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A Global Urban Risk Index

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Abstract

Which cities have the highest risk of human and economic losses due to natural hazards? And how will urban exposure to major hazards change over the coming decades? This paper develops a global urban disaster risk index that evaluates the mortality and economic risks from disasters in 1,943 cities in developing countries. Concentrations of population, infrastructure, and economic activities in cities contribute to increased exposure and susceptibility to natural hazards. The three components of this risk measure are urban hazard characteristics, exposure, and vulnerability. For earthquakes, cyclones, floods, and landslides, single hazard risk indices are developed. In addition, a multi-hazard index gives a holistic picture of current city risk. Demographic-economic projection of city population growth to 2050 suggests that exposure to earthquake and cyclone risk in developing country cities will more than double from today's levels. Global urban risk analysis, as presented in this paper, can inform the prioritization of resources for disaster risk management and urban planning and promote the shift toward managing risks rather than emergencies.

This paper is a product of the Urban and Disaster Risk Management Unit; East Asia and Pacific Region; the Environment and Energy Team, Development Research Group; and the Urban and Disaster Risk Management Department. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at hbrecht@worldbank.org, udeichmann@worldbank.org, and hwang4@worldbank.org.

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1 Introduction

The potential for losses from natural hazards is particularly high in urban areas. 1.5% of the world's land is estimated to produce 50% of worldwide Gross Domestic Product (GDP). The same area accommodates about one-sixth of the world's population (World Bank 2009). Concentrations of population, industry, infrastructure, and economic activities in cities contribute to increased exposure and susceptibility to natural hazards. In fact, the ongoing process of urbanization is one of the main reasons for the staggering increase in disaster death tolls and economic losses over the past decades (e.g., Quarantelli 1996, Wisner 2003, Pelling 2003, Lall and Deichmann 2012).

The impacts of disasters are on the rise. Statistics show that, even when adjusted for inflation, the losses caused by natural catastrophes have been rising at an increasing pace since 1950, even when considering improvements in record keeping over time that could bias such comparisons. In the period between 1990 and 1999 the costs of disasters in constant dollars were more than 15 times higher than during the period 1950-59 (World Bank 2006). The number of people affected by natural hazards each year nearly quadrupled from 1975-84 to 1996-2005 (EM-DAT 2007). Several factors contribute to this increase, for example land use changes, social inequalities, subsidence, and environmental degradation (e.g., Smith 2012, Mileti 1999, Blaikie et al. 1994). Studies suggest that climate change has not significantly

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contributed to this increase (e.g., Bouwer, 2011; Neumayer and Barthel, 2010; IPCC, 2012). The main driver of risk is population pressure and economic growth in vulnerable locations, for example, in coastal areas susceptible to cyclones. The world's low lying coastal elevation zone covers 2% of the world's land area but contains 10% of the world's population (McGranahan et al. 2007). In the last 30 years, global population living in flood plains increased by 114% and in cyclone prone coastlines by 192% (UN-ISDR, 2011). Due to the global urbanization process, cities are becoming increasingly predestined for risks. Estimates by the United Nations suggest that over 50% of the world's population already lives in urban areas (UN 2008). Cities are predicted to absorb most of the future growth in the world population: the UN estimates that the urban population share will rise to 70% by 2050 (UN Population Division 2012). Cities in East Asia, for instance, absorb two million new urban residents every month (Gill and Kharas 2007) and are projected to triple their built up areas in the coming two decades (Angel et al. 2005).

While natural hazards and ongoing urbanization are inevitable, disaster losses can be minimized through adequate disaster risk management. Reducing risks *ex-ante* through risk assessments, land use planning, building codes, early warning systems, adequate watershed management, and contingency planning leads to significantly reduced disaster impacts. The earthquake in Chile in March 2010 was one of the ten most powerful earthquakes recorded in the last century. It released 500 times more energy than the earthquake that struck Haiti in January 2010. Yet, only 521 people died in Chile, whereas Port-au-Prince was catastrophically affected with tens of thousands of deaths. The main reason for this difference is that buildings in Chile are built to codes and are regularly inspected whereas Haiti effectively has no building codes.

Because of the enormous loss potential that has developed and is expanding in the narrowest of urban space, disaster risk reduction efforts need to be intensified in cities. Human losses associated with natural disasters and economic damages relative to the size of the economy are larger the poorer a country is (Skidmore and Toya 2007). Almost 80% of deaths from disasters in the first decade of this century were in developing nations (Zakour and Gillespie 2013) and economic losses are 20 times greater as a percentage of GDP in developing countries than in developed ones (World Bank 2006,). To secure steady advances towards poverty alleviation and economic growth in the developing world, suitable risk reduction strategies must be developed and mainstreamed into urban planning and development strategies. Otherwise, years of development and accumulated wealth are repeatedly destroyed and eroded through repeated disasters.

Given the intrinsic high loss potential from natural hazards in urban areas, it comes as a surprise that relatively little is known about global patterns of vulnerability and risk potential of cities. Which cities are likely to be affected by a disaster? Which cities have the highest risk of mortality due to disasters? Which cities are most at risk of economic losses due to natural hazards? And which of the world's regions will experience the largest increase in urban hazard risk? Efforts to assess urban risks so far have mainly focused on single cities, identifying inner-city hotspots. But a comprehensive ranking of the global cities' risk to guide priorities in building resilience has been lacking. Building on complementary country level risk assessments, this study creates a disaster risk ranking of large cities in the less developed world. Risk levels of 1,943 cities in 110 countries are evaluated and compared. The five following features characterize the analysis in this paper:

- Risks are assessed for urban agglomerations with more than 100,000 inhabitants.
- For each city, mortality risk and economic risk are calculated by taking into account three components of risks: hazard, exposure, and vulnerability.
- The loss potentials are expressed in relative levels.
- Four major natural hazards, namely earthquakes, cyclones, floods, and slides are considered in this study. Urban risks are identified for each of these hazards separately. In addition, a multi-hazard index gives a holistic picture of city risk.
- Expected urban risk exposure to earthquakes and cyclones in the year 2050 is determined using a demographic-economic projection model.

By disclosing risks to cities, the results presented here can raise awareness, inform resource planning, inspire further research, particularly at local levels, and promote the shift towards managing risks rather than emergencies.

2 Background

The assessment of risk is highlighted as a central activity in defining priorities and building resilience in the Hyogo Framework for Action 2005-2015 (UN-ISDR 2005), signed by 168 nations and international organizations at the 2005 World Conference on Disaster Reduction. Risk identification supports a wide range of decision-making processes for different actors on how risk should be managed from the public to the private sector (e.g., Hsu et al. 2012, Cutter and Finch 2008, Fuessel 2007). Quantifying risk and estimating future losses are not only the first steps in any disaster risk reduction program; the resulting scenarios of a risk assessment are increasingly incorporated into sustainable development approaches in different sectors in order to climate- and disaster-proof investments. Once the severity and geographical extent of risks have been assessed and the drivers of risk are better understood, appropriate and cost-effective countermeasures can be systematically identified and implemented. Depending on the scale, risk assessments support multiple applications, for example, urban planning, investment prioritization, land use planning, building codes, and disaster risk financing solutions.

A range of perspectives on risk assessments and indices has emerged, ranging from quantitative calculations on losses to qualitative analysis capturing also intangible impacts. Interesting initiatives have developed mainly at national level but a few have also been completed at global as well as urban scale.

Global level: Two main risk assessment initiatives have been undertaken with the goal of identifying multi-hazard risk worldwide on the basis of grid cells with sub-national extent. First, the *Global Disaster Hotspots*, developed by the World Bank and Columbia University (Dilley et al. 2005, Lerner-Lam 2007) produced detailed geospatial data on risks of mortality and economic losses for six major natural hazards.

The results enabled a global assessment of risk levels and the identification of areas where the potential for disaster impacts is large. Second, the *Global Assessment Report 2009* (UN-ISDR 2009) is a multiple agencies effort that developed the Global Disaster Hotspots further by using enhanced modeling techniques and improved data layers. An update of this 2009 global risk analysis was released in the *Global Assessment Report 2011* (UN-ISDR 2011).

National level: An example of a comprehensive multi-hazard risk index that assigns overall risk values on a national level is the *Disaster Risk Index* (DRI) (Peduzzi et al. 2009). The DRI calculates three factors on a national resolution for 200 countries: risk of mortality, the relative vulnerability of each hazard type, and the physical exposures of populations to hazard. Another example for a risk assessment on national scale, covering a multitude of countries, is the study by McGranahan et al. (2007), which ranks countries according to their population shares in the low elevation coastal zones.

Urban level: With the rise of megacities, risk assessments have increasingly taken place at the city-level, identifying inner-city areas of high risks and loss potential (e.g., World Bank 2010b). However, only a few limited initiatives exist which assess the overall risk of numerous cities in the form of an index to compare and rank cities with each other. Efforts in this area to date have been confined to relatively limited sets of locations and hazards. The Munich Reinsurance Group developed the *Natural Hazard Index for Megacities* for 50 cities with high global economic significance (Munich Re 2005). The index has an economic emphasis and is geared towards the risk of material losses which is suitable from an insurance perspective. Hanson et al. (2011) ranked 136 port cities around the world that have more than one million inhabitants. The study examines the risks of coastal areas due to storm surge and high winds, taking into account predictions of climate change, subsidence, and population growth. Brecht et al. (2012) determined the impact of sea level rise and intensified storm surges in developing countries and highlight the major cities worldwide that are located in storm-surge zones. Furthermore, methodologies have been developed that propose indicators to estimate the overall risk of cities. Indicators include, for example, population density or number of hospital beds (e.g., Davidson 1997, Cardona 2005). These methodologies have been applied for risk identification in only a handful of cities, since data availability of the indicators at the city level hampers the implementation of them on a broader scale.

3 Motivation

Why is a global urban risk index useful? First, an index combines a set of indicators, which are derived from extensive datasets. It aggregates information and summarizes a body of knowledge from a wide range of disciplines. It filters information for the reader and translates research into easy to understand results. This makes indices appealing tools.

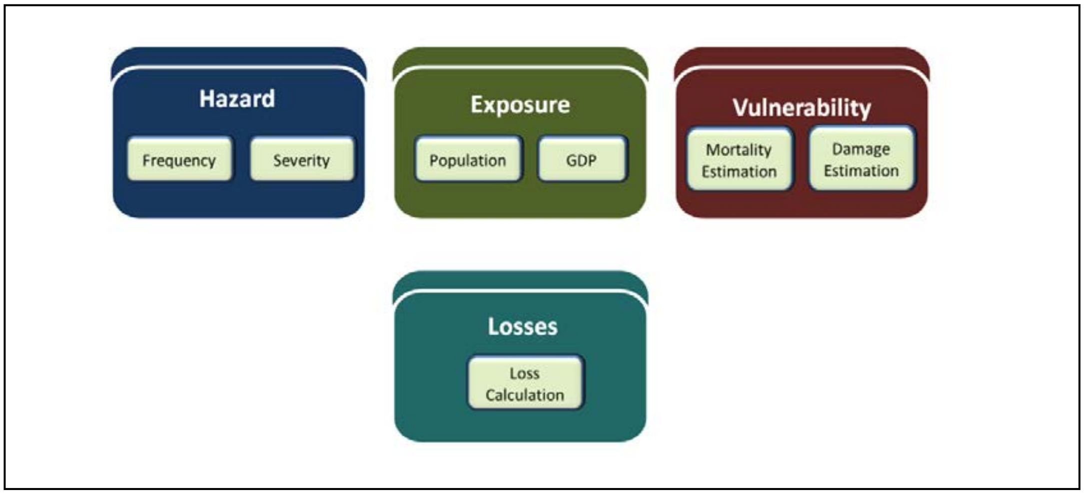
Second, a global urban risk index enables the comparison of risk levels in cities in a self-explanatory manner. As the international development community gradually shifts from financing post-disaster relief towards financing disaster prevention (see for example, Ashdown 2011), a global risk index gives reference points for investment decisions. It yields the basis for decisions on where funding for disaster risk reduction should be allocated. It allows comparability and the prioritization of programs in areas where hazard risk is greatest and where investment benefits are maximized. Cutter (2001) stresses that geographic comparisons across regions with a systematic approach in methodologies and data are crucial to prioritize risk reduction strategies or poverty reduction goals. Yet, disaster research has usually gravitated toward group or community studies as opposed to large-scale projects (Tierney 2002).

Third, an index facilitates comparisons over time. It can update on the progress in making cities more resilient and points to persistent long-term urban hotspots in which integration of risk reduction in urban planning needs to be prioritized.

4 Methodology

Risk expresses the possibility of future disaster, that is the possibility that a hazardous event will happen and that exposed and susceptible elements are in the way. It is defined as the probable value of losses that will occur in the event of a disaster. In this study, we use a risk model that is built upon a sequence of four modules: hazard, exposure, vulnerability, and losses (Figure 1).

Figure 1: The four components of the Global Urban Risk Index



4.1 Assessing hazards

Hazard refers to the possible occurrence of physical events that may have adverse effects on vulnerable and exposed elements (White 1973). The hazard module in this index assesses the risks from four different natural hazards: earthquakes, landslides, floods, and cyclones. We determine risks for each hazard individually and a multi-hazard index gives an overall picture of city risk. To estimate the likelihood of a hazard striking a given city, we take advantage of global hazard data sets developed by different organizations (Table 1).

The data sets depict the geographic distribution of hazard risk in a grid format with a resolution of 1 km^2. Hazard frequency and, when available, severity are derived from historic events, from modeled probabilities or from a combination of both. Historic events are used to calculate cyclone hazard risk for cities. To estimate cyclone risk, we combined more than 2,800 historic cyclone tracks in the time period from 1975 to 2007 and their modeled wind speed plumes (Figure 2), resulting in a global grid, that shows how many times each grid cell has been struck by a cyclone (frequency) and with what wind speed (severity) (Figure 3).

Landslide hazards are summarized as probabilities. These probabilities are derived through a combination of trigger and susceptibility factors defined by various parameters, including slope, lithological or geological conditions, soil moisture condition, vegetation cover, precipitation, seismic conditions, and Shuttle Radar Topography Mission (SRTM) elevation data.

Table 1: Data sources for the hazard component

Hazard	Description	Unit	Source
Cyclones	Tropical cyclones wind speed buffers based on compilation of tracks (1975-2007) and GIS modelling.	Estimated Saffir-Simpson categories	UNEP/GRID-Europe
Floods	Flood frequencies generated by GIS modelling, observed flood data from 1999 to 2007, obtained from the Dartmouth Flood Observatory (DFO) and the UNEP/GRID-Europe PREVIEW flood dataset.	Expected average number of event per 100 years	UNEP/GRID-Europe/ Dartmouth Flood Observatory
Earthquakes	Modified Mercalli Intensity based on GIS modelling using the Global Seismic Hazard Assessment Program (GSHAP) dataset.	Simulated Modified Mercalli Intensity (MMI)	Center for International Earth Science Information Network (CIESIN), Columbia University
Landslides	Landslide probabilities triggered by earthquakes and precipitation based on GIS modelling taking into account slope factor, lithological (or geological) conditions, soil moisture condition, vegetation cover, precipitation, and seismic conditions.	Expected annual probability and percentage of pixel of occurrence of a potentially destructive landslide event times 1,000,000	Norwegian Geotechnical Institute / International Centre for Geohazards

Note: See Dilley et al. (2005) and UN-ISDR (2011) for details.

To calculate earthquake and flood risks, combinations of historic events and modeled probabilities are used. We overlaid the resulting hazard grids with city footprints to identify the maximum hazard probability for each of the cities. This is accomplished by assigning the value of the grid cell with highest hazard denomination within a city footprint as the city's hazard severity.

Figure 2: Wind field of Hurricane Katrina in 2005

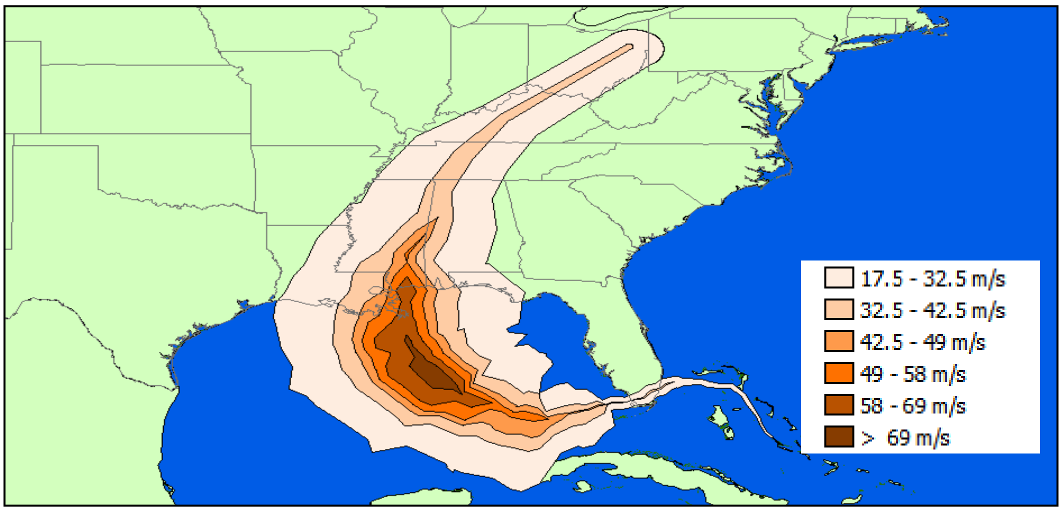
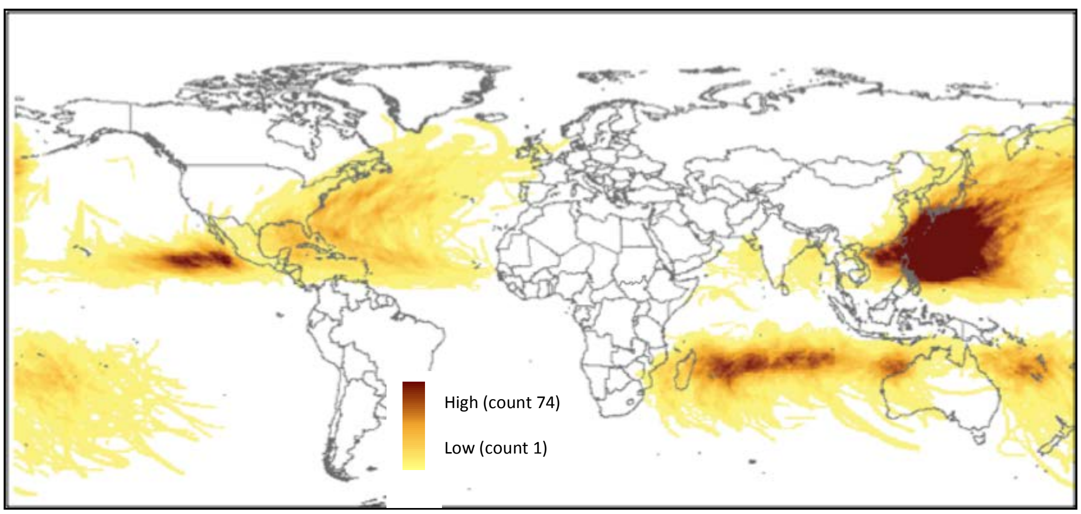


Figure 3: Global cyclone frequency 1975-2007



4.2 Quantifying exposure

The exposed elements at potential risk from hazards are people, buildings, transport infrastructure, economies, and communities. In a rapidly urbanizing world, the increasing concentration of people and economic assets in cities is leading a sharp rise of urban hazard risk and is a main driver for the increase in disaster losses. Growing exposure and delays in reducing vulnerabilities result in an increased number of natural hazards and greater levels of loss.

The impact of a disaster is dependent on the extent of the exposed elements that are in harm's way, i.e. on the number of people and the amount and value of infrastructure that are affected by the disaster. The exposure module in this study is an inventory of assets at risk at the city level. We consider two asset classes: City population and city GDP. City population numbers are based on the "Henderson City Dataset" (Table 2).

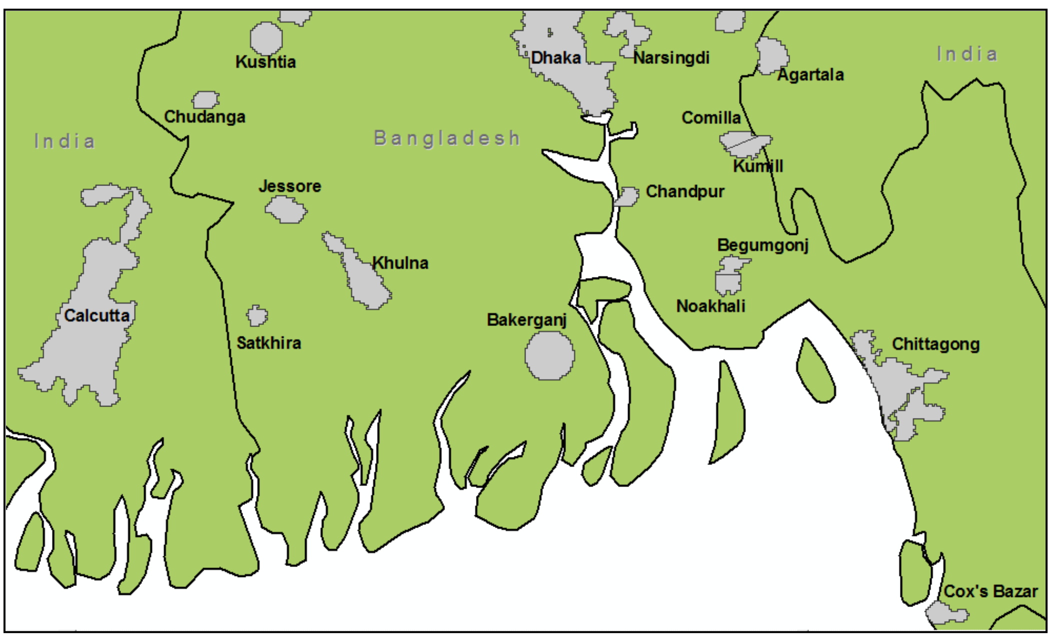
Table 2: Data sources for the exposure component

Dataset	Description	Unit	Source
Henderson City Data	Data set of cities worldwide with more than 100,000 inhabitants. The data includes city names, countries, codes, coordinates, and population numbers of the years 1960, 1970, 1980, 1990, and 2000.	Inhabitants per urban agglomeration	Prof. J. Vernon Henderson, Brown University
GRUMP	Global urban footprint grid based largely on NOAA's night-time light satellite data from 1994/5 coupled with settlement information.	Urban population distribution and the global extents of human settlements	Center for International Earth Science Information Network (CIESIN), Columbia University
GDP	Sub-national Gross Regional Product (GRP) estimates and national Gross Domestic Product (GDP) data are allocated in proportion to the population residing in that cell. The approach distinguishes between rural and urban regions.	US$ per 1 km^2 grid cell	World Bank

All cities in less developed countries with more than 100,000 inhabitants in the year 2000 are selected from this database. This results in a city dataset with 1,943 cities. Cities in this context are entire urban agglomerations with suburban fringe and adjacent towns.

To determine urban GDP and hazard severity, we define a city footprint for each of the city points from the Henderson data. To define a footprint for each city, we match the city points of the Henderson data with the Global Rural-Urban Mapping Project (GRUMP) raster data by the Center for International Earth Science Information Network (CIESIN) at Columbia University. GRUMP is a global urban footprint grid based largely on NOAA's night-time light satellite data (e.g., Elvidge et al. 2010) coupled with settlement information. For each of the 1,943 cities, we identify a corresponding urban area in GRUMP, which represented the city's urban footprint. Where multiple city points fall within a large continuous area, we use Thiessen polygons to allocate a portion of the area to each urban point, creating a unique urban footprint for each city (Figure 4).

Figure 4: Integration of GRUMP data and Henderson Cities



We use the footprints to calculate city GDP by using a global GDP grid with a resolution of approximately 1km^2. The GDP figures for cells within a city footprint are added up which resulted in the city GDP. By overlaying the footprints with the natural hazard grids, the footprints are the basis for identifying if a city is exposed to natural hazards, and if so, with what maximum hazard probability.

4.3 Calculating vulnerability

The term ‘vulnerability’ is derived from the Latin word *vulnerare*, which means 'to wound'. Broadly, vulnerability refers to the extent to which a person, structure, or service is likely to be damaged by the impact of a disaster. It explains why, with a given hazard severity, people and assets are more or less likely to experience damages or losses and why they do or do not fail to be resilient in the face of a threatening event. For the purpose of a risk assessment, vulnerability is usually disaggregated into categories such as physical, social, economic, or environmental. While physical vulnerability of the built environment, for example, is influenced by building age and construction type, social vulnerability is affected by lack of access to resources or limited access to political power.

Vulnerability reduction is a core element in disaster risk management. The concept of vulnerability has helped to highlight the role of social and physical factors that have an impact on the constitution of risk (Hewitt 1983). By using the notion of vulnerability, disasters are not simply viewed as the result of a natural event but rather as the result of the vulnerability of a society, its infrastructure, economy, and environment, all of which are determined by human behavior. The focus shifts to what makes a natural hazard and unnatural disaster (World Bank 2010a). Governments and citizens can appreciably reduce vulnerability, and therefore risk, through sensible combinations of prevention, insurance, and preparedness.

Vulnerability is not easily quantifiable and researchers have struggled to develop appropriate metrics for vulnerability (Adgers 2006). Ways to determine vulnerability include deductive, inductive, and combined methods. Deductive approaches use quantitative methods based on historical patterns of past disasters and their damages and losses. Inductive approaches determine risks through combining weighted variables for vulnerability. For example, factors such as GDP, poverty rates, or population density are taken as indicators of how vulnerable a place is. An obstacle to inductive modeling is the lack of accepted procedures for assigning values and weights to the different vulnerability factors that contribute to risk. An obstacle to deductive approaches is that the data on losses during past hazards is insufficient, especially on larger scales, and often not methodologically recorded. Despite this weakness, deductive modeling offers a viable option to risk indexing in many contexts and is helpful, especially for risk comparisons on larger scales.

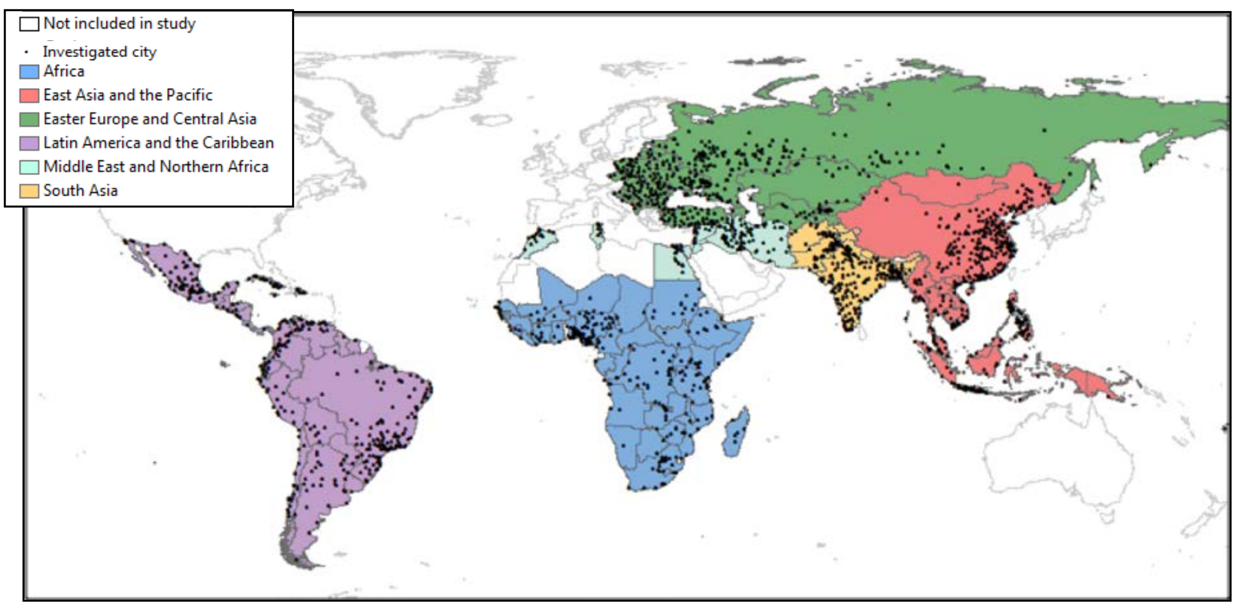
In this study, we use deductive methods to determine two dimensions of vulnerability. Vulnerability to mortality is calculated based on historical disaster mortality in precedent hazard events and vulnerability to economic losses is determined through past economic losses in disasters. We extract the loss data on number of deaths and amount of economic losses from the Emergency Events Database (EM-DAT) (http://www.em-dat.net) for the period from 1980 to 2007 (Table 3). EM-DAT is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) which classifies an event as a disaster and includes it into EM-DAT if at least one of the following criteria applies: Ten or more people were killed, 100 or more people were affected, a declaration of a state of emergency was made, or an appeal for international assistance was made. EM-DAT records more than 600 disasters globally each year. For each event, the database lists the type of disaster, the country, the date, death tolls, estimated damage, and the number of affected people. Aggregating over more than 8,000 entries in EM-DAT helps compensate for missing data and reporting inaccuracies.

Table 3: Data sources for the vulnerability component

Dataset	Description	Unit	Source
EM-DAT (Emergency Events Database)	International disaster database for major hazards across the world, listing country, date, death tolls, estimated damage, number of homeless and affected people. The database contains over 14,000 disasters and is compiled from various sources, including UN agencies, NGOs, insurance companies, research institutes, and press agencies.	Number of fatalities/economic losses per disaster	Centre for Research on the Epidemiology of Disasters (CRED) http://www.em-dat.net/

We calculate different vulnerability coefficients, or loss weights, for the two vulnerability categories of population and GDP. Weights are obtained for all of the four hazard types for each of the 25 World Bank clusters. Clusters are agglomerations of countries according to standard classifications of the World Bank. They stem from seven geographical regions (Africa, East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia) (Figure 5) and four different wealth classes (high, upper-middle, lower-middle, and low). We calculate the coefficients on a regional basis rather than for each country, or even city, due to an insufficient number of hazard and loss events. The weights are an aggregate index of relative losses over a 27 year period. They represent an estimate of the proportion of persons killed during that period in the area that is exposed to that hazard. For example, to calculate mortality loss weights for a hazard *h* for a certain cluster *c*, the death tolls for that hazard (e.g. earthquakes) in the years from 1980 to 2007 are extracted from EM-DAT for all countries within that cluster and aggregated: M_{ch}.

Figure 5: The six regions covered in the study



Then, using the raster layers on the extent of each hazard, we sum up the population in the earthquake affected areas from the year 2000 for that cluster: P_{ch}. We calculate a simple mortality rate for the hazard for the cluster:

$$r_{ch} = M_{ch}/P_{ch}$$

4.4 Determining urban risk

Building upon the first three modules of hazard, exposure, and vulnerability, we determine the probability of mortality and economic losses from catastrophic events for each city. The vulnerability coefficients are used as weights that are combined with both the exposure data per city and the city-specific hazard severity. For example, for each city i that is in an earthquake-prone area, we compute the city-specific earthquake mortality rate M_{ice} by multiplying the cluster-specific earthquake mortality rate r_{ce} by the city population P_i and the city-specific earthquake severity W_{ie}.

$$M_{ice} = r_{ce} P_i W_{ie}$$

To compute a weighted multi-hazard index value for mortality that reflects total estimated impacts from all disaster types for a city, we follow this method for each hazard h. Since the degree of hazard (h_d) for each of the five hazards is measured on a different scale (for example, frequency counts for cyclones versus probability index values for landslides), the accumulated mortality numbers are not easily comparable across hazards and simply adding the resulting values would result in an index unduly dominated by a hazard type h that happens to be measured on a scale with larger values. Before combining the hazards into a multi-hazard index, we apply a uniform adjustment by deflating the weighted hazard-specific mortality figures, so that the total mortality in each region adds up to the total recorded in EM-DAT.

$$M^*_{ich} = M'_{ih} M_{ch} \,/ \sum_{i=1}^{n} M'_{ih}$$

where n is the number of cities per cluster and M'_{ih} is the hazard-specific city mortality rate (h_d P_i r).

We calculate the combined, mortality-weighted multi-hazard city risk value Y_i^* as the sum of the adjusted individual hazard mortality estimates for a given city:

$$Y_i^* = \sum_{h=1}^{4} M^*_{ih}$$

Reporting actual mortality numbers would portray an unrealistic impression of precision. To avoid literal interpretation of the disaster index as the number of persons expected to be killed in a 20-year period and in recognition of the many limitations of the underlying data, we convert the resulting measures into index values from one to ten, classifying the global risk distribution into deciles and providing relative presentations of disaster risk.

4.5 Interpretation

The calculated risks in the index assign a value to the city as a whole and are based on the three factors of hazard severity in the city, city population, and the vulnerability of the particular World Bank cluster. The mortality risk in a city is the potential extent of total fatality numbers that a city could incur rather than the extent of risk that a single person experiences in that city. Similarly, economic risk mirrors total potential damage extent.

Result interpretation needs to consider that a number of constraints. In an index, interesting and idiosyncratic detail is hidden, and indexing cannot replace detailed research at local level. Constraints in globally available data limit the sophistication of the methods that were employed to investigate urban risk on a global level. Although we use the best available data, gaps in the data limit our analysis. For example, deductive modeling has weaknesses in determining risk in contexts where disasters occur infrequently and where historical data are scarce. Moreover, disaster loss data in EM-DAT is recorded on country-level and does not allow for a differentiation between urban and rural loss rates and vulnerabilities. The relatively small number of disaster events leads us to calculate vulnerability coefficients on regional levels using groups of countries. Aggregating across more than 8,000 entries in EM-DAT helps compensate for missing data and inaccuracies and reflect broad patterns of vulnerability. It cannot, however, reveal protection mechanisms (land use planning, regulations) that individual cities might have implemented. Another limiting factor is the relatively crude delineation of some hazards. For example, earthquakes with pathological damage patterns are represented incompletely. The cities investigated in this study stem from the Henderson city database (see Table 2). This data set contains cities worldwide with more than 100,000 inhabitants. While it has extensive coverage globally, some cities are left out in the database and are consequently not included in the index. Finally, for a few clusters insufficient historic loss data were available for landslide hazards (i.e. Middle East and Northern Africa High Income, Middle East and Northern Africa Lower Middle Income, all clusters in the Africa region, and Eastern Europe and Central Asia Lower Middle Income). The countries belonging to those clusters were therefore not included in the landslide analysis.

In recognition of these limitations, the modest objective of the study is to provide a relative presentation of disaster risk instead of an absolute one. We therefore convert the absolute city risk values, calculated in the risk model, into comparative index values.

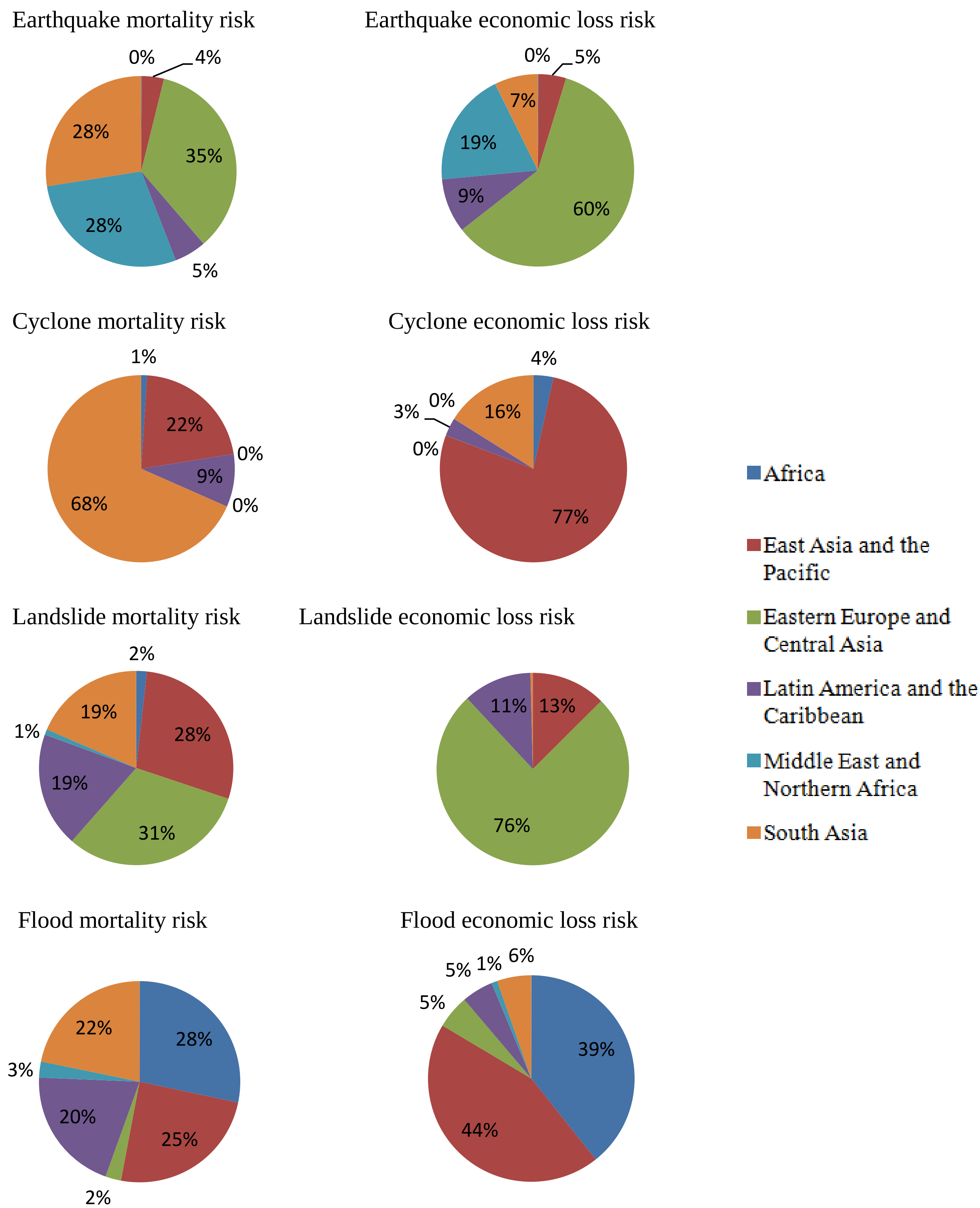
While the index cannot provide the detail needed to identify concrete risk reduction measures, it assesses the relative importance of risk at regional level and identifies areas where more attention is needed.

5 Results

Global Distribution. The number of exposed urban dwellers to certain hazards has implications for the weight given to reduce the risk of specific hazards. In this analysis, by far the greatest number of the investigated urban population in less developed countries is exposed to flood hazards, approximately 1.1 billion. Around half that number (560 million) are at risk to earthquakes and also to landslides (660 million). Finally, nearly 90 million of the study's urban population is exposed to cyclone hazards.

Regional Distribution. Between 1980 and 2006, Pakistan and the US both experienced nineteen major earthquakes (>5.0 on Richter scale). While in Pakistan 74,112 people died during these earthquakes, in the US only 145 people were killed. This enforces the concept that tragedies are not caused by the earthquake itself, but rather by dire construction practices and missing policies. The deaths and devastation in disasters result from human action or inaction. Typically, wealthy regions and countries are at higher risk in terms of economic losses but suffer fewer fatalities whereas poor countries experience high mortality risks and lesser economic risks. The results in Figure 6 reflect this trend. This figure shows the accumulated shares of urban economic and mortality risks by region and hazard. Within the individual regions, significant differences can be found in terms risks to mortality and economic loss risks. For example, while urban mortality loss risk to cyclones is greatest in South Asia (68%), the share of urban cyclone economic loss risk in the same region is only 16%. The wealthier East Asian countries bear the greatest burden of urban economic loss risk (77%) whereas East Asia's urban mortality risk is comparatively lower. Next to wealth, the type of disaster is a decisive factor for overall risk. Fatalities from severe earthquakes, for example, are usually far larger than fatalities from severe floods or cyclones under equal vulnerability conditions.

Figure 6: Regional shares of urban risks for four different hazards



5.1 Ranking risks by country

The five most at risk countries for urban mortality and economic loss risk from four investigated hazards are presented in Table 4. Some risks are highly concentrated in certain countries. India, Pakistan, and Bangladesh, for example, account for 68% of cumulative urban mortality risk to cyclones out of all investigated cities. Economic loss risk from cyclones, on the other hand is highest in East Asia, where China alone accounts for 53% of the cumulative urban economic loss risk for cyclones. Earthquake risk is highly concentrated in Turkey and Iran, both of which together account for 47% of all investigated cumulative urban earthquake risk of economic losses. Economic risk to earthquakes is also high in Hungary and Romania, both of which lay in one of the largest well-defined seismic-active areas of Europe. The high density of urban inhabitants in out-of-date infrastructure contributed to past significant past earthquake losses in the category of upper middle income countries in Eastern and Central Europe, which led a large economic vulnerability coefficient in this study.

Table 4: The five most at risk countries for urban mortality and economic loss risk per hazard

	Earthquake Risk		Cyclone Risk	
	Mortality	Economic Loss	Mortality	Economic Loss
1	Turkey	Turkey	India	China
2	Iran	Iran	Pakistan	Myanmar
3	India	Hungary	Bangladesh	Vietnam
4	Pakistan	Romania	China	India
5	Egypt	Russia	Myanmar	Pakistan

	Landslide Risk		Flood Risk	
	Mortality	Economic Loss	Mortality	Economic Loss
1	Turkey	Turkey	South Africa	South Africa
2	Philippines	Philippines	India	Vietnam
3	India	Russia	China	China
4	Guatemala	Guatemala	Argentina	Indonesia
5	Indonesia	China	Bangladesh	India

5.2 Ranking risks by city

The cities with the highest mortality and economic loss risk by hazard are listed in Table 5 to Table 8. The tables show the five most at risk cities by hazard in each of the six investigated regions. The ranking gives an indication of the cities most worthy of further and more detailed investigation. The data provide for interesting comparisons. For example, Metro Manila, one of the world's most disaster prone cities, is listed in the tables as being highly at risks from the three hazards of earthquakes, floods and landslides. In 2012, the city again experienced devastating floods with almost two thirds of the city area being submerged after a week of torrential rains. Tehran is also highly at risk, especially from earthquakes and floods. This fact has sparked repeated discussions among the country's leaders about moving the capital to a less risky region. A striking, but also sobering, result is the magnitude of risk in certain cities. In South Asia, the top five ranked cities for cyclone mortality risk bear 62% of all cumulative mortality loss risk in that region. Cumulative economic loss risk for landslides in Eastern Europe and Central Asia amounts to 51% for the top five ranked cities in that category. All of those five cities are in Turkey. In Africa, Addis Ababa accounts for 31% of the cumulative earthquake mortality risk in that region and the top five cities altogether bear 59% of Africa's earthquake mortality risk.

A number of smaller cities with less population and wealth are set to swell with rapid increases in population and asset exposure. These include, for example, Toluca in Mexico and Conakry in Guinea. While the absolute exposure of these cities is currently relatively low, the rapid increase in population growth will pose significant challenges for these cities in the coming years.

Table 5: Regional top 5 cities most at risk to earthquakes

	Mortality risk		Economic loss risk	
Region	Country	City	Country	City
Africa	Ethiopia	Addis Ababa	Uganda	Kampala
	Uganda	Kampala	Ethiopia	Addis Ababa
	Malawi	Blantyre	Malawi	Blantyre
	Kenya	Nakuru	Kenya	Kisumu
	Burundi	Bujumbura	Kenya	Nakuru
East Asia	Philippines	Metro Manila	Indonesia	Jakarta
	Indonesia	Jakarta	Philippines	Metro Manila
	China	Tianjin	China	Beijing
	China	Beijing	China	Tianjin
	Indonesia	Bandung	Indonesia	Yogyakarta
Eastern Europe and Central Asia	Turkey	Istanbul	Turkey	Ankara
	Turkey	Ankara	Hungary	Budapest
	Turkey	Izmir	Turkey	Izmit
	Romania	Bucharest	Turkey	Istanbul
	Turkey	Bursa	Turkey	Izmir
Latin America and the Caribbean	Mexico	Mexico City	Peru	Lima
	Peru	Lima	Mexico	Mexico City
	Chile	Santiago	Mexico	Tijuana
	Colombia	Bogota	Colombia	Bogota
	Mexico	Guadalajara	Chile	Santiago
Middle East and Northern Africa	Egypt	Cairo	Iran	Tehran
	Iran	Tehran	Egypt	Cairo
	Iran	Mashhad	Iran	Raja'ishahr
	Iran	Esfahan	Egypt	Shubra El-Kheima
	Tunisia	Tunis	Iran	Ahvaz
South Asia	India	Kolkata	India	Delhi
	Bangladesh	Dhaka	India	Kolkata
	Pakistan	Karachi	Pakistan	Karachi
	India	Delhi	Pakistan	Lahore
	Pakistan	Lahore	Bangladesh	Dhaka

Table 6: Regional top 5 cities most at risk to cyclones

	Mortality risk		Economic loss risk	
Region	Country	City	Country	City
Africa	Mozambique	Quelimane	Mozambique	Quelimane
	Mozambique	Beira	Mozambique	Beira
	Madagascar	Toamasina	Madagascar	Toamasina
	Madagascar	Mahajanga	Madagascar	Mahajanga
East Asia	Myanmar	Yangon	China	Shenzhen
	China	Shanghai	Myanmar	Yangon
	Vietnam	Hai Phong	Vietnam	Hai Phong
	China	Fuzhou	China	Shanghai
	China	Dongguan	China	Dongguan
Latin America and the Caribbean	Dominican Republic	Santo Domingo	Mexico	Cancun
	Jamaica	Kingston	Jamaica	Kingston
	Cuba	La Habana	Mexico	Ciudad Madero
	Mexico	Cancun	Dominican Republic	Santo Domingo
	Dominican Republic	La Romana	Mexico	Mazatlan
South Asia	India	Chennai	India	Chennai
	Pakistan	Karachi	Pakistan	Karachi
	Bangladesh	Chittagong	India	Visakhpatnam
	India	Visakhpatnam	Bangladesh	Chittagong
	Bangladesh	Khulna	Bangladesh	Khulna

Note: No cyclone risk was measure in the Middle East, Northern Africa, Eastern Europe, and Central Asia

Table 7: Regional top 5 cities most at risk to landslides

	Mortality risk		Economic loss risk	
Region	Country	City	Country	City
Africa	Sierra Leone	Freetown		
	Guinea	Conakry		
	Nigeria	Lagos		
	Côte d'Ivoire	Abidjan		
	Ethiopia	Adis Abeba		
East Asia	Philippines	Metro Manila	Philippines	Metro Manila
	Indonesia	Surabaya	China	Shenzhen
	Philippines	Baguio	Indonesia	Surabaya
	Vietnam	Ho Chi Minh	Indonesia	Yogyakarta
	Indonesia	Padang	China	Hong Kong SAR, China
Eastern Europe and Central Asia	Turkey	Manisa	Turkey	Izmit
	Turkey	Izmir	Turkey	Manisa
	Russia	Petropavlovsk-Kamatskij	Turkey	Kahramanmaras
	Turkey	Kahramanmaras	Turkey	Izmir
	Turkey	Erzurum	Turkey	Erzurum
Latin America and the Caribbean	Guatemala	Guatemala City	Guatemala	Guatemala City
	Ecuador	Quito	Brazil	Vitoria
	Colombia	Bogota	Peru	Lima
	Peru	Lima	Ecuador	Quito
	Brazil	Vitoria	El Salvador	San Salvador
Middle East and Northern Africa	Iran	Tehran	Bahrain	Al-Manamah
	Iran	Rasht	Djibouti	Djibouti
	Iran	Shiraz	Iran	Tehran
	Iran	Tabriz	Iran	Mashhad
	Iran	Khorramabad	Iran	Esfahan
South Asia	India	Imphal	India	Imphal
	India	Mumbai	India	Srinagar
	India	Srinagar	India	Thane
	Pakistan	Peshawar	India	Bhiwandi
	Pakistan	Islamabad	India	Chandigarh

Note: Due to lack of data, economic loss risk for landslides could not be calculated in Africa.

Table 8: Regional top 5 cities most at risk to floods

	Mortality risk		Economic loss risk	
Region	Country	City	Country	City
Africa	South Africa	Cape Town	South Africa	Cape Town
	South Africa	Pretoria	South Africa	Durban
	South Africa	Durban	South Africa	Pretoria
	South Africa	Port Elizabeth	South Africa	Port Elizabeth
	Nigeria	Lagos	South Africa	Alberton
East Asia	Indonesia	Jakarta	Vietnam	Ho Chi Minh
	China	Wuhan	Indonesia	Jakarta
	Philippines	Metro Manila	Philippines	Metro Manila
	Vietnam	Ho Chi Minh	Vietnam	Hanoi
	Vietnam	Hanoi	Cambodia	Phnom Penh
Eastern Europe and Central Asia	Uzbekistan	Tashkent	Russia	Moscow
	Uzbekistan	Namangan	Poland	Warszawa
	Uzbekistan	Andijan	Uzbekistan	Tashkent
	Russia	Moscow	Poland	Kattowitz
	Tajikistan	Khujand	Turkey	Ankara
Latin America and the Caribbean	Argentina	Buenos Aires	Argentina	Buenos Aires
	Venezuela	Caracas	Brazil	Sao Paulo
	Brazil	Sao Paulo	Uruguay	Montevideo
	Argentina	Rosario	Venezuela	Caracas
	Venezuela	Maracaibo	Mexico	Mexico City
Middle East and Northern Africa	Iran	Tehran	Iran	Ahvaz
	Iran	Ahvaz	Iran	Tehran
	Iraq	Al-Basrah	Iran	Rasht
	Iran	Shiraz	Iran	Shiraz
	Morocco	Casablanca	Iran	Abadan
South Asia	Bangladesh	Dhaka	India	Kolkata
	India	Kolkata	India	Delhi
	India	Delhi	Bangladesh	Dhaka
	Bangladesh	Chittagong	India	Surat
	Pakistan	Karachi	Pakistan	Karachi

Figure 7: Urban mortality risk

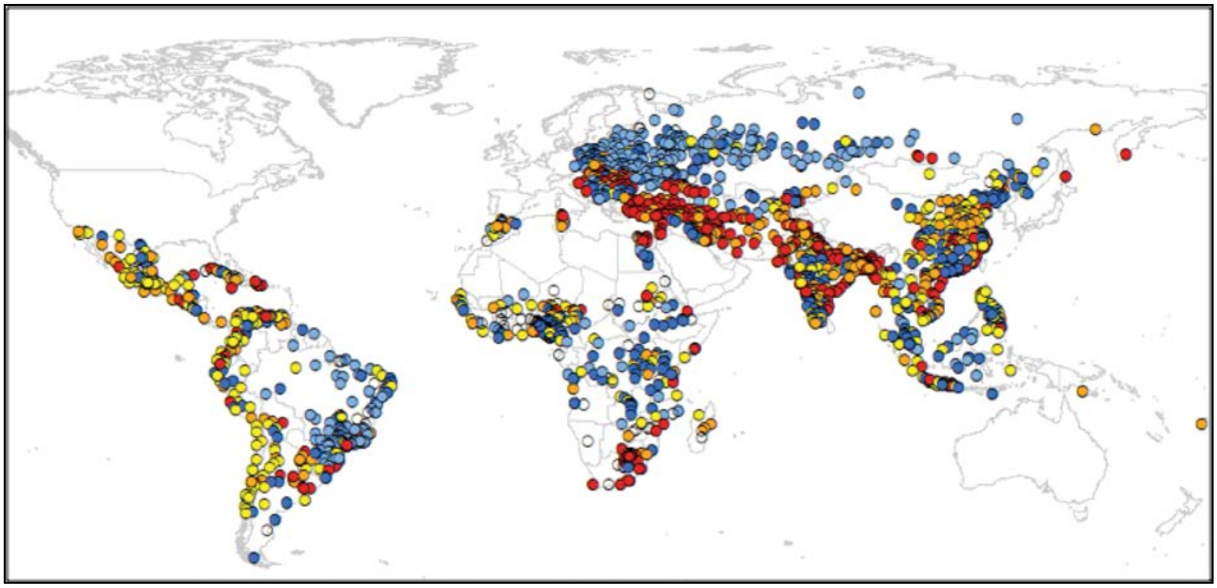
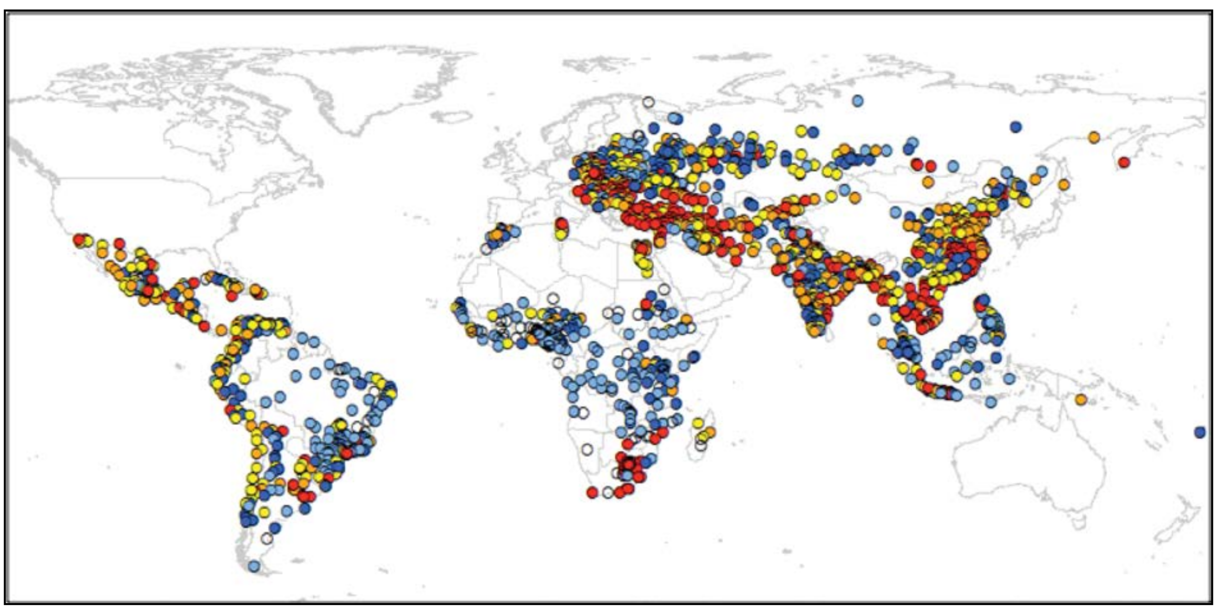


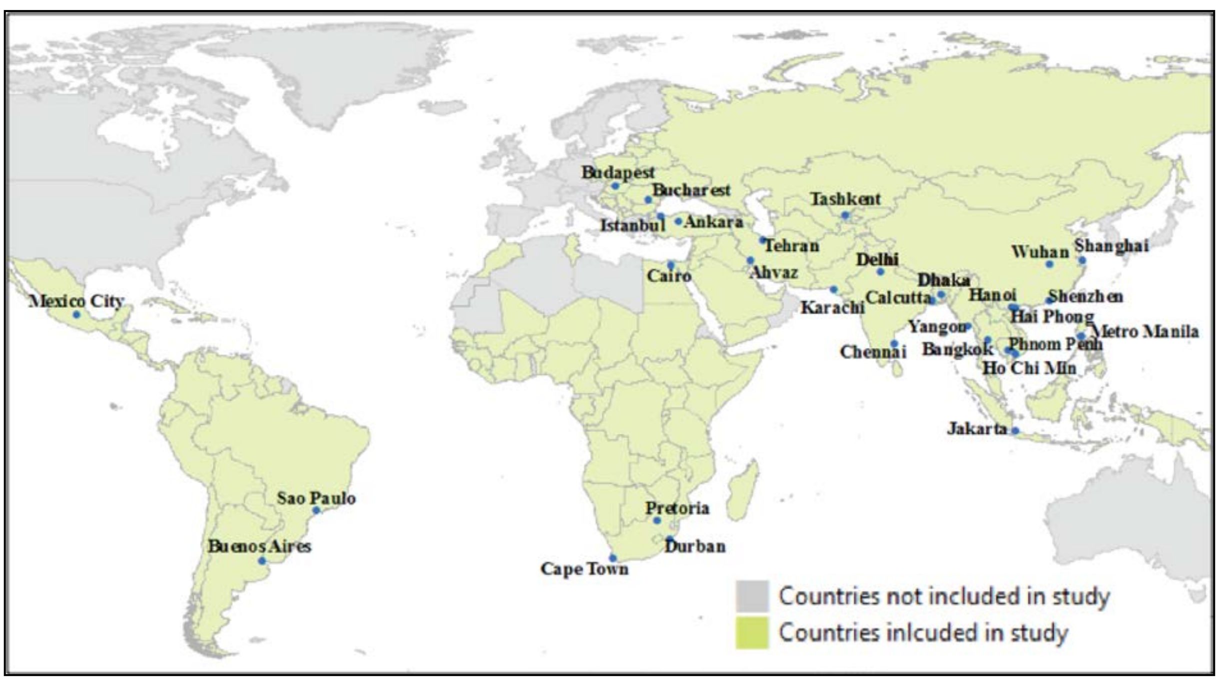
Figure 8: Urban economic loss risk



Urban multi-hazard mortality risk for all 1,943 investigated cities is shown in Figure 7. The values are calculated as the sum of the adjusted individual mortality estimates from the four hazards, and the results are grouped into five classes, using quintiles. Mortality risk is significant in regions exposed to repeated, severe flooding and storms along the eastern continental shorelines but also in the earthquake prone regions of Eastern Europe and the Middle East. The regional differences in risks are in part due to differences in population size but also the degree of hazard severity and frequency across regions. Additionally, the differences reflect the variation in vulnerability. Similarly, economic risk is shown in Figure 8.

Figure 9 shows the cities most at risk, taking into account both economic and mortality risk from all hazards. To determine these, we calculated percentiles of the hazard-specific mortality of all the cities using 15 classes (6.66 percentile, 13.33 percentile, etc.). The same was done for economic risk. Cities that fall into the class above the highest percentile (93.33) for both mortality and economic risk are included in the maps. Of these highest ranked thirty cities, eleven are in East Asia, five are in South Asia, five are in Eastern Europe and Central Asia, three in Latin America, three in Sub-Saharan Africa and three in the Middle East and Northern Africa. Some of these city results are closely tied with high hazard risk from several hazards (for example, Tehran), others are particularly at risk due their size (for example, Metro Manila) and yet others are in the top 30 list due to their high vulnerability (for example, Ankara).

Figure 9: 30 cities most at risk



6 Sensitivity analysis

Sensitivity analysis, applied to a risk assessment, is a method used to understand how risk estimates depend on the variability and uncertainty of the factors used in the analysis. It determines how the different factors used in the index construction process affect the outputs, and it plays an important role in the verification and validation of the model. According to Saltelli at al. (2000) a sensitivity analysis is conducted to determine, for example, a) if the model resembles the system under study; b) the factors that most influence the output variability and therefore require special attention; c) the model parameters that are insignificant and that can be omitted; and d) which factors interact with each other. It is the final step in index development analysis, which examines the sensitivity of the model to changes in its inputs, and that gives an indication on the level of confidence or uncertainty. In existing risk and vulnerability indices, this last step has often been omitted.

In the Urban Risk Index, sources of uncertainties include: a) the underlying hazard models, b) the delineation of cities, c) the global grids for GDP and population, and d) the vulnerability coefficients. Future work on the index could conduct local sensitivity analysis by varying these input factors one at a time and examine the impact, while the other factors remain constant. Since the index measures relative values, the sensitivity of the relative, not absolute, values would need to be examined. These analyses could be developed for the individual four single hazard indices.

For the multi-hazard index, which simply adds the values of the single hazard indices, it would be interesting to determine which of the four indices have the largest influence in the overall urban multi-hazard risk. The percentage values to which the single hazard indices contribute to the overall index vary largely from 0-100% for all four hazards. We carried out a preliminary analysis that investigates how the top 20 cities of the multi-hazard mortality index change if one single hazard value is removed. If the landslide results are omitted from the overall index, only one city out of the top 20 cities changes. If the flood index values are omitted, three cities change in the top 20. Removing the cyclones from the overall index, results in a change of six cities and, finally, excluding earthquakes results in a change of seven cities in the top 20 cities. This corresponds to the fact that earthquakes, on average, cause large fatality numbers.

7 Future urban hazard risk

Between 2010 and 2050, urban areas will receive almost 2.7 billion additional residents according to UN estimates. Almost all of this net growth—a result of migration, natural increase and absorption of nearby rural areas—will occur in developing countries. Larger cities also mean greater exposure of people and, because urban dwellers tend to be more productive than rural ones, an even greater increase of exposure of economic assets. We develop a demographic-economic model of city-level population growth to derive an estimate of future population exposure to earthquakes and cyclones up to 2050.

Population projections for countries tend to be more accurate than those for cities. Since international population movements are typically far smaller than within-country migration, demographic models based on fertility and mortality work well to forecast national population totals. But at the city level, migration and the future fertility of these new migrants become more important factors. Migration, in turn, responds to economic dynamics, so commonly used demographic models do not yield reliable predictions (World Bank 2009). Instead, city level projections require consideration of various endogenous and exogenous factors, such as technological change, economic growth and development, as well as national population growth. In order to project future urban growth locations, it is critical to understand the underlying forces that drive this transformation.

We based our projections on a global study of determinants of city growth by Henderson and Wang (2007). This paper empirically modeled the urbanization process between 1960 and 2000. We focus on the projection of future city growth to the year 2050 at the global scale while following the city growth modeling framework and key variables developed by Henderson and Wang (2007). The model is set up as a three-stage procedure. In the first stage, we develop a city growth empirical model of “core cities” with more than 100,000 population-essentially re-estimating a modified version of the Henderson–Wang model and use the estimated parameters to produce corresponding city population projections to 2050. In the second stage, we extend the projections to “broader cities” of more than 50,000 population by extrapolating city growth dynamics in different city size groups. These smaller cities are important because many will enter our category of larger cities within the next four decades. In the third and final stage, we use the UN Population Division country level urban population projections (to 2050) to make our city population projections conform to these national urban totals.

We extend Henderson and Wang’s (2007) modeling framework and datasets covering core cities with more than 100,000 population (as of year 2000) and estimate corresponding city population projections in ten year intervals from 2010 to 2050. The projection in this stage covers 2,186 cities.

The core city growth model is estimated using the Ordinary Least Squares estimation. The dependent variable is the city population growth rate of city *i* in country *j* over a 10-year period $\left(\Delta \ln n_{ijt} = \ln n_{ijt} - \ln n_{ijt-1}\right)$. The independent variables include both country and city level characteristics. At the country level, we add the national population growth over the same period $\left(\Delta \ln \text{nat\_pop}_{jt}\right)$, the share of urban population $\left(\text{urban\_rate}_{jt-1}\right)$, the share of population between 15 to 24 years of age $\left(\text{r\_pop\_15\_24}_{jt-1}\right)$, the percentage of adults with secondary education $\left(\text{pct\_sec\_edu}_{jt-1}\right)$ in the base year, and a dummy indicating landlocked countries.

At the city level, we include the city population growth in the previous period $\left(\Delta \ln n_{ijt-1}\right)$ in order to capture strong time persistence often observed in the city growth empirical literature. In addition we consider factors that determine the economic attractiveness of a city relative to its national peers. The growth of a city-specific market potential measure in the previous period $\left(\Delta \ln MP_{ijt-1}\right)$ is added as a crude representation of the extent of market demand for a city's products. The market potential of city *i* is the distance discounted sum of populations of all other cities in the country excluding city *i*. d_{ik} is the distance from city *i* to *k*.

$$MP_{ijt} = \sum_{\substack{k \in j \\ k \neq i}} \frac{n_{kjt}}{d_{ik}}$$

For other geographical control variables, we include distance to coasts $\left(\ln \text{distance\_coast}_{ij}\right)$ and a dummy for a capital city. Coastal locations facilitate imports and exports and make a city an attractive location for investment. The seat of government usually attracts a disproportionate share of migrants to capital cities. Finally, we add interaction terms to capture heterogeneous contributions of different covariates, which include $\ln n_{ijt-1} \times \Delta \ln MP_{ijt-1}$, and $\ln n_{ijt\text{-}1} \times \text{pct\_sec\_edu}_{jt-1}$.

The estimation results of the base sample covering 1960 to 2000 are reported in Table 9. All covariates are significant and have expected signs, which can be easily interpreted. Henderson and Wang (2007) provide detailed interpretation of a similar set of estimation results.

Table 9: City growth estimation results of core cities with more than 100,000 population

Dependent variable	$\Delta \ln n_{ijt} = \ln n_{ijt} - \ln n_{ijt-1}$
Estimation method	OLS
$\Delta \ln \text{nat\_pop}_{jt}$	0.699***
	(0.076)
urban_rate_{jt-1}	-0.067***
	(0.022)
$\text{r\_pop\_15\_24}_{jt-1}$	0.471**
	(0.192)
$\Delta \ln n_{ijt-1}$	0.181***
	(0.031)
$\ln n_{ijt-1} \times \Delta \ln MP_{ijt-1}$	-0.153***
	(0.026)
$\text{pct\_sec\_edu}_{jt-1}$	-0.005**
	(0.002)
$\ln n_{ijt\text{-}1} \times \text{pct\_sec\_edu}_{jt-1}$	0.0004***
	(0.00016)
$\Delta \ln MP_{ijt-1}$	2.360***
	(0.355)
Dummy for a landlocked country	-0.046*
	(0.023)
Dummy for a capital city	0.079***
	(0.018)
$\ln \text{distance\_coast}_{ij}$	0.006***
	(0.001)
Constant	Yes
Observations	4,014
R^2	0.383

Note: 1. Robust standard errors are in parentheses. 2. * significant at 10%; ** significant at 5%; *** significant at 1%.

To project future city level population, the estimation results are sequentially applied to each city's decadal population. For example, the expected city population growth in year t+1 (say, 2010) is used to compute the market potential measure in year t+1, which in turn is used to predict the city population growth in year t+2 (2020). The educational attainment, specifically the percentage of adults with secondary education, represents human capital accumulation and is an indirect measure of technological progress. Its projection from 2010 to 2050 is imputed using a simple projection equation capturing stable correlation with GDP per capita.[2] Other national level exogenous variables, such as projections of national population growth and urbanization rate, are from the UN Population Division projections. In this way, we estimate city population projections of 2,175 core cities of more than 100,000 population.

In the second stage, we extend the city population projections to 8,301 cities of more than 50,000 population. The data are from the CIESIN (2010), but they only contain estimates for a single point in time, for the year 2000. We also note that data for these 8,301 cities have been collected from different sources and city definitions are not completely harmonized with the aforementioned city profiles of 2,175 core cities with more than 100,000 population.[3]

These data limitations do not allow a full-fledged panel data analysis as in the first stage core city modeling, and we cannot identify city-specific growth dynamics. In order to circumvent this problem, we extrapolate city growth dynamics from the first stage core city growth modeling results. A key assumption, derived from the *systems of cities* literature, is that a city's growth dynamics crucially depend on its rank in the urban hierarchy.[4] In other words, the relative city population size in a competing region determines its future growth when other exogenous variables are controlled for.

[2] The percentage of adults with secondary education of country *j* in year *t* is predicted using GDP per capita projections of Hawksworth (2006).

$$\begin{aligned}\text{pct\_sec\_edu}_{jt} &= \underset{(0.008)}{0.870}\times \text{pct\_sec\_edu}_{jt-1} - \underset{(2.832)}{9.537}\times \ln GDPpc_{jt} \\ &\quad + \underset{(0.384)}{1.545}\times\left(\ln GDPpc_{jt}\right)^2 - \underset{(0.017)}{0.075}\times\left(\ln GDPpc_{jt}\right)^3 + \text{constant}\end{aligned}$$

Robust standard errors are in parentheses. All coefficients are significant at 1%. $R^2 = 0.835$.

[3] In contrast to the previous analysis we include cities in industrialized countries in these projections.

[4] A basic model of multiple types of cities involves different types of urban specialization, where different types of cities are specialized in different products and resulting in different city sizes. See Henderson (1974), and Duranton and Puga (2002) for a review.

We first reclassify the 2,175 core cities (of more than 100,000 population) into 16 regions following the regional classification employed in the 2009 World Development Report (World Bank 2009): Australia and New Zealand, Central America and Caribbean, Central Asia, Caucasus and Turkey, Eastern Africa, Eastern Europe and Russia, Middle Africa, North America, Northeast Asia, Northern Africa, South America, Southeast Asia and Pacific, Southern Africa, Southern Asia, Western Africa, Western Asia, and Western Europe. In each WDR region, we group its constituent cities into quintile subgroups according to their relative city population size in 2000, and compute in each quintile group the mean values of each of the regressors of Table 9. These quintile mean values represent region-specific average attributes of each quintile group cities. For example, the largest quintile group cities in Western Africa is assumed to share the same city-specific attributes and dynamics (such as previous growth rates of city population and market potential), while conditioned by country-specific exogenous growth paths (such as projected national population growth, and urbanization rates).

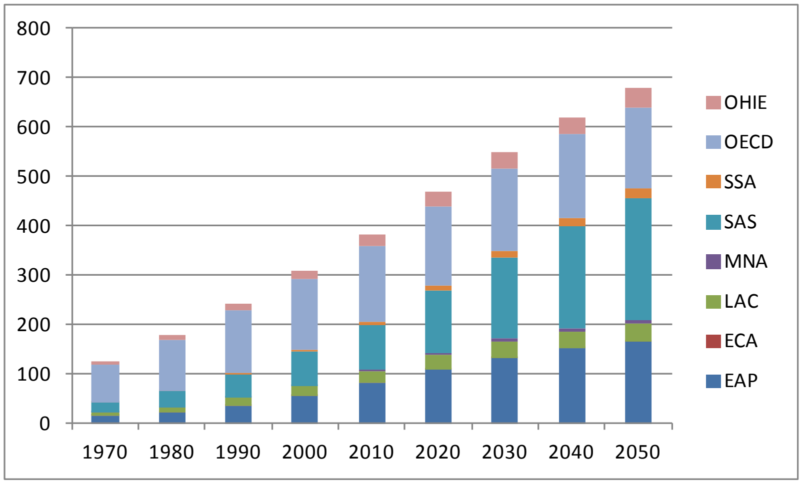
We repeat the same region-specific quintile grouping for 8,301 broader cities of more than 50,000 population. Based on its quintile group, each city in this broader set is then assigned the growth attributes (listed in Table 9) extrapolated from corresponding core city statistics in the same quintile group of the same region. In this way we identify city growth dynamics of each 8,301 broader cities, and sequentially project city population growth rates and corresponding city population sizes backward (from 2000 to 1970) and forward (from 2000 to 2050).

In the third and final stage, we harmonize our projections with UN Population Division national urban population projections (to year 2050) as these are the most widely used national estimates of future urban and rural population. We adjust city population projections $\left(\text{city pop}_{\text{ij,t}}^{\text{adj. proj}}\right)$ such that national urban population growth rates are the same as the UN Population Division's country projections. Specifically,

$$\text{city pop}_{\text{ij,t}}^{\text{adj. proj}} = \text{city pop}_{\text{ij,t}}^{\text{ini. proj}} \times \frac{\sum_{\text{k}\in j} \text{city pop}_{\text{kj,2000}}^{\text{ini. proj}}}{\sum_{\text{k}\in j} \text{city pop}_{\text{kj,t}}^{\text{ini. proj}}} \times \frac{\text{urban pop}_{\text{j,t}}^{\text{UNPD}}}{\text{urban pop}_{\text{j,2000}}^{\text{UNPD}}}.$$

Aggregating urban population projections with data on the spatial distribution of cyclones and earthquakes described earlier shows that population exposure to those hazards is likely to more than double by 2050 (Figure 10 and Figure 11). The largest urban cyclone exposure is expected to be in South Asia while the largest earthquake exposure will be found in East Asia and the Pacific. Figure 12 shows the data for individual cities in map form.

Figure 10: Population in large cities exposed to cyclones (1970-2050)



Note: OHIE=Other high income economies, OECD=Organization for Economic Cooperation and Development, SSA=Sub-Saharan Africa, SAS=South Asia, MNA=Middle East and North Africa, LAC=Latin America and the Caribbean, ECA=Europe and Central Asia, EAP=East Asia and the Pacific.

Figure 11: Population in large cities exposed to earthquakes (1970-2050)

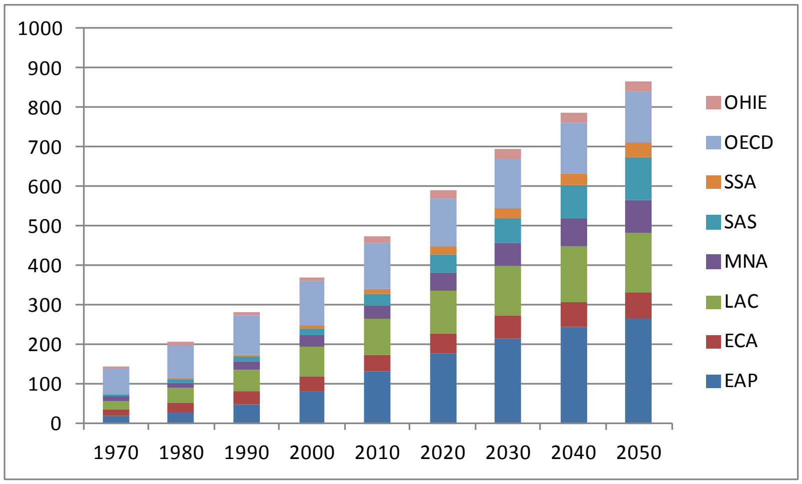
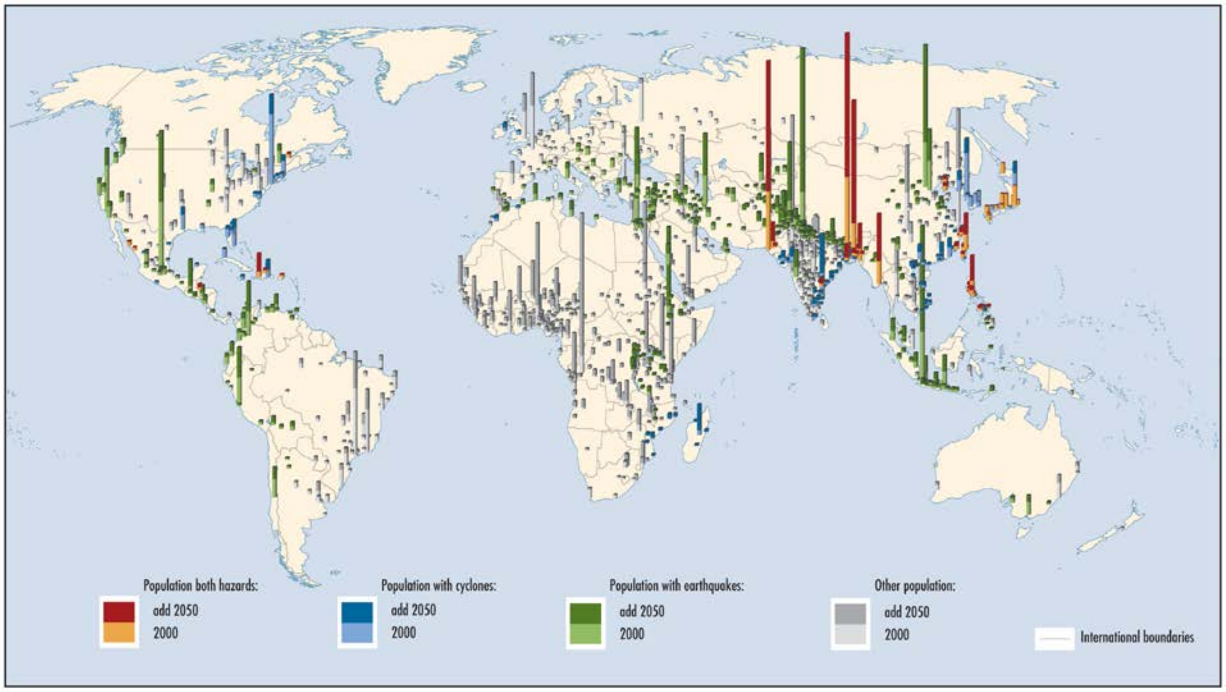


Figure 12: Exposure to cyclones and earthquakes in large cities in 2000 and 2050



Note: Map produced by Brian Blankespoor, DECRG; see also World Bank (2010).

8 Conclusion

This study assesses the risk of mortality and economic loss from catastrophic events in cities of developing countries worldwide with a population greater than 100,000. We calculate risk by combining the three modules of hazard, exposure, and vulnerability. The urban hazards are determined by overlaying the city locations with hazard severity grids; regional vulnerability coefficients are based on loss data from past events; and exposure is defined through city population and city GDP. We developed four single hazard risk indices and in addition, a multi-hazard index gives a holistic picture of city risk. The absolute risk values are converted into index values, classifying the results into relative presentations of risk. Expected urban risk exposure in the year 2050 is determined through projections of future city population growth. The results suggest that populations exposed to earthquake and cyclone risks will more than double by 2050 in developing country cities.

By revealing risk levels, this paper contributes to the knowledge on the variation of urban risks. Such knowledge is useful for local and national planners, as well as international donors. Disclosing risks to cities raises awareness, informs the prioritization of resources, inspires further research, particularly at local levels, and promotes a shift towards managing risks rather than emergencies.

The index also provides a baseline for channeling international interest and funding for detailed urban multi-hazard risk assessments. These detailed assessments of the hazards, elements at risks, and the present and future vulnerabilities are required to gain a deep understanding for effective risk reduction and financial risk transfer mechanisms. Once the underlying risks in a city are known, the key drivers of risk can be addressed through a range of policy options, for instance, through building codes, environmental rehabilitation, land use planning, and early warning. Since the current lack of integration of urban development and risk reduction increases vulnerabilities and expected future losses, a shift to proactive and preventive urban planning underpinned with the principle of diminishing risk is needed. This increased role of spatial and localized urban planning as a tool for reducing disaster is perhaps the most important public policy recommendation from this paper.

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