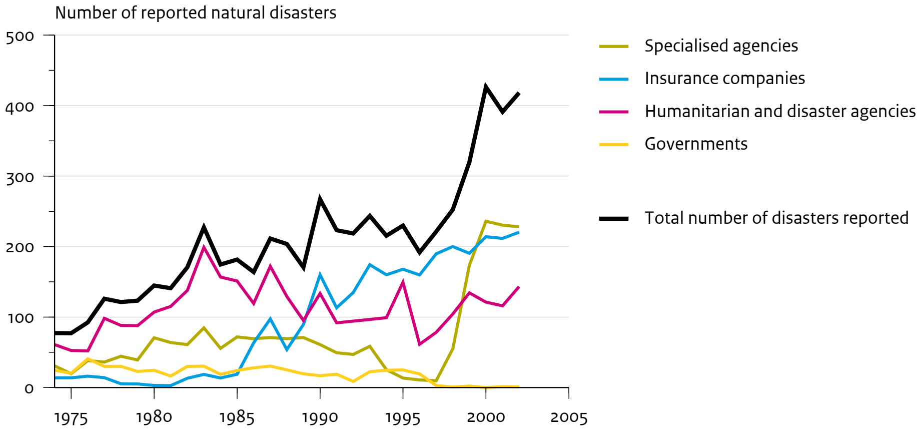
Disaster data compared across databases
One way of checking the reliability of the EM-DAT database is by comparing it to other databases. This has been done by Guha-Sapir and Below (2002). They compared EM-DAT to two commercial databases: NatCat, maintained by Munich Re, and Sigma, maintained by Swiss Re. The comparison of databases was found to be less than easy. Each institute uses its own definitions, disaster thresholds and geographical units. The same conclusion was drawn by Gall et al. (2009) who compared four databases for economic losses (EM-DAT, NATHAN, SHELDUS and Storm Events).

Despite these differences, global loss data from EM-DAT and NatCat compare reasonable well (Munich Re). For global loss data over the 1980–2009 period, a good correspondence was found, see Figure A.2. The correlation between both loss series is R=0.94 which is reasonably good.

It should be noted that the strength of the result shown in Figure A.2 depends on the mutual dependence of the databases. If both institutions gather their data independently, it is a strong result. If they cooperate, comparable results are less surprising. Unfortunately, we are uncertain about the extent of the cooperation between CRED and Munich Re, although we know that they do cooperate, to a certain degree.

We realise that the uncertainty inferences described above do not represent a full uncertainty analysis for the CRED database. For example, we do not have detailed

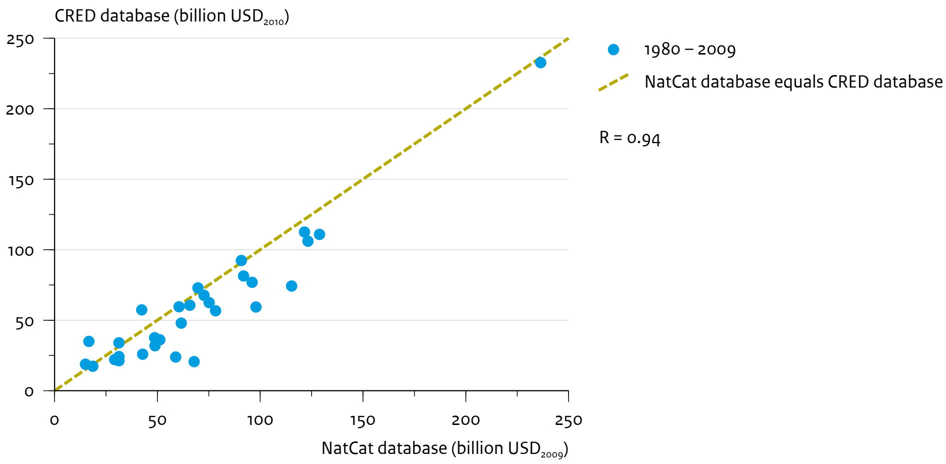
Figure A.1
Sources reporting data on natural disasters to EM-DAT



Source: PBL

Example of bias due to reporting intensity over time. The number of natural disasters seems to grow exponentially over the 1974–2002 period (black line). However. the contribution of specialised agencies increases 'explosively' from 1997 onwards, leading to a distortion of the total curve. Source: EM-DAT database. Source: Guha-Sapir et al. (2004), used with permission.

Figure A.2
Global economic losses due to weather-related disasters, according to CRED and NatCat databases



Source: PBL

confidence limits for any disaster burden caused by disaster 'x' in country 'y'. Our reasoning is more of a circumferential nature: CRED is a highly esteemed database, its data are applied in many reports and articles, and it seems to compare well to other databases.

Definition issues

There are four issues worth mentioning on the use of the CRED database.

First, the loss data in EM-DAT are direct losses. Direct losses reflect damages to public infrastructure, buildings, machinery, or crops. In the case of complete destruction, direct losses are often equivalent to the replacement costs of the structure. However, there are also indirect costs. Indirect loss is a loosely applied concept in the literature; it captures anything from economic losses associated with lost revenue, business closures, lost income to societal losses (e.g. lost cultural assets and memorabilia, stress, depression, trauma), or environmental damages (e.g. loss of species and habitat, ecosystem services). Thus, the losses presented in this report are only a fraction of the total losses generated by a specific disaster (Gall et al., 2009).

Second, one specific disaster may hit several countries. In such a case, one specific disaster is spread over more than one record in EM-DAT. Thus, graphs as shown in Figure 3.2D or 5.4 may contain disasters which are double or triple. Note that disaster burden statistics are not influenced here.

Third, the definition of disaster type (climatological, hydrological or meteorological) is not unambiguous in all cases. For example, hurricane Katrina was categorised in EM-DAT as a meteorological disaster. However, much of the disaster burden was due to flooding, which is a hydrological disaster. CRED does not apply a kind of 'fuzzy attribution' where a disaster could belong to two disaster types.

Fourth, the geographical attribution of a disaster may become complicated if countries fall apart. A recent example is the division of Sudan into Sudan and South Sudan. Other examples are the former Sovjet Union, Yugoslavia and Czecho-Slovakia. As long as analyses aggregate over regions which contain the larger countries, no uncertainties occur in disaster burden statistics. However, care should be taken to aggregate disaster burden using both old and new country names.

Appendix B Normalisation

Disaster burden for pre-defined regions can be expressed in several ways. Here, a number of methods from the literature are summarised for disaster losses. Different correction methods are denoted by the term 'normalisation'. For more details the reader is referred to Neumayer and Barthel (2011, Sections 2, 3 and 4). Normalisation for the number of people affected or the number of people killed are also given.

The CRED database EM-DAT contains losses for individual disasters on a country level and expressed in dollars for the year the disaster occurred. If the loss due to a disaster 'i' in a certain region is denoted by $L_{i,t}$, with t the year of disaster occurrence, the total disaster loss in year t is simply gained by adding all losses in that region:

$$L_t = \sum_{i=1}^{N} L_{i,t} \tag{1}$$

The disadvantage of using L_t is that losses cannot be compared due to inflation over time. Therefore, disaster losses used in this report were corrected for inflation. The base year for correction is 2010:

$$L_t^{2010} = L_t * \frac{GDP\ deflator\ 2010}{GDP\ deflator\ t} \equiv L_{1,t} \tag{2}$$

These inflation corrected losses $L_{1,t}$ were used in Chapters 3, 4 and 5. The unity of $L_{1,t}$ is denoted as 'USD_{2010}'.

Next to an inflation correction, losses can be corrected for changes in wealth in the region over time: a disaster with a certain loss x will have a much higher impact in a historical year when wealth was low, than in a more recent year for which wealth has risen. To correct for changes in wealth, losses can be corrected as follows:

$$L_{2,t} \equiv L_{1,t} * \frac{Wealth\ in\ 2010}{Wealth\ in\ year\, t} \approx L_{1,t} * \frac{GDP_{2010}}{GDP_t^{2010}} \tag{3}$$

In Equation (3) wealth has been replaced by the GDP in that region because 'wealth' in a country or region is often unknown while GDP information is available in many instances. Certainly, GDP and wealth are not the same: the first is a flow, the second a stock. However, if it is assumed that GDP and wealth are equal, apart from some constant α, it can be seen from (3) that this constant will disappear due to the GDP ratio taken.

The correction given in (3) is known as the traditional approach for normalising disaster losses (Neumayer and Barthel, 2011, and references therein). This approach is attractive since it adjusts past disaster damage for changes in wealth, to make them comparable to absolute contemporaneous disaster damage. In other words, past disasters would have caused more damage had they hit the same region today, and normalisation accounts for the fact that most places have become wealthier over time.

Neumayer and Barthel argue that the traditional normalisation approach has the advantage of making disaster losses comparable over time for the same region. However, different regions will have different levels of wealth. Thus, the impact of a disaster with losses x may have a marginal impact on the economy in a wealthy region, while it has a huge impact in poor countries. They propose the following normalisation method to correct for that:

$$L_{3,t} \equiv \frac{Loss\ in\ year\ t}{Wealth\ in\ year\ t} = \frac{L_{1,t}}{Wealth_t^{2010}} \approx \frac{L_{1,t}}{GDP_t^{2010}} \tag{4}$$

Since (4) relates losses to wealth (GDP) the indicator $L_{3,t}$ allows one to compare the impact of disasters across countries or regions.

A disadvantage of $L_{3,t}$, compared to $L_{2,t}$, is that the substitution of GDP for 'wealth' may lead to a certain distortion of results: a country or region may be very wealthy but still have a relatively low GDP. The indicator $L_{i,3}$ is also denoted as an Actual-to-Potential-Loss-Ratio (APLR). Since $L_{2,t}$ and $L_{3,t}$ have advantages and disadvantages, Neumayer and Barthel (2011) analyse global and regional disaster losses both ways and discuss differences in loss calculations (Figures 3 to 7).

In the same way the number of people affected could be normalised for temporal and spatial differences. Thus, if the total number of people affected in a region is defined as

$$A_{1,t} \equiv \sum_{i=1}^{N} A_{i,t} \tag{5}$$

normalisations can be made by defining

$$A_{2,t} \equiv A_{1,t} * \frac{Population\ in\ 2010}{Population\ in\ the\ year\ t} \tag{6}$$

or

$$A_{3,t} \equiv \frac{A_{1,t}}{Population\ in\ the\ year\ t} \tag{7}$$

In the ideal case the indicators $L_{2,t}$, $L_{3,t}$, $A_{2,t}$ and $A_{3,t}$ should be calculated for small regions or countries. However, the

CRED database EM-DAT does not contain population and GDP data on individual countries or individual years. Therefore, normalised indicators were calculated in this report rather crudely by using population and GDP data on the country-aggregated regions of OECD, BRIICS and RoW countries (Figure 2.2).

Appendix C Construction of future flooding impact maps in detail

Flood maps

For the exposure to floods existing data were used (see Section 2.3) presenting flood- prone areas. For the analyses of people and economic value at risk due to floods for the year 2010 as well as for the year 2050 the same flood map was used. Furthermore the Dartmouth database is a collection of floods in the past that really happened between 1985 and 2010. Most floods were mapped, but not all. Also floods before 1985 were not mapped. But by using the floodplains of the GLWD this problem could be overcome. It should be noted that the GLWD might exaggerate potential floods because freshwater marches is in the same class as the floodplains.

Population and GDP maps

Similar to scaling up the flood data, the spatial information on population and Gross Domestic Product (GDP) had to be scaled down. The data about population and GDP are derived from the Global Integrated Sustainability Model[1] (GISMO), which is related to IMAGE. The GISMO population data is available on a 0.5 by 0.5 degrees spatial level. The GDP data is available on a national spatial level but technical stored on 0.5 by 0.5 degrees. Population data is divided into urban and rural population data, for 2010 and 2050. The GDP is based on the purchasing power parity (PPP). The GDP-PPP is used as an approximation for the value of goods at a certain location (grid cell). In order to combine the population with the more detailed flooding data, the GISMO results were further scaled down from 0.5 by 0.5 degrees to 30 by 30 arc seconds (one cell of 0.5 degrees contains 3600 cells of 30 arc seconds).

A linear downscaling technique was used. Three data sets made the downscaling possible: (i) the Landscan 2007 population data set which counts the population on a spatial scale of 30 by 30 arc seconds for the whole world, (ii) the CIESIN GPW3: GRUMP urban and rural extent data set which distinguish urban and rural land use, and (iii) GLOBCOVER 2006, the Global Land cover database which was used to not allocate population in bare areas.

Population was allocated and scaled down in three steps. In the first step the urban and rural population was separately scaled down. In this step the Landscan 2007 population data was assigned urban or rural by using the GRUMP urban or rural extent. The GISMO urban population in a certain year could only be allocated at a GRUMP urban extent. For each of the 3600 30 seconds cells within a 0.5 degrees cell, the fraction of urban population was calculated using the Landscan 2007 data. In order to do so the Landscan 2007 data were clipped by the urban areas of GRUMP. The GISMO urban population at the 0.5 degrees scale was spread over the 30 seconds cells using the calculated fractions.

The same action was done for the rural population. The Landscan 2007 population data was clipped by the rural GRUMP extent. Then, the fraction of population within the rural extent on 30 seconds spatial scale within the 0.5 degrees cell was calculated using Landscan. Finally, the GISMO rural population data over a certain year was spread out within a cell of 0.5 degrees using the calculated fraction on the 30 arc seconds spatial scale.

In the second step the 0.5 by 0.5 degrees cells which did not have a GRUMP urban spatial extent but that did have a GISMO-assigned urban population, were scaled down. Because there was no location of urban areas available the urban and rural population for these 0.5 degrees, cells were summed. So, in this step the total population was assigned only using the Landscan 2007 data set. The procedure was identical. Within the remaining 0.5 degrees cells the fraction population in a 30 arc seconds cell was calculated using the Landscan data. The total GISMO population of the 0.5 degrees cell was spread using the fraction at 30 arc seconds. By using the fraction of Landscan population the highly dense population areas (which might be urban) remained highly dense.

In the third and last step the 0.5 by 0.5 degrees cells that did not even have population according to the Landscan data set, but that did have urban or rural population according to GISMO, were assigned. The population was spread evenly in the 30 arc seconds cells. But population was not assigned in 30 arc seconds cells that have a land cover (derived from the globcover 2000 map) classification consisting of bare areas, water bodies or permanent snow and ice. Finally, the totals of the 0.5 degrees cells were checked against the totals of the 30 arc seconds cells within a 0.5 degrees cell. The check was satisfactory.

In the first two steps there will be no population in 30 arc seconds cells where there is no population according to the Landscan data. This means that there is no spread of population. If there is no population in 2007 in a 30 arc seconds cell, there will be no population in the scaled down GISMO population of any year in that specific cell. So, urban expansion was not taken into account.

Concerning the downscaling from cells of 0.5 degrees to cells of 30 arc seconds, the greatest uncertainty is in the assignment of population using fractions based on the

Landscan population 2007. In reality, a cell of 30 arc seconds containing 70% of the population within a 0.5 degrees cell in Landscan 2007, will not necessarily contain 70% of the population in 2050. As a consequence of this method, a 30 arc seconds cell within a 0.5 degrees cell counting 0% population in 2007, will also count 0% population in 2050. That is, especially near cities, not the case in reality. Hence, land use change to urban land use was not included. Also, very dense populated cells were in absolute terms growing faster while in reality maybe less dense cells are in absolute terms growing faster. This implies that urban expansion at locations which are prone to floods were not included in the analysis.

Another uncertainty comes from the GRUMP urban rural extent data. The urban rural extent was about the present situation. It is static: urbanisation is not included. There is also discussion about the definition of urban areas. The GRUMP urban rural extent was chosen because it is available on a detailed (30 arc seconds) scale. The urban extent for some locations is exaggerated (i.e. for the Netherlands). But by using the fractions given by the Landscan data, this over-estimation was adjusted.

The Landscan data on population was chosen instead of the Gridded Population of the World (GPW) on which the GRUMP data set is based. 'The strength of the Landscan database lies in its detailed resolution and the, compared to GPW, advanced modelling used to allocate the population within sub-national administrative boundaries' (Meijer et al. 2006).

There are no global data available on the actual value of buildings, infrastructure and goods. Therefore, GDP was used as an approximation of the value at risk. From GISMO the GDP was available per country. In order to regionalise the GDP purchasing power parity (PPP) per capita was chosen on a national level. Using the GDP per capita made it possible to connect it to the population map. So, the GDP was scaled down and regionalised using the scaled down population data and the purchasing power parity per capita on a national level. This was simply done by multiplying the population by the corresponding PPP. The assumption was that in places where a lot of people live with a high PPP, the value (of buildings, infrastructure and goods) will be high as well. Regional differences within countries were not taken into account. The regional difference in value (GDP) was due to regional difference in population density. It should be noted that this method is an approximation of the value at risk.

Note

1 Http://themasites.pbl.nl/en/themasites/gismo/index.html.

Appendix D Event report for four severe disasters

This appendix gives event reports for four severe disasters:

1. Geophysical event: earthquake and tsunami, Asia and Africa, in 2004.
2. Meteorological event: hurricane Katrina, United States, in 2005.
3. Hydrological event: floods, China, 1998.
4. Climatological event: heatwave, drought and wildfires, Russia, 2010.

These disasters reports have been taken from the Munich Re website on disasters.

Figure D.1
Example of a geophysical disaster

Earthquake and tsunami, South/Southeast Asia and East Africa (26 December 2004)

MR Touch Natur al hazards – Event report

Geo Risk s Research , NatCatSERVICE

Photo: Munich Re

Type of event: Earthquake, tsunami
Date: 26.12.2004

Region affected: Bangladesh, India, Indonesia, Kenya, Madagascar, Malaysia, Maldives, Myanmar, Seychelles, Somalia, Sri Lanka, Tanzania, Thailand

Overall losses: US$ 10,000 m*
Insured losses: US$ 1,000 m*
Fatalities: 220,000

MR catastrophe category: 6

* Original losses

Shortly before the end of 2004, the second strongest earthquake ever recorded produced one of the worst human disaster of recent decades.

Event report
The hypocenter of the 26 December 2004 quake was 10 km deep, about 250 km south of Banda Aceh, a town on the northern tip of Sumatra. With a magnitude of 9.0, it was the second strongest earthquake to have occurred since the beginning of instrumental reco rds at the end of the 19th century. The quake triggered an unexpectedly large sea wave that reached heights of 10 meters in some places.
The area hit by the tsunami extended several thousand kilometers – from Thailand and Malaysia in the east via Sri Lank a, India, and the Maldives to Kenya and Somalia in the west, some 5,000 km from the epicenter. 13 countries in two continents were hit.

Losses
In most areas, victims and losses were restricted to the first one or two kilometers from the coastline. Owing to the coastal region's tourist significance and the end -of-year peak season, the victims came from many parts of the world.

Summary of losses in South/Southeast Asia and East Africa
Coastal regions destroyed over thousands of kilometers, islands flooded and sunken. Fishing villages, tourist centers, petrochemical and chemical plants flooded, damaged/destroyed, Infrastructure destroyed, traffic routes interrupted. Hundreds of thousands of fishing boats capsized, military vessels damaged. Power lines cut, telecommunications and water supply interrupted. Tens of thousands injured, millions affected.

Source: Website Munich Re

Figure D.2

Example of a meteorological disaster

Hurricane Katrina, United States (25–30 August 2005)

MR Touch Natur al hazards – Event report

Geo Risk s Research, NatCatSERVICE

Photo: Munich Re

Type of event: Tropical cyclone
Dat e: 25–30.8.2005

Region affected: United States
(esp. New Orleans, Biloxi)

Overall losses: US$ 125,000 m*
Insured losses: US$ 62,200 m*
Fatalities: 1,322

MR catastrophe category: 6

* Original losses

2005 was the most active hurricane season since recordings began and the most expensive in the history of the insurance industry.

Event report

Hurricane Katrina was the eleventh tropical cyclone of the season, developing from a low-pressure vortex over the Bahamas on 23 Au gust 2005. It made landfall near Miami on 25 August and crossed the eastern part of the Gulf of Mexico in the days that followed. Due to the high water temperatures, the storm intensified to a Category 5 storm on the Saffir-Simpson Scale, with peak gusts o f up to 340 km/h. Katrina maintained this strength as it crossed the oilfields off the coast of Louisiana and Mississippi. On 25 August, it hit the US mainland as a Category 3 storm 50 km east of New Orleans. The wind and storm surge damage was horrendous. New Orleans was flooded. Many offshore plants in the Gulf of Mexico were destroyed.

Losses

Overall losses came to US$ 125bn, of which some US$ 6 2.2bn was insured. More than 1,300 people died in the catastrophe. Hurricane Katrina was thus the most expensive single event to date in original values for both the economy and the insurance industry.

Summary of losses in the US

Levee systems damaged over a total of 270 km, levees breached. Many towns and cities swamped, 80% of New Orleans flooded. Hundre ds of thousands of buildings, homes damaged/destroyed. Oil industry affected, offshore platforms damaged/destroyed. 90% of oil production in the Gulf of Mexico halted. Oil tanker leakages. Millions of trees and power lines downed. Millions of households wi thout electricity. Telecommunications interrupted. Highway bridge collapsed. Factories, shops closed. Air traffic interrupted, railways destroyed. Water supply affected, sanitation system destroyed. Losses in fishery sector. Millions of people homeless, 1.5 million evacuated.

Source: Website Munich Re

Figure D.3
Example of a hydrological disaster

Floods, China (Summer 1998)

MR Touch Natur al hazards – Event report

Geo Risk s Research , NatCatSERVICE

Photo: Wolfgang Kron

Type of event: Flood
Date: May – September 1998

Region affected: China (Jangtse, Songhua)

Overall losses: US$ 30,700 m*
Insured losses: US$ 1,000 m*
Fatalities: 4,159

MR catastrophe category: 6

* Original losses

A series of flood waves kept the people on the Yangtze in a state of anxiety for six long weeks. At the same time, the Songhua region in northern China was hit by major floods.

Event report
The flood year of 1998 was the worst catastrophe year since 1954, when 30,000 people died in the Wuhan region. Six flood waves coming in close succession from Sichuan took the dykes all along the middle reaches of the Yangtze to the limits of their flood - resistance capacity. Hundreds of thousands of people fought desperately to prevent the dykes from collapsing: to no avail in many places. The river overtopped its banks, flooding large areas of the flat terrain on both sides of the river – sometimes up to a depth of several metres.

Losses
The overall loss totalled roughly US$ 25bn. At the same time, there was a major flood on the Songhua River in the highly industrialised province of Heilongjiang in the north of the country. Here, too, losses ran into the billions. The flood year of 1998 led to China rethinking its policy towards flood risk, culminating in a flood protection programme with massive improvements in the dyke systems.

Summary of losses in China
Hundreds of thousands km^2 of land flooded. 2 mill ion homes destroyed, 7.5 million damaged. Severe losses in agriculture and infrastructure. 120 million people affected.

Source: Website Munich Re

Figure D.4
Example of a climatological disaster

Heat wave, drought, wildfires in Russia (Summer 2010)

MR Touch Natural hazards – Event report

Geo Risks Research, NatCatSERVICE

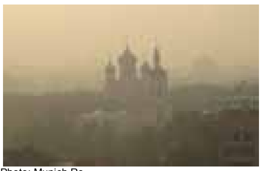


Photo: Munich Re

Type of event: Heat wave, drought, wildfire
Date: July – Sept. 2010

Region affected:
Russia (esp. Moscow region)

Overall losses:
US$ 3,600m (wildfires, drought)*
Insured losses:
US$ 20m (wildfires)*
Fatalities:
56,000 (excess mortality rate)

MR catastrophe category: 6

* Original losses

From July to September 2010, Moscow and central parts of Russia were firmly locked in the grasp of an unprecedented heat wave. Extreme dryness led to the outbreak of numerous wildfires which cloaked parts of the country in toxic smoke.

Event report
The Russian summer of 2010 will go down in history as the hottest to date. In July and August, meteorologists measured the highest temperatures ever since records first began some 130 years ago. The extreme dryness which was associated with the heat also promoted the outbreak of fires. Almost all the fires in more densely populated areas were caused by people.

Losses and fatalities
All in all, the 30,376 fires including 1,162 peat fires, claimed 130 lives. As many as 147 settlements were partly or completely destroyed. Flames ravaged 1.25 million hectares of land including 2,092 hectares of peat moor. Firefighting efforts are estimated to have cost the Russian government 19 billion roubles (US$ 630m).
The long heat wave, extreme dryness and smog caused considerable health problems. Moscow's inhabitants suffered under a dense cloud of smoke which enveloped the city. In addition to toxic gases, it also contained considerable amounts of particulate matter. Mortality increased significantly: the number of deaths in July and August was 56,000 higher than in the same months in 2009.

Summary of losses
Lack of rain, temperatures up to 45°C. Worst drought in 130 years. Toxic smog, esp. in Moscow. 2,500 homes burnt. Severe losses to agriculture, forestry and infrastructure.

Source: Website Munich Re

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