Annex 1A Robustness of findings on pace of urbanization

This report characterizes South Asia's pace of urbanization during 2000–11 as slower than that in the East Asia and Pacific region in the same period and slower than that experienced by today's developed countries when they were at roughly similar levels of urbanization.

As the main text notes, however, comparisons of levels and rates of growth of urban population shares across countries—both in South Asia and globally—are complicated by the lack of a consistent definition of what constitutes "urban." Different countries use different criteria to officially define urban areas.[1] These differences are reflected in the main source of statistics for performing regional and global comparisons of the pace of urbanization in this report—the United Nations' *World Urbanization Prospects* (WUP) database.[2] So, characterizing South Asia's pace of urbanization as *relatively slow* may be an artifact of the data, especially considering the hidden urbanization identified in the main text.

This annex presents the results of an assessment of the robustness of a relatively slow pace of urbanization. The analysis involves two interrelated sets of exercises, both based on defining a number of non–South Asian comparison groups to assess India's pace of urbanization against.[3] In the first set, the comparison groups are defined using WUP data under different assumptions for the size of potential biases in official estimates of both India's level and pace of urbanization.[4] The basic question this first set of exercises seeks to address is, how large would the biases in official data have to be to overturn a conclusion of a relatively slow pace of urbanization? In the second set, India's pace of urbanization is assessed against comparison groups based on a common or similar definition of urban.

Robustness exercise 1: Comparison of countries in the WUP database

Definition of comparison groups

In the first set of exercises, India's pace of urbanization is assessed against three alternative sets of comparison groups: one global, one limited to countries from East Asia and Pacific, and one limited to current members of the Organisation for Economic Co-operation and Development (OECD). Each comparison group is selected by matching India's level of urbanization in 2001 (under different assumptions for the level of bias) with those of other countries in the WUP database. The comparison groups, therefore, consist of countries with initial levels of urbanization similar to that of India in 2001.[5] Matches since 1950 are searched for.[6,7] This allows India's pace of urbanization during 2001–11 to be compared with the pace of other countries (during an equivalent 10-year period) when they were at an equivalent initial level of urbanization. For example, in the East Asia and Pacific comparison group, India's pace of urbanization during 2001–11 is compared with that of the Republic of Korea during 1970–80.[8]

For each set of comparison groups, three different assumptions are considered for India's initial level of urbanization in 2001.

- *2001 urban share of population = 27.8 percent*. This figure corresponds to the urban share of the population as officially reported in India's 2001 census.
- *2001 urban share of population = 40 percent*. This figure implies that India's urban share as officially reported in the 2001 census was significantly biased downward. An assumed 2001 urban share of 40 percent is consistent with results from Denis and Marius-Gnanou (2011) based on the e-Geopolis definition of urban areas as agglomerations of built-up area with a population of more than 10,000.
- *2001 urban share of population = 50 percent*. This figure implies an even more significant downward bias in India's urban share as officially reported in the 2001 census. An assumed 2001 urban share of 50 percent is consistent with the results of the agglomeration index (AI), which defines as urban all those areas within 60 minutes' travel time of a city with a population of 50,000 or more and with a population density of at least 150 people per square kilometer. Given that India's average population density in 2012 was 421.1 people per square kilometer, the AI using a population density threshold of 150 people per square kilometer should provide an *extreme upper-bound estimate* of India's level of urbanization.

Likewise, three different assumptions for the bias in the estimate of India's pace of urbanization derived from official data are considered:

- *No bias*. The growth rate of India's urban share of the population during 2001–11 was 1.15 percent a year, which corresponds to the growth rate calculated using official data from the 2001 and 2011 censuses.
- *25 percent bias*. The growth rate of India's urban share derived from official data is biased downward by 25 percent, implying a "true" urban share growth rate of 1.44 percent a year.
- *50 percent bias*. The growth rate of India's urban share derived from official data is biased downward by 50 percent, implying a "true" urban share growth rate of 1.73 percent a year.

All possible permutations of these two sets of assumptions for India's initial level and pace of urbanization for the three comparison groups are considered in the analysis.[9]

Results

The results of the first set of robustness exercises are reported in table 1A.1. Each cell reports the percentage of countries in the comparison group that, starting from a similar initial level of urbanization, have growth rates of urban shares (over the relevant historical periods) greater than that assumed for India.[10] For the global groups, panel A shows that if no bias in either India's level of urbanization in 2001 or its pace of urbanization during 2001–11 is assumed, then the comparison group consists of 62 countries. Of these 62, 88.7 percent experienced a faster pace of urbanization than India. If, however, it is instead assumed, for example, that India's "true" level of urbanization in 2001 was 50 percent (while continuing to assume no bias in its pace of urbanization), the size of the comparison group falls to 53 countries, of which 60.4 percent had faster paces of urbanization than India. Similarly, if it is assumed that India's pace of urbanization during 2001–11 as estimated from official data is biased downward by 50 percent (while assuming no bias in the level of urbanization in 2001), then 67.7 percent of the 62 comparator countries had faster paces of urbanization. To generate a result of fast relative urbanization in India—that is, its pace of

TABLE 1A.1 Percentage of countries in comparison group with a faster pace of urbanization under different assumptions

A: Global comparison group			
	Assumed urban share, 2001 (percent)		
Assumed bias in urban share growth rate	**27.82 (n = 62)**	**40 (n = 56)**	**50 (n = 53)**
No bias (1.15%)	88.7	78.6	60.4
25% bias (1.44%)	80.6	62.5	37.7
50% bias (1.73%)	67.7	50.0	26.4
B: East Asia and Pacific comparison group			
	Assumed urban share, 2001 (percent)		
Assumed bias in urban share growth rate	**27.82 (n = 8)**	**40 (n = 1)**	**50 (n = 4)**
No bias (1.15%)	75.0	100.0	75.0
25% bias (1.44%)	75.0	100.0	50.0
50% bias (1.73%)	62.5	100.0	50.0
C: OECD comparison group			
	Assumed urban share, 2001 (percent)		
Assumed bias in urban share growth rate	**27.82 (n = 3)**	**40 (n = 6)**	**50 (n = 12)**
No bias (1.15%)	100.0	83.3	58.3
25% bias (1.44%)	100.0	66.7	41.2
50% bias (1.73%)	100.0	66.7	25.0

Panel B: East Asia and Pacific comparison groups

n = 8: Mongolia (1955–65), Korea, Rep. (1960–70), Indonesia (1985–95), China (1990–2000), Malaysia (1960–70), Myanmar (2000–10), the Philippines (1950–60), Thailand (1985–95)

n = 1: Korea, Rep. (1970–80)

n = 4: Korea, Rep. (1975–85), Malaysia (1990–2000), Mongolia (1975–85), the Philippines (1990–2000)

Panel C: OECD comparison groups

n = 3: Korea, Rep. (1960–70), Slovenia (1960–70), Turkey (1955–65)

n = 6: Korea, Rep. (1970–80), Turkey (1975–85), Slovak Republic (1970–80), Poland (1950–60), Ireland (1950–60), Portugal (1975–85)

n = 12: Korea, Rep. (1975–85), Norway (1960–70), Finland (1955–65), Mexico (1960–70), Estonia (1950–60), Portugal (1995–2005), Switzerland (1960–70), Poland (1965–75), Ireland (1965–75), Slovak Republic (1980–90), Spain (1950–60), Slovenia (1990–2000)

Note: OECD = Organisation for Economic Co-operation and Development.

urbanization is faster than at least half the countries in the comparison group—it is necessary to assume that India's urban share of the population in 2001 was at least 50 percent (as opposed to the official figure of 27.8 percent) and that its pace of urbanization as estimated from official data is biased downward by at least 25 percent.

Although the groups are much smaller, similar results hold for the comparisons with both the East Asia and Pacific and OECD groups. For the OECD group, it is again necessary to assume that India's urban share in 2001 was at least 50 percent and that the estimated pace of urbanization was biased downward by at least 25 percent to generate a result of fast relative urbanization. For the East Asia and Pacific group, even under these assumptions, India's pace of urbanization can best be described as moderate (50 percent of comparator countries urbanizing faster and 50 percent slower).[11]

Robustness exercise 2: Comparisons based on a common definition

The second set of robustness exercises takes advantage of work by International Growth Center researchers that provides estimates of India's urban share of the population for 2001 and 2011 based on alternative definitions (see, in particular, Jana, Sami, and Seddon, n.d.). They estimate the urban share of the population based simply on the number of people living in settlements that have a population in excess of 5,000—regardless of whether the census classifies them as urban or rural. Using this definition, they estimate that India's urban share in 2001 was 43 percent and that it had increased to 47 percent by 2011, thereby implying a growth rate of the urban share of 0.89 percent a year.[12]

The advantage of this very simple definition of urban is that many countries in the WUP database, primarily in Africa and the Middle East, officially define urban areas in either the same or a very similar way (using a similar population threshold). Bairoch and Goertz (1986) provide historical estimates of urban shares from the 19th and early 20th centuries for many of today's developed countries based on the same definition of urban. This allows two further comparisons to be undertaken to assess the relative pace of India's urbanization based on a common or similar definition of urban. In the first comparison, India's pace of urbanization is assessed for the period 2001–11 based on the 5,000 population threshold criterion against other countries in the WUP database that used the same or a similar definition of urban when they were at a similar initial level of urbanization. In the second comparison, India's pace of urbanization is assessed against the historical experiences of today's developed countries for which Bairoch and Goertz provide data and for which we are able to match on the initial level of urbanization.

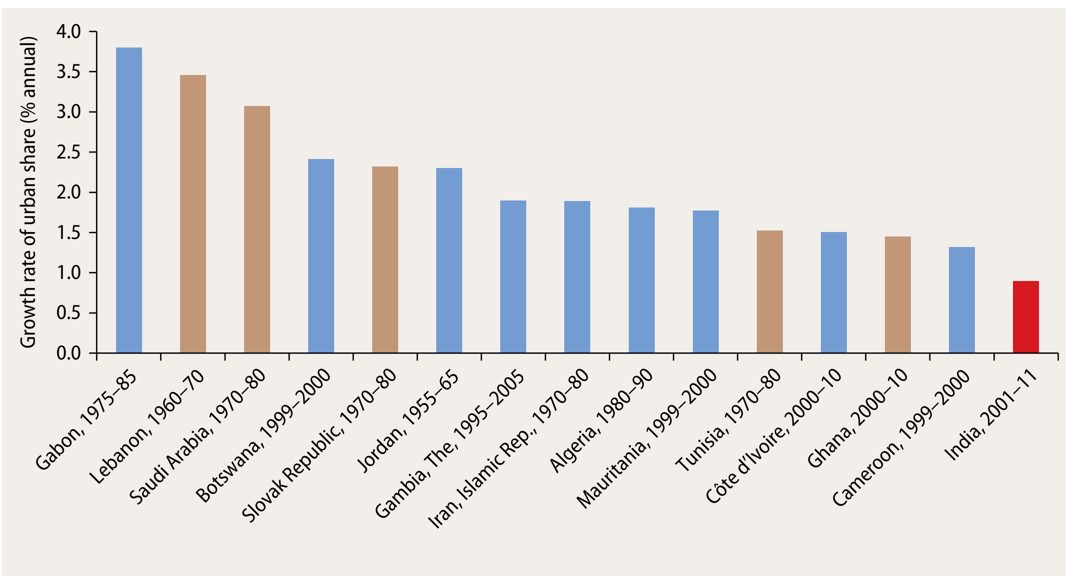
Relative to other countries in the WUP database

Figure 1A.1 shows the results of the first comparison—against other countries in the WUP database. There are 14 country urbanization episodes against which to compare India's pace of urbanization. In all 14, the growth rate of the urban share during the relevant period starting from a similar initial level is greater than the growth rate that India experienced between 2001 and 2011. Indeed, the most slowly urbanizing country in the comparison group—Cameroon for 1995–2005—still had an estimated pace of urbanization almost 50 percent faster than India's between 2001 and 2011.[13]

Relative to OECD countries historically

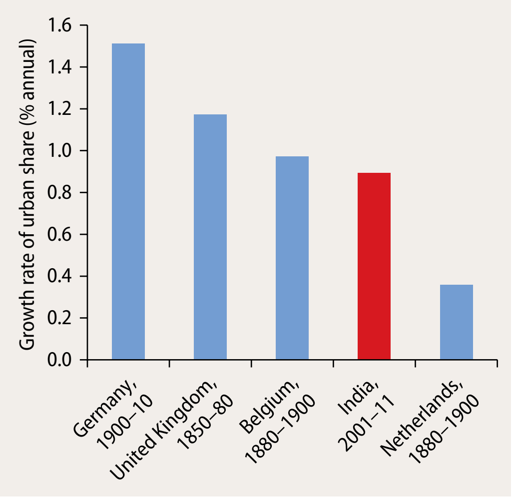
The results of the second comparison are shown in figure 1A.2. In particular, the figure shows the four current OECD member

FIGURE 1A.1 Pace of urbanization for countries when urban is defined as all settlements with a population of more than 5,000



Note: Brown shading = perfect match on definition of urban; blue shading = close, but not perfect, match on definition of urban.

FIGURE 1A.2 India's pace of urbanization compared with the historical experiences of selected OECD member countries



countries that match India using the historical data from Bairoch and Goertz (1986). Out of these four countries, only the Netherlands experienced a slower pace of urbanization during the relevant historical time period.

Conclusion

Based on the findings from the two sets of exercises reported here, the characterization of South Asia's pace of urbanization during 2001–11 as having been relatively slow appears to be reasonably robust. The first set of exercises shows that it would require India's "true" urban share of the population in 2001 to have been at least 50 percent and the estimate of the growth rate of its urban share based on official census definitions to have been biased by at least 25 percent to generate a finding of fast urbanization in comparison with the global and OECD groups. Even under these assumptions, India's pace of urbanization would have still been slower than at least 25 percent of countries in each of the comparison groups. The second set of exercises shows that, when a more uniform definition of urban areas across countries is adopted, India's pace of urbanization during 2001–11 appears slow relative to the comparators that can be identified in the WUP database (mainly in Africa and the Middle East) and the historical experiences of Belgium, Germany, and the United Kingdom (but not the Netherlands) at a similar stage of urbanization.

Notes

1. It is important to note that the official census definition of urban for India includes census towns. Census towns are settlements that are administratively rural but that meet the following three criteria: population in excess of 5,000 persons, population density greater than 400 people per square kilometer, and at least 75 percent of male main workers involved in agricultural pursuits.
2. See http://esa.un.org/unpd/wup/ for the most recent revision of the database.
3. This annex focuses exclusively on India given that it accounts for 75 percent of South Asia's overall population. Trends at the regional level, including the overall assessment of the relative pace of urbanization, are primarily driven by trends in India.
4. Although it is assumed, in this first set of exercises, that potential biases exist in estimates of both India's level and pace of urbanization based on its official definition of urban, no biases in official estimates for other countries arising from their definitions of urban are assumed. This approach is likely to bias the results against a conclusion of a relatively slow pace of urbanization for India given that hidden urbanization is unlikely to be a phenomenon completely exclusive to India.
5. The comparison groups exclude all countries whose populations in 2010 were less than 1 million and all overseas territories, departments, and regions of France, the Netherlands, and the United Kingdom. This prevents the small island nations or dependencies from being included in the comparison groups.
6. To qualify as a potential match, a country-year observation in the WUP database must have an estimated urban share of the population that is within at least 2 percentage points of India's assumed urban share of the population in 2001.
7. More precisely, the search for potential matches is performed for the period 1950–2000 to

enable the calculation of growth rates of urban shares over 10-year periods.

8. The exact period of comparison depends on the level of bias assumed in India's 2001 level of urbanization.
9. India's pace of urbanization is therefore assessed against a total of 27 different comparison groups—9 global comparison groups, 9 East Asia and Pacific comparison groups, and 9 OECD comparison groups.
10. A full set of summary statistics for each comparison group is available on request.
11. Some caution is, however, required here given the small size of the comparison group.
12. This figure implies a slower pace of urbanization than obtained using India's official definition of urban, suggesting that the pace of urbanization as estimated using official data may actually be biased downward (as opposed to the assumption of upward bias explored in the first robustness exercise).
13. Cameroon experienced a growth rate of its urban share of 1.32 percent per year during 1995–2005 starting from a base urban share of 42.6 percent. By contrast, based on the 5,000 settlement population threshold, India had an annual growth rate of its urban share of 0.89 percent during 2001–11 starting from a base of 43 percent.

References

Bairoch, P., and G. Goertz. 1986. "Factors of Urbanization in the Nineteenth Century Developed Countries: A Descriptive and Econometric Analysis." *Urban Studies* 23 (4): 285–305.

Denis, E., and K. Marius-Gnanou. 2011. "Toward a Better Appraisal of Urbanization in India: A Fresh Look at the Landscape of Morphological Agglomerates." Online article. *Cybergeo: European Journal of Geography*. https://cybergeo.revues.org/24798.

Jana, A. N. Sami, and J. Seddon. n.d. "How 'Urban' Is India?" http://www.theigc.org/wp-content/uploads/2014/08/Arindam-Jana.pdf.

Annex 1B Pairwise livability comparisons methodology

Measuring livability

The livability index that underlies figure 1.10 in the main text of chapter 1 was constructed to facilitate pairwise comparisons, where sufficient data exist, between South Asian cities and cities in other regions of the world. This annex provides a brief overview of the methodology underlying the construction of the index as well as its four subindices. Further details can be found in Amirtahmasebi and Kim (2014).

Calculation of South Asian cities' livability performance

The livability index is calculated, using equation (1B.1), as the geometric mean of performance across four subindices for education, health, environment, and safety:

$$Livability_i = [Educ_i \times Health_i \times Envir_i \times Safety_i]^{1/4}. \quad (1B.1)$$

$Livability_i$ is the value of the livability index for city *i*, and $Educ_i$, $Health_i$, $Envir_i$, and $Safety_i$ denote city *i*'s scores on the education, health, environment, and safety subindices, respectively.[1] The livability index has a potential range of 0–100, as do each of the subindices; 100 indicates the maximum assumed level of performance.

The subindices for education, health, environment, and safety are, in turn, each calculated as a simple average of several indicators, with the exception of the safety subindex, for which only a single indicator is used. Table 1B.1 lists the indicators used in the construction of each subindex, along with accompanying data sources. Where possible, data at the city or metropolitan level were used. Where such data were unavailable, as for indicator *H1*, national or, for Indian cities, state data were used instead.

Indicators not expressed as a percentage—*H1*, *H2*, *E1,* and *S1*—are normalized to a scale of 0–100, where a higher score indicates better performance on an indicator. For *H1*, normalization is performed using equation (1B.2), and for the remaining indicators using equation (1B.3):

$$trans_i = \frac{(actual_i - min)}{(max - min)} \times 100 \quad (1B.2)$$

$$trans_i = 100 - \left[\frac{(actual_i - min)}{(max - min)} \times 100\right]. \quad (1B.3)$$

The term $trans_i$ is the transformed indicator value for city *i*; $actual_i$ is the raw (that is, untransformed) observed value of the indicator for city *i*; *min* is the minimum assumed value that the raw indicator can take, and *max* is the

TABLE 1B.1 Indicators used in construction of the livability index

Indicators(s)	Time period	Data sources
Health		
H1: Life expectancy at birth	2006–10 (year varies by city)	UNDP (2011); Registrar General of India (2013); UNIDO Statistics database; World Bank national-level data;
H2: Under-5 mortality rate (per 1,000 live births)	2010–11	WHO Global Health Observatory Data Repository; Afghanistan Mortality Survey (2010); National Statistics Bureau, Bhutan
Environment		
E1: PM_{10} level (micrograms per cubic meter)	2008–11 (year varies by city)	WHO Outdoor Air Quality Data 2006–08; European Environmental Agency; Clean Air Initiative Asia 2010; Ministry of Environment, Science and Technology, Nepal; Ambient Air Quality of Kathmandu Valley 2007; Indian Ministry of Environment and Forests, National Ambient Air Quality Status 2008–09
E2: Population served by waste water collection (%)	2007–11 (year varies by city)	International Benchmarking Network for Water and Sanitation Utilities; World Bank World Development Indicators; Siemens Green City Index; Muzzini and Aparicio (2013a, 2013b)
E3: Population with solid waste collection (%)	2007–11 (year varies by city)	World Bank (2012); Muzzini and Aparicio (2013); Siemens Green City Index
Safety		
S1: Homicides per 100,000 population	2006–08 (year varies by city)	India National Crime Records Bureau's Statistics 2007; Pakistan National Police 2011; Brazil National Police 2011; United Nations Office on Drugs and Crime (2009); National Coroner and Forensic Sciences Institute, Bogotá Chamber of Commerce, Security Observatory 2011; Colombia National Police 2011; UN Surveys on Crime Trends and Operations, 2006
Education		
E1: Literacy rate (percent)	2006–11 (year varies by city)	Government of National Capital Territory of Delhi; Demographic and Health Surveys for Bangladesh (2011), Pakistan (2006–07), and Nepal (2011); Statoids data on Brazilian states and Istanbul Metropolitan area, Martin Prosperity Institute
E2: Primary school enrollment rate (percent)	2006–11 (year varies by city)	Demographic and Health Surveys for Bangladesh (2011), Nepal (2011), and Pakistan (2006–07); Martin Prosperity Institute Database 2011; World Bank Education Statistics Databank; India National Family Health Survey (NFHS-3); UNICEF (2011)

Note: PM_{10} = particulate matter less than 10 micrometers in diameter; UNIDO = United Nations Industrial Development Organization; WHO = World Health Organization.

maximum assumed value of the raw indicator. For indicator *H1*, *max* = 83 years, the life expectancy in Japan in 2011 (and the highest life expectancy globally); *min* is taken to be 20 years.[2] For indicator *H2*, the assumptions are *max* = 187 per 1,000 live births and *min* = 0, where *max* is equal to the under-5 mortality rate in Sierra Leone (the country with the highest under-5 mortality rate) in 2011. For indicator *E1*, *max* = 199.7 micrograms per cubic meter (the PM_{10} concentration for Lahore) and *min* = 18 micrograms per cubic meter (the PM_{10} concentration for Thimphu). For indicator *S1*, *max* = 70 homicides per 100,000 (equal to Honduras's homicide rate in 2011) and *min* = 0.

Selection of comparator cities

The livability index was initially constructed for 11 matched pairs of South Asian and non–South Asian developing-country cities for which sufficient data were available.[3] In each case, matching was based on three main variables: city population, area of the city, and city population density.[4] From these 11 matched pairs, 4 were chosen to construct figure 1.10: Delhi and Istanbul (Turkey), Karachi and São Paulo (Brazil), Kathmandu and Medellín (Colombia), and Dhaka and Bogotá (Colombia). In each case, the comparator city represents a reasonable benchmark to whose performance levels the South Asian city in question might reasonably aspire.

Notes

1. By calculating the index based on the geometric, as opposed to arithmetic, mean, we assume that a city's overall livability depends on the interaction between the four areas covered by the subindices. A city that scores zero on, say, the education subindex will therefore also score zero on its overall livability, irrespective of its performance on the three other subindices.
2. The selection of the *max* and *min* values for indicators *H1* and *H2* follows UNDP (2013). The formulas to normalize indicators (equations [1B.2] and [1B.3]) are likewise based on UNDP (2013).
3. The cities for which the livability index was initially constructed are: Kabul (Afghanistan); Dhaka (Bangladesh); Thimphu (Bhutan); São Paulo (Brazil); Ouagadougou (Burkina Faso); Nanjing (China); Bogotá and Medellín (Colombia); Cairo (Egypt); Chennai, Delhi, Kolkata, and Mumbai (India); Casablanca (Morocco); Yangoon (Myanmar); Kathmandu (Nepal); Lagos (Nigeria); Lahore and **Karachi** (Pakistan); Cape Town (South Africa); Colombo (Sri Lanka); and Istanbul (Turkey).
4. An attempt was also made to use gross domestic product (GDP) per capita as a matching variable; however, the ability to satisfactorily match on GDP per capita was limited by available data.

References

Amirtahmasebi, R., and S. Kim. 2014. "Beyond Economic Growth: Livability Performance in SAR cities." Background paper for this report, World Bank, Washington, DC.

Muzzini, E., and G. Aparicio. 2013. *Bangladesh: The Path to Middle-Income Status from an Urban Perspective.* Washington, DC: World Bank.

Registrar General of India. 2013. *SRS Based Abridged Life Tables 2003-07 to 2006-10.* Details available at http://www.censusindia.gov.in/vital_statistics/SRS_Based/SRS_Based.html [retrieved July 16, 2014].

UNDP (United Nations Development Programme). 2011. *Inequality-Adjusted Human Development Index for India's States.* New Delhi: UNDP India.

———. 2013. *Human Development Report 2013—The Rise of the South: Human Progress in a Diverse World.* New York: UNDP. http://www.refworld.org/docid/514850672.html.

UNICEF (United Nations Children's Fund). 2011. *The State of the World's Children 2011: Adolescence – An Age of Opportunity.* New York: UNICEF.

United Nations Office on Drugs and Crime. 2009. "UN Surveys on Crime Trends and Operations of Criminal Justice System (UN-CTS)." Data covering the period 2003 to 2008. United Nations, New York.

World Bank. 2012. *WHAT A WASTE; A Global Review of Solid Waste Management.* Washington, DC: World Bank.

———. 2013. *Urban Growth and Spatial Transition in Nepal: An Initial Assessment.* Washington, DC: World Bank.

Annex 2A Nighttime lights and economic activity

Chapter 2 uses nighttime lights data for three main purposes: (1) to proxy for a district's level of economic activity in 2010 in the construction of the productivity component of the prosperity index (see "Measuring differences in subnational performance"); (2) to derive, using the methodology of Henderson, Storeygard, and Weil (2011, 2012), district estimates of real gross domestic product (GDP) growth for the period 1999–2010, both for the construction of the dynamism component of the prosperity index ("Measuring differences in subnational performance") and to analyze spatial patterns of economic growth ("Spatial patterns of economic growth"); and (3) to help analyze spatial patterns of physical urban expansion ("Rapid relative expansion of urban footprints and the rise of the multicity agglomeration"). In all cases, the nighttime lights product used is the Global Radiance Calibrated Nighttime Lights product[1] that measures the intensity of nighttime lights as an average over all cloud-free nights in a given year on a digital number (DN) scale that ranges from 0 to 1,500.

Whereas box 2.1 provides an overview of the methods used in applying the nighttime lights data, with the full details available in a background paper by Roberts (2014), this annex presents more detailed evidence of the correlation between the intensity of nighttime lights, as measured by an area's aggregate DN value, and economic activity. In particular, it presents evidence, based on regression analysis, of statistically significant relationships between, first, the intensity of nighttime lights and levels of GDP, and second, the growth in intensity of nighttime lights and real GDP growth. The analysis uses both cross-country data and data for a limited sample of Indian districts. The existence of these statistically significant relationships helps justify the use of the lights data both to proxy for levels of economic activity and to construct estimates of real GDP growth. The procedure by which estimates of real GDP growth were derived is also described.

Correlation between intensity of nighttime lights and levels of real GDP

Columns (1)–(3) of table 2A.1 report regression results for South Asian countries based on pooled data for 1999 and 2010. The results in columns (1) and (2) show that the aggregate intensity of a South Asian

TABLE 2A.1 South Asian country and Indian district GDP levels are strongly predicted by the intensity of nighttime lights

	South Asian countries			Indian districts	
	ln(GDP)	ln(GDP)	ln(GDP)	ln(GDP)	ln(GDP)
	(1)	(2)	(3)	(4)	(5)
ln(DN)	1.0904***	1.1047***	0.0236	0.8397***	0.8244***
	(0.0763)	(0.1263)	(0.1205)	(0.0293)	(0.0301)
D_{2010}	0.5176	0.8984	0.0027	0.4950***	−1.5021
	(0.4598)	(2.4466)	(0.1078)	(0.0984)	(1.3523)
D_{2010}* ln(DN)		−0.0281			0.1927
		(0.1601)			(0.1267)
ln(electric)			0.7755***		
			(0.0932)		
Constant	9.9885***	9.7960***	7.0801***	1.5430***	1.6929***
	(1.2174)	(1.9186)	(0.8006)	(0.2971)	(0.3048)
Observations	14	14	10	568	568
R^2	0.866	0.866	0.992	0.635	0.637
Adjusted R^2	0.842	0.826	0.988	0.633	0.635
F	102.1937	66.1338	298.3375	453.7163	319.6072
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000

Note: Robust standard errors in parentheses; *** statistically significant at 1 percent level; D_{2010} is a dummy variable that takes the value 1 for 2010 observations and zero otherwise; F is the test statistic for an F-test of the joint significance of all explanatory variables with Prob > F being the corresponding p-value. Data for both real GDP and electricity consumption were taken from World Bank World Development Indicators.

country's nighttime lights—that is, its aggregate DN value—is strongly correlated with its level of real GDP, with an estimated elasticity of GDP with respect to lights of about 1.1, which is stable over time. A salient feature of the results is that the relationship between lights and real GDP is statistically significant at the 1 percent level even though the regressions are based on a sample of just 14 observations (one for each of the seven sample countries for 1999 and 2010).[2] The results in column (3) provide evidence that the relationship between lights and GDP works through electricity consumption. Electricity consumption is therefore a crucial part of the transmission mechanism that links lights to real GDP and helps explain the strength of its predictive power. Columns (4) and (5) report results for similar pooled regressions for Indian districts.[3] These results confirm that the same statistically significant positive relationship between nighttime light intensity and levels of real GDP that holds for South Asian countries also holds for Indian districts, albeit with a less impressive (though still very good) fit.

Correlation between the growth of nighttime light intensity and real GDP growth

Table 2A.2 presents results from regressions of the (natural) log change of GDP[4] on the (natural) log change in the intensity of nighttime lights for 1999–2010 for three samples of countries: a comprehensive global sample of countries covering all income levels, countries classified as either low- or middle-income by the World Bank, and a sample of South Asian countries for which the data necessary to run the regressions were available. The results in columns (1) and (3) show that a statistically significant positive relationship exists between the growth in the intensity of a country's nighttime lights and its growth of real GDP irrespective of whether the global sample or the sample restricted to just low- and middle-income countries is used.

TABLE 2A.2 A country's GDP growth is positively correlated with the growth in intensity of its nighttime lights

	Δln(GDP, local currency units)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δln(DN)	0.2284*** (0.0384)	0.1014** (0.0470)	0.2452*** (0.0427)	0.1512** (0.0627)	0.8055 (0.5378)	0.8099 (0.4604)	0.9292 (0.5391)
Δln(electric)		0.2867*** (0.0571)		0.1701** (0.0740)			0.2467 (0.1046)
Constant	0.2835*** (0.0245)	0.2420*** (0.0304)	0.3085*** (0.0281)	0.3100*** (0.0436)	0.5493*** (0.0773)	0.5052*** (0.0541)	0.2962 (0.1078)
Sample	*Global*	*Global*	*LIC and MIC*	*LIC and MIC*	*South Asia*	*South Asia*	*South Asia*
Observations	185	129	126	81	7	6	5
R^2	0.162	0.269	0.210	0.196	0.222	0.462	0.664
Adjusted R^2	0.157	0.257	0.204	0.176	0.066	0.327	0.328
F	35.3223	23.1317	32.9555	9.5283	2.2437	3.0953	3.6023
Prob > F	0.0000	0.0000	0.0000	0.0002	0.1944	0.1533	0.2173

Note: Robust standard errors in parentheses; *** statistically significant at 1 percent level; ** significant at 5 percent level; F is the test statistic for an F-test of the joint significance of all explanatory variables with Prob > F being the corresponding p-value. The equation for column (6) drops the outlier Bhutan. Electric power consumption data, which were taken from World Bank World Development Indicators, are missing for Afghanistan, Bhutan, and Maldives. The p-values for Δln(DN) in the equations for columns (5)–(7) are 0.194, 0.153, and 0.227, respectively. The p-value for Δln(electric) in the equation for column (7) is 0.142. LIC = low-income countries; MIC = middle-income countries.

Columns (2) and (4) show that this relationship continues to hold even after controlling for electricity consumption, indicating that changes in nighttime light intensity have some ability to predict economic growth independently of changes in electricity consumption. Finally, columns (5)–(7) demonstrate the continued existence of a positive linear relationship between the growth of nighttime light intensity and GDP even when attention is restricted to just South Asian countries. This relationship is not, however, statistically significant on account of the extremely small sample involved.[5] The results reported in table 2A.2 are generally consistent with those in Henderson, Storeygard, and Weil (2011, 2012) despite differences in both the underlying nighttime lights data set and sample period (see Roberts [2014] for more details).

Table 2A.3 shows that, once the outliers of Gadchiroli and Raigarh are excluded, there is a statistically significant relationship between GDP growth and nighttime lights growth for (the limited sample of) Indian districts for which GDP data were available for 1999 and 2010.

TABLE 2A.3 Indian district GDP growth is positively correlated with the growth in the intensity of a district's lights

	Δln(GDP)	Δln(GDP)
	(1)	(2)
$\Delta\ln(DN_{2010})$	0.1433 (0.0968)	0.2316*** (0.0390)
Constant	0.5998*** (0.0179)	0.6170*** (0.0137)
Observations	47	45
R^2	0.128	0.426
Adjusted R^2	0.109	0.413
F	2.1896	35.3334
Prob > F	0.1459	0.0000

Note: Robust standard errors in parentheses; *** statistically significant at the 1 percent level; F is the test statistic for an F-test of the joint significance of all explanatory variables with Prob > F being the corresponding p-value. The equation for column (2) excludes two outliers (Gadchiroli and Raigarh). The p-value for Δln(DN) in the equation for column (1) is 0.146, and in the equation for column (2) it is 0.000.

Construction of estimates of real GDP growth from nighttime lights data

District estimates of real GDP growth during 1999–2010 are derived from the nighttime lights data using the regression results in column (3) of table 2A.2. In particular, for any given district *i*, its rate of real GDP growth is derived by, first, substituting the natural log change in its aggregate DN value over this period into the fitted equation:

$$\Delta\ln(GDP_i^E) = 0.3085 + 0.2452\Delta\ln(DN_i) \tag{2A.1}$$

in which $\Delta\ln(GDP_i^E)$ is the district's estimated real GDP growth rate during 1999–2010. This growth rate is converted into an annual average by dividing by the number of years (11).

Notes

1. The latest version of this product is available for download from http://ngdc.noaa.gov/eog/dmsp/download_radcal.html. The results reported in both chapter 2 of the main report and this annex are based on an earlier (pre-general release) version of this product that was supplied by the National Oceanic and Atmospheric Administration's National Centers for Environmental Information Earth Observation Group.
2. The only South Asian country not present in the sample is Maldives.
3. An absence of readily available data on electricity consumption prevented the estimation of a regression for Indian districts that included this variable. Data on GDP for Indian districts is from the Planning Commission, Government of India.
4. The log-difference regressions in table 2A.2 follow Henderson, Storeygard, and Weil (2011, 2012) in measuring GDP in (constant price) local currency units.
5. The p-values for the slope coefficients in the regressions in columns (5)–(7) of table 2A.2 are, nevertheless, quite low considering the sample sizes.

References

Henderson, J. V., A. Storeygard, and D. N. Weil. 2011. "A Bright Idea for Measuring Economic Growth." *American Economic Review* 101 (3): 194–99.

———. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review* 102 (2): 994–1028.

Roberts, M. 2014. "Urbanization in South Asia: A View from Outer Space." Background paper for this report, World Bank, Washington, DC.

Annex 2B Robustness of nighttime lights results on expansion of urban footprints

In the main text of chapter 2, nighttime lights data are used to study the pace of expansion of urban night-lit area, which is used as a proxy measure of the overall built-up urban area. Based on nighttime lights data, it was concluded that, for the South Asia region overall, urban area expanded at a rate of slightly more than 5 percent a year between 1999 and 2010, roughly twice as fast as the rate of urban population growth for the period. Rates of expansion were found to be fastest in Afghanistan and Bhutan, but much slower in Bangladesh, Nepal, and Pakistan.

One concern in using the pace of expansion of urban night-lit area as a proxy measure for the pace of expansion of built-up urban area arises from the widespread power supply outages in the region. In particular, the nighttime lights data for both 1999 and 2010 are constructed as daily averages over all cloud-free nights within each year. Consequently, if the prevalence and duration of outages has changed systematically between the two years, the estimates of the pace of expansion of built-up urban area based on nighttime lights data will be biased. More (less) severe outages between 1999 and 2010 might be expected to bias downward (upward) estimates of the pace of expansion based on the lights data. These concerns apply particularly to Bangladesh and Pakistan, two of the countries that have seen the slowest rates of growth of urban lit area, given that, out of a global sample of 128 countries, they rank as first and fifth, respectively, in World Bank Enterprise Surveys data on the number of electrical outages that firms suffer in a typical month.[1]

To assess the robustness of the findings on the pace of expansion of urban night-lit area to concerns about power outages, work was undertaken in collaboration with the producers of the nighttime lights products—the National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric Administration—to "trim out" abnormally dimly lit nights, which could be the result of power outages, from the yearly averages. More specifically, the nighttime lights data were reprocessed by NGDC for 1999 and 2010 so that instead of, for each pixel, calculating the average over all cloud-free nights, the average was only calculated over those nights that had a level of light intensity (that is, a DN value) in excess of the median.

Having reprocessed the data to create this new "trimmed" nighttime lights product, total urban night-lit area—defined as the total area with a level of light intensity in excess of DN = 13—was calculated for 1999 and 2010 for each country, and the corresponding growth rates of urban night-lit area were also

TABLE 2B.1 Comparison of growth rates of urban night-lit area as calculated using the trimmed and nontrimmed nighttime lights data products

	Nontrimmed			Trimmed			
	Area		Annual growth (percent)	Area		Annual growth (percent)	Difference
	1999	2010		1999	2010		
Afghanistan	195	1,349	19.22	281	1,736	18.00	−1.22
Bangladesh	4,940	7,210	3.50	7,549	10,622	3.15	−0.34
Bhutan	62	253	13.64	98	456	15.00	1.36
India	174,308	421,935	8.37	273,514	620,768	7.74	−0.63
Nepal	989	1,037	0.43	2002	1,914	−0.41	−0.84
Pakistan	51,664	79,181	3.96	81,911	132,647	4.48	0.52
Sri Lanka	4,697	8,337	5.35	6,840	12,107	5.33	−0.03
South Asia	**236,855**	**519,302**	**7.40**	**371,295**	**780,250**	**6.96**	**−0.44**

Note: "Difference" is the trimmed growth rate minus the nontrimmed growth rate. Area is measured in number of pixels in the nighttime lights data sets, which are approximately 1 square kilometer at the equator. Maldives is excluded from the calculations owing to data unavailability.

calculated. The corresponding calculations were then performed using the nontrimmed lights data. Comparing the rates of growth of urban night-lit area from the trimmed data with those from the nontrimmed data enables an assessment of the robustness of the findings on the pace of expansion—in particular, the finding of overall rapid expansion of urban night-lit area—to power outage concerns.

Results[2]

Table 2B.1 shows the results of the comparison between the trimmed and nontrimmed data for all countries, as well as the region overall, excluding Maldives. As might be expected, for both 1999 and 2010, the total area classified as urban using the DN = 13 threshold is, for each country, greater when using the trimmed data than it is when using the nontrimmed data.[3] Nevertheless, the growth rates of urban night-lit area calculated using the trimmed data are remarkably similar to those calculated using the nontrimmed data. Moreover, the ranking of countries using pace of expansion of urban night-lit area is the same using both data sets. These results provide confidence in the overall findings on the pace of expansion using the nighttime lights data. In particular, they confirm the basic finding at the regional level that the growth of urban night-lit area—and so, presumably, built-up urban area—has been rapid relative to urban population growth.

Notes

1. Firms in Bangladesh suffer, on average, 64.5 outages per month, and firms in Pakistan 31.7 outages per month. The rankings of the remaining South Asian countries (with the exception of Maldives, for which no data are available) in terms of the average number of outages per month are as follows: India—14th (13.8 outages per month); Afghanistan—18th (11.5 outages); Nepal—26th (8.7 outages); Sri Lanka—51st (4.1 outages), and Bhutan—100th (0.8 outages). The average duration of outages ranges from a minimum of 0.6 hours (Bhutan) to a maximum of 2.6 hours (Afghanistan). See http://www.enterprisesurveys.org for further information.
2. The overall result on the pace of expansion of urban night-lit area using the nontrimmed data—in particular, the estimated growth rate of 7.4 percent a year for the region overall between 1999 and 2010—differs from the rate of slightly more than 5 percent a year reported in the main text. Whereas the results reported in the main text use the Global Radiance Calibrated Nighttime Lights product, the robustness results described in this annex are based on the Average Visible Nighttime Lights product (this latter product can be downloaded from http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html).

This is because of the inherent technical difficulties involved in reprocessing the global radiance lights product to trim out observations. Regardless of the exact lights data product used, the basic result of overall rapid expansion of urban night-lit area remains the same.

3. Trimming out the bottom 50 percent of cloud-free observations inevitably raises the average DN value for all countries.

Annex 6A Data Collection and Methods Used for Classification of Cities by Climate Risk

To group cities according to shared characteristics, the various indicators under consideration were transformed for ease of comparability. The typology first classifies cities by risk of earthquakes and hydrometeorological (hydromet) hazards: high, moderate, or low. Second, it groups them by their future climate risk outlook. Third, it groups cities by relative size within South Asia. It is important to note that these figures are relative within South Asia alone and do not take into account comparisons with cities in other regions. Figures 6A.1, 6A.2, and 6A.3 show the taxonomic trees of South Asian cities for three risk combinations.

Sources of data for taxonomic trees

One of the biggest challenges of this endeavor has been to find comparable city-level data across the eight South Asian countries for natural hazard risks, climate projections, present and future populations, and socioeconomic vulnerability. Some of this information is not yet available at the local level, while other data exist in disaggregated form across national censuses. Because of data and time limitations, this effort relies on readily available data sets that estimate local risk and demographic and socioeconomic characteristics. For climate and risk data, it is important to keep in mind that these are global or regional projections and that local topographical and climatic conditions may be quite different. For demographic and socioeconomic vulnerability data, the statistics used refer to data for 2000 or to state, district, or provincial data. In many data sets and maps, information is not available for the smaller cities and countries, especially Bhutan, Maldives, and Sri Lanka. Chapter 6 provides boxes on the largest cities in these countries to partially fill the gap. The main sources of data and data analysis methods are briefly summarized below.

Urban economic and mortality loss estimates. The report draws on data from Brecht, Deichmann, and Wang (2013), who model the economic and mortality loss rates of 1,943 urban agglomerations from World Bank client countries that had populations greater than 100,000 in 2000 due to floods, cyclones, landslides, and earthquakes. Although drought is one of the most important hazards in South Asia, its impact on cities is difficult to quantify and is not included in this model. The data set includes 232 urban agglomerations in South Asia, including 6 cities in Afghanistan, 28 in Bangladesh, 144 in India, 5 in Nepal, and 50 in Pakistan.

FIGURE 6A.1 Taxonomic tree of South Asian cities with mainly earthquake risk

Risk type	Current level of risk	Future hydromet risk outlook	Size of city	Vulnerability level	Number of and sample cities
Earthquake risk only	High	Severe	Large	Vulnerable	None
				Low-moderate	None
			Small to medium	Vulnerable	None
				Low-moderate	3: Kathmandu, Jalandhar, Dehradun
		Moderate	Large	Vulnerable	1: Meerut
				Low-moderate	1: Faisalabad
			Small to medium	Vulnerable	None
				Low-moderate	None
	Moderate	Severe	Large	Vulnerable	None
				Low-moderate	None
			Small to medium	Vulnerable	7: Shahjahanpur, Mazar-i-Sharif
				Low-moderate	7: Thimphu, Shimla
		Moderate	Large	Vulnerable	None
				Low-moderate	None
			Small to medium	Vulnerable	4 in Uttar Pradesh, IN
				Low-moderate	6: Panipat and 5 cities in Punjab, PK

Sources: Center for International Earth Science Information Network (http://www.ciesin.org); UN *World Urbanization Prospects: 2011 Revision* (http://esa.un.org/unpd/wup); Brecht and others 2012; Brecht, Deichmann, and Wang 2013; Hallegatte and others 2013; Hirabayashi and others 2013; OPHI 2013; PICIRCA 2013.

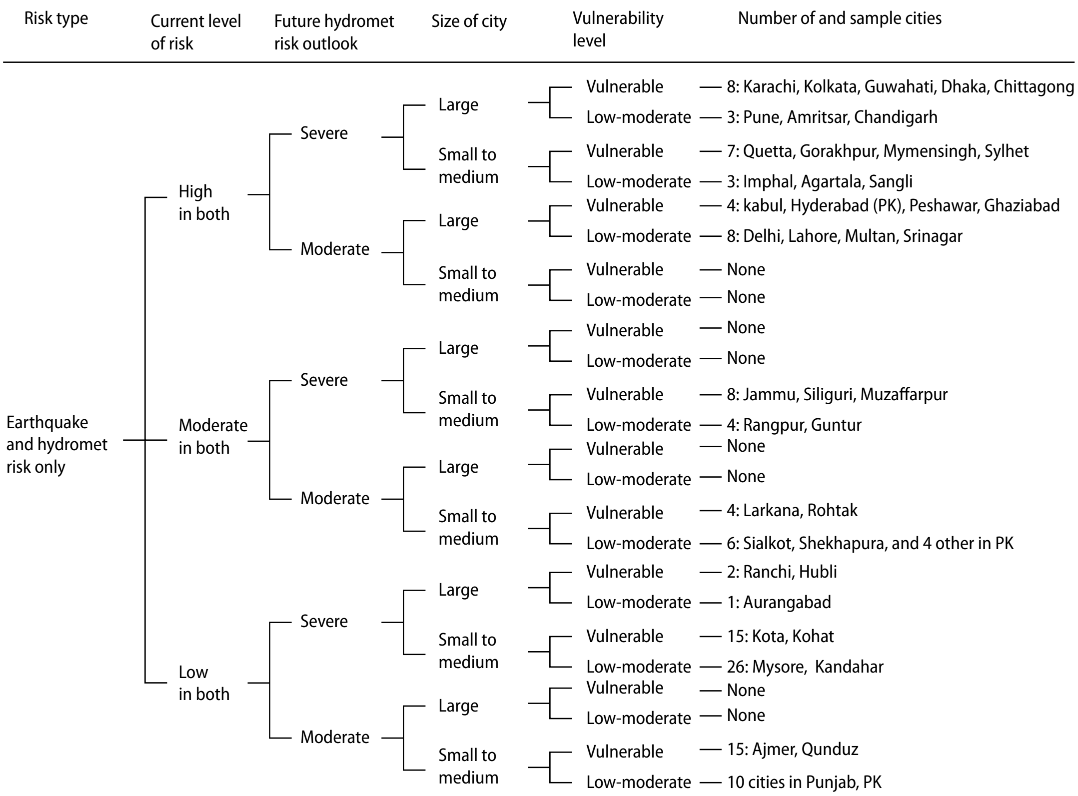
Note: IN = India; PK = Pakistan.

FIGURE 6A.2 Taxonomic tree of South Asian cities with mainly hydromet risk

Risk type	Current level of risk	Future hydromet risk outlook	Size of city	Vulnerability level	Number of and sample cities
Hydromet risk only	High	Severe	Large	Vulnerable	10: Khulna, Patna, Gwalior
				Low-moderate	10: Chennai, Kochi, Surat, Colombo
			Small to medium	Vulnerable	9: Brahmapur, Cuttack, Cox's Bazar
				Low-moderate	5: Pondicherry, Nellore
		Moderate	Large	Vulnerable	None
				Low-moderate	None
			Small to medium	Vulnerable	None
				Low-moderate	None
	Moderate	Severe	Large	Vulnerable	4: Mumbai, Bangalore, Indore, Bhilai
				Low-moderate	9: Madurai, Rajkot
			Small to medium	Vulnerable	19: Raipur, Pabna, Birganj
				Low-moderate	14: Kandy, Jaffna, Kurnool, Pokhara
		Moderate	Large	Vulnerable	4: Jodhpur, Jaipur, Bhopal
				Low-moderate	None
			Small to medium	Vulnerable	2: Mirpur Khas, Tando Adam
				Low-moderate	1: Hisar

Sources: Center for International Earth Science Information Network (http://www.ciesin.org); UN *World Urbanization Prospects: 2011 Revision* (http://esa.un.org/unpd/wup); Brecht and others 2012; Brecht, Deichmann, and Wang 2013; Hallegatte and others 2013; Hirabayashi and others 2013; OPHI 2013; PICIRCA 2013.

FIGURE 6A.3 Taxonomic tree of South Asian Cities with earthquake and hydromet risks



Sources: Center for International Earth Science Information Network (http://www.ciesin.org); UN *World Urbanization Prospects: 2011 Revision* (http://esa.un.org/unpd/wup); Brecht and others 2012; Brecht, Deichmann, and Wang 2013; Hallegatte and others 2013; Hirabayashi and others 2013; OPHI 2013; PICIRCA 2013.
Note: PK = Pakistan.

Brecht, Deichmann, and Wang (2013) estimate the average potential economic and mortality losses an agglomeration may experience during a 27-year period for each hazard (see their paper for a more detailed discussion of their methodology).

Future climate impacts. This report examines the future risk outlook for flooding and temperature extremes for the same 232 metropolitan areas, in addition to Malé (Maldives); Thimphu (Bhutan); and Colombo, Kandy, Sri Jayewardenepura Kotte, Moratuwa, Negombo, Jaffna, and Dehiwala–Mount Lavinia (Sri Lanka), for a total of 241 cities. Because of the small size of Maldives, global projections generally do not cover this geography. As an initial attempt to estimate whether and by how much the future hazard frequency outlook is changing at the local level, this report draws on four recently published global hazard frequency projections[1]:

- Hirabayashi and others (2013) model the frequency of future flood occurrence. They estimate the frequency of occurrence of present-day 100-year floods for the period 2071–2100.
- Temperature anomaly data are based on the World Bank's *Turn Down the Heat* report (PICIRCA 2013). Current global average temperatures are 0.8 degrees Celsius above preindustrial levels, which is associated with significant observed climate impacts.
- The city value for both flood and temperature projections was determined by

overlaying city points over the projection map and sampling the cell value beneath the point.

- Risks due to storm surge and sea-level rise are examined drawing on Hallegatte and others (2013) and Brecht and others (2012). The first data set (Hallegatte and others 2013) estimates risks to 136 port cities worldwide based on their populations and economic exposure to a baseline 100-year flood in 2005 and 2050, given projected increases in population and economic development, static storm conditions, and increases in sea-level rise and land subsidence. The second report (Brecht and others 2012) considers 393 coastal cities in developing countries and estimates current and future impacts of a 100-year storm surge on coastal populations, economies, and ecosystems in place as of 2000. They assume current 1-in-100-year storm surge intensity with 10 percent and 15 percent intensification by 2100 and make other assumptions for sea-level rise, geological uplift, and land subsidence.

Note

1. Data for geography and climate are derived from Center for International Earth Science Information Network (http://www.ciesin.org) and UN *World Urbanization Prospects: 2011 Revision* (http://esa.un.org/unpd/wup); data on multidimensional poverty are excerpted from OPHI (2013).

References

Brecht, H., S. Dasgupta, B. Laplante, S. Murray, and D. Wheeler. 2012. "Sea-Level Rise and Storm Surges: High Stakes for a Small Number of Developing Countries." *Journal of Environment and Development* 21 (1): 120–38.

Brecht, H., U. Deichmann, and H. G. Wang. 2013. "A Global Urban Risk Index." Policy Research Working Paper 6506, World Bank, Washington, DC.

Hallegatte, S., C. Green, R. J. Nicholls, and J. Corfee-Morlot. 2013. "Future Flood Losses in Major Coastal Cities." *Nature Climate Change* 3: 802–6.

Hirabayashi, Y., R. Mahendran, S. J. Koirala, L. Konoshima, D. Yamazaki, S. Watanabe, H. Kim, and S. Kanae. 2013. "Global Flood Risk under Climate Change." *Nature Climate Change* 3: 816–21.

OPHI (Oxford Poverty and Human Development Initiative). 2013. Global Multidimensional Poverty Index. Online database. http://www.ophi.org.uk/multidimensional-poverty-index.

PICIRCA (Potsdam Institute for Climate Impact Research and Climate Analytics). 2013. *Turn Down the Heat: Climate Extremes, Regional Impacts, and the Case for Resilience.* Washington, DC: World Bank.