

Future flood losses in major coastal cities

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Supplementary Methods

A first screening study by Hanson and colleagues¹ provided a global overview of coastal flood exposure in world coastal cities, including rankings. That study considered several drivers of floods including demographic and socio-economic changes (including urbanization), climate-induced sea-level rise, and human-induced subsidence where appropriate.

The methodology was based on determining the numbers of people and the value of assets that would be exposed to extreme water levels in the absence of coastal defenses and protection. The reference extreme water level was the 100-year coastal flood event. This metric of exposure reveals much about the risks faced in each city, because people in the flood plain rely on formal or informal flood defenses, and thus will be at some level of risk. This risk could arise from a failure of existing flood defenses due to breaching, or from a high return-period event which exceeds the height of existing protection and overtops the defense. In other words the exposure metric can be viewed as a worst case scenario, and exposure can translate into major losses during extreme events (e.g. New Orleans and Hurricane Katrina in 2005).

While the first screen exercise¹ considered how exposure will change in response to socio-economic drivers of economic and population growth, and in response to environmental changes (e.g., sea-level rise, subsidence), a more interesting and useful question is how losses would evolve. To look at economic losses, it necessary to take into account infrastructure-based adaptation (e.g., upgrading dikes and sea walls) and consider how these actions might be taken over time to mitigate flood risk and reduce losses from a city to a global scale. This is what is done by the present analysis.

1. Assessing current flood risks

The investigation took the form of an elevation-based GIS (Geographical Information Systems) analysis.^{2,3}

1.1. Current population and population exposure

Population exposure is taken from Hanson and colleagues, following the methodology used in previous studies.^{1,4} In each 50 cm “elevation layer” from current mean sea level (e.g., the area located between 0.5 and 1 m above normal sea level), exposed population is computed using topographic and population data.

Topographic data is the 90m resolution data from the Shuttle Radar Topography Mission (SRTM), except in the USA where 30m SRTM data is available, and in the UK, where a 10m Digital Elevation Model (provided by Infoterra) was used. Population data for the selected cities were taken from Landsat 2002 and constrained using city extents from post code data. Postcodes were largely taken from Risk Management Solutions (RMS) geocoding data and, in the USA, Metropolitan Statistical Areas (MSAs) from Census. Where postcode data were unavailable, internet-based city maps were used. The 1km resolution Landsat 2002 data was resampled to 100m for all cities, with the exception of those in the USA and UK, which were resampled to 30m. From this process, we obtain the number of inhabitants who would be flooded by various water levels, assuming no protection and uniform inundation.

At the pixel level, the SRTM elevation data can have errors of up to 10 m, which is large compared with sea level changes we are considering. These errors, however, are much lower in flat areas, where flood risks are concentrated, and have a large long-wavelength component (at the continent scale) that is not a problem when investigating local elevation differences; complete analyses are available in the literature.⁵ However, this dataset is not adequate for the engineering design of sea walls and dykes. Nevertheless, when aggregated over larger areas (e.g., neighbourhoods), this data is able to provide a fair estimate of the elevation and can, therefore, be used to estimate the exposed population and assets and to rank cities according to their risk level to identify where detailed analyses are most necessary.

1.2. Asset exposure

The exposed population was translated into exposed assets using an estimate of the amount of capital per inhabitant. This capital per inhabitant was computed from the GDP per capita in each country and an estimate of the ratio of “produced capital” to GDP.

The ratio of produced capital to GDP is calculated using the World Bank dataset published with the “Changing Wealth of the Nations” report⁶. As shown in Figure S1, there is almost a linear relationship between the two. To calculate the average ratio, we averaged the ratio of produced capital to GDP for all countries, with a weight calculated on the basis of each country’s population. The resulting ratio is equal to 2.8 and is applied to all countries. This ratio is significantly lower than the value of 5 used in the previous exposure analysis.¹

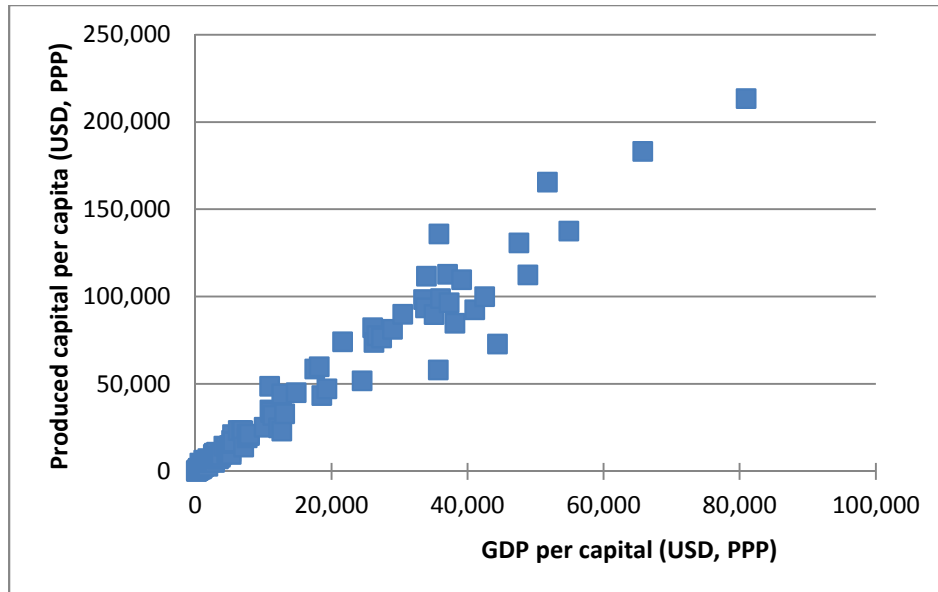


Figure S1. Relationship between GDP per capita and produced capital per capita (in USD, purchase power parity (PPP) exchange rate). Data from the World Bank.

1.3. Data on current defense levels in coastal cities

There is no global database of defense level in coastal cities, but patchy evidence is available on many of them with a bias towards richer countries and cities. It could be assumed that optimal defenses are present in all coastlines, designed using cost-benefit analyses as a decision framework.

However, it is observed that optimal defenses are rather exceptional and this assumption appears more useful as a baseline than a realistic description of existing protection. The recent landfall of Sandy illustrates for instance that Greater New York, despite having a larger GDP than London, Tokyo and Amsterdam, is currently only protected to a standard of roughly a 1 in 100 year flood with little formal flood defenses compared to those that exist for many European and Asian cities, and even New Orleans. The emphasis is on flood warning and evacuation as it is in most of the USA. Shanghai, a developing country city with a lower GDP than New York City and European cities, has a relatively high protection level similar to London. These examples highlight that protection levels are also strongly influenced by cultural, political and historical issues.

Here, we collected evidence on existing defenses starting from a previous analysis⁷, and we completed the defense database with estimates from the authors. Because of the uncertainty in some cases, we built two data sets, one with maximum protection level and minimum protection levels.

This defense database should not be considered as complete or exhaustive. Instead, it is a starting point created from limited information. We invite knowledgeable people to correct and improve the database using more detailed information as appropriate.

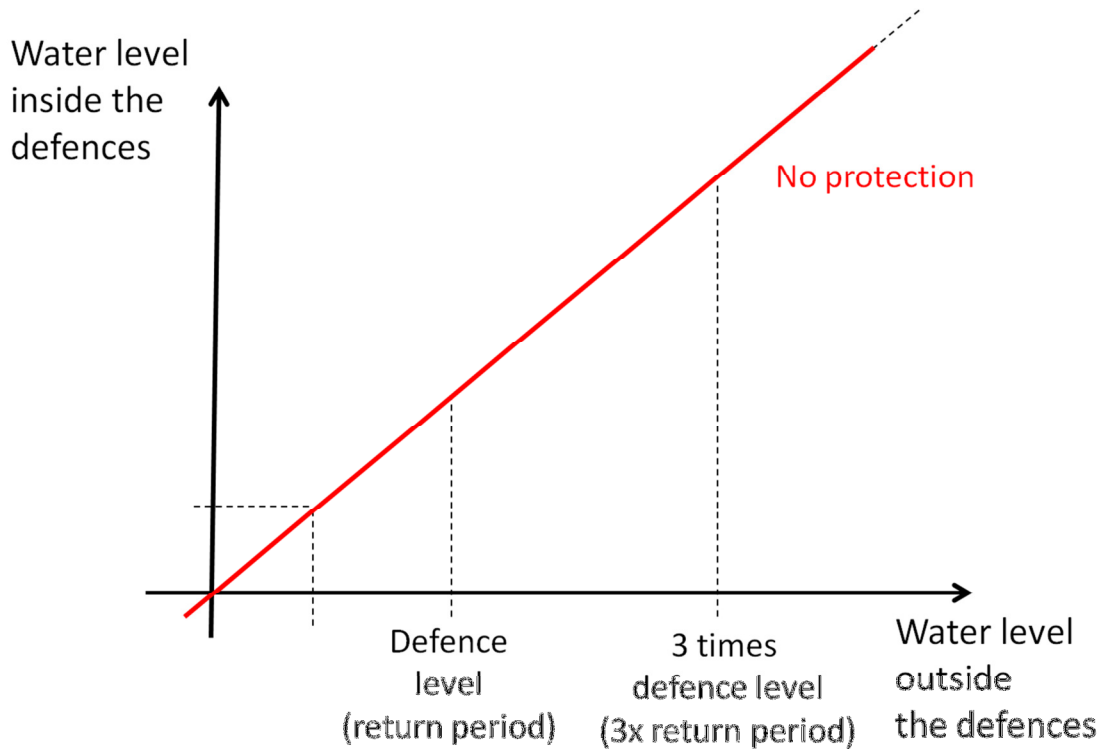
1.4. Water level in the city, accounting for defenses

The DIVA database provides information about the 10-yr, 100-yr and 1000-yr water levels on 12,148 segments around the world coasts.⁸ For all cities, these values were translated into water level probability distribution functions, assuming that these functions are in logarithm form.

To assess flood losses, however, what matters is the water level within the defense system. To assess the probability distribution function of water levels within the defenses, assumptions are required on defense failure probabilities. In this analysis, we assume that defenses are designed to resist to a given standard of protection, expressed in terms of return period, and this standard of protection corresponds to a given defense water level.⁹

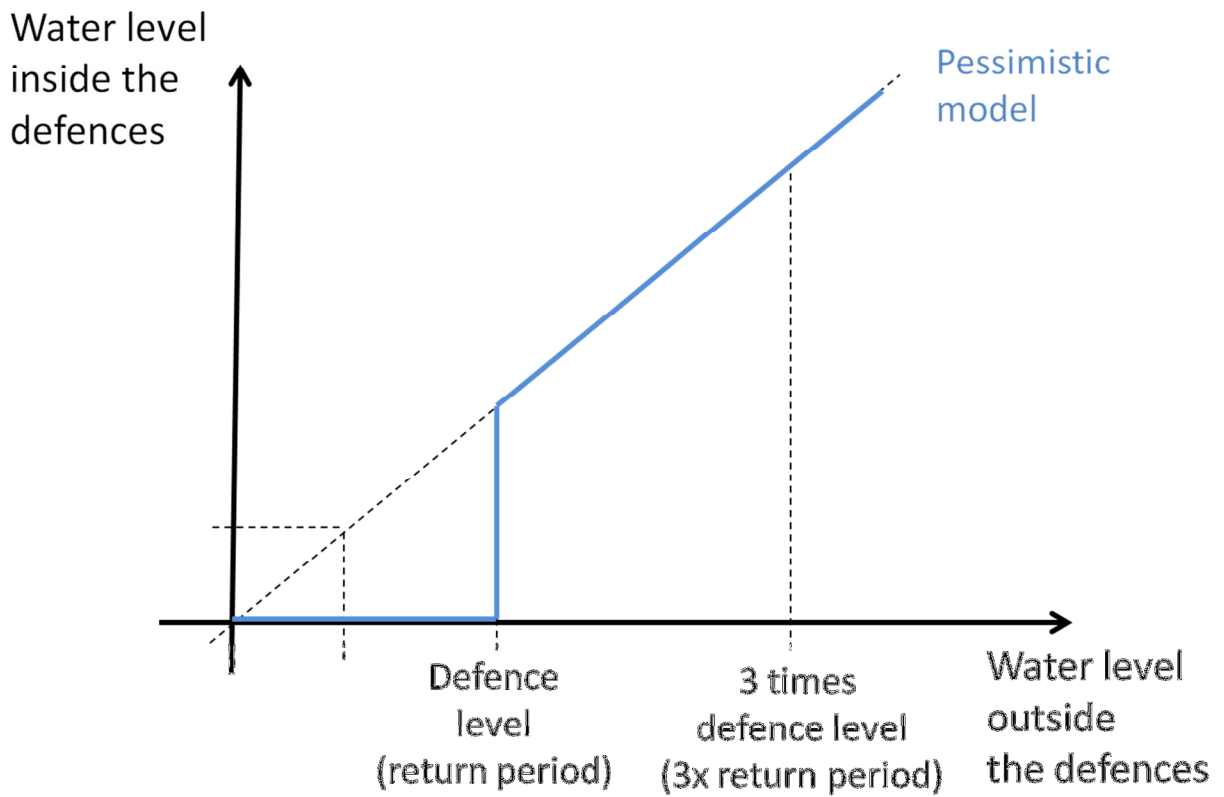
We assume that when the water level is below the designed defense level, failure probability is zero. Several simple assumptions can be made on how defenses behave when the defense level is exceeded, since this resistance depends on the protection type and characteristics (e.g., dikes vs. seawalls).

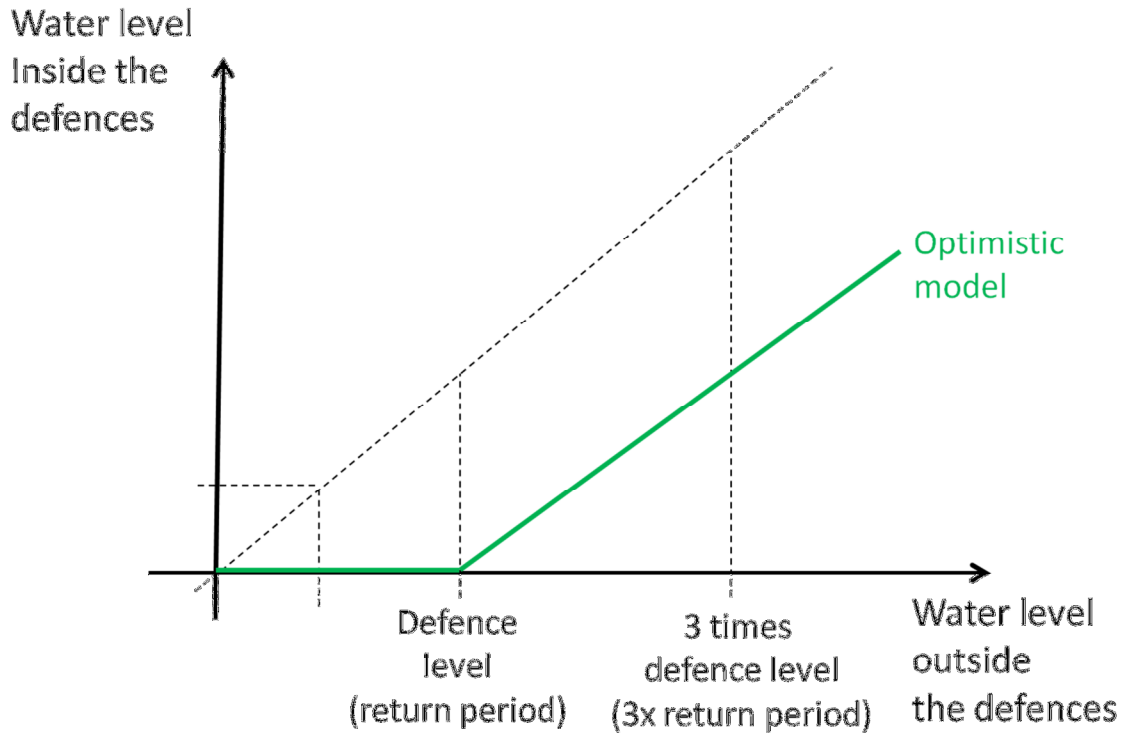
Here, we consider three distinct failure models, which in simple terms describe the range of possible behaviors (see also, Figure S2):



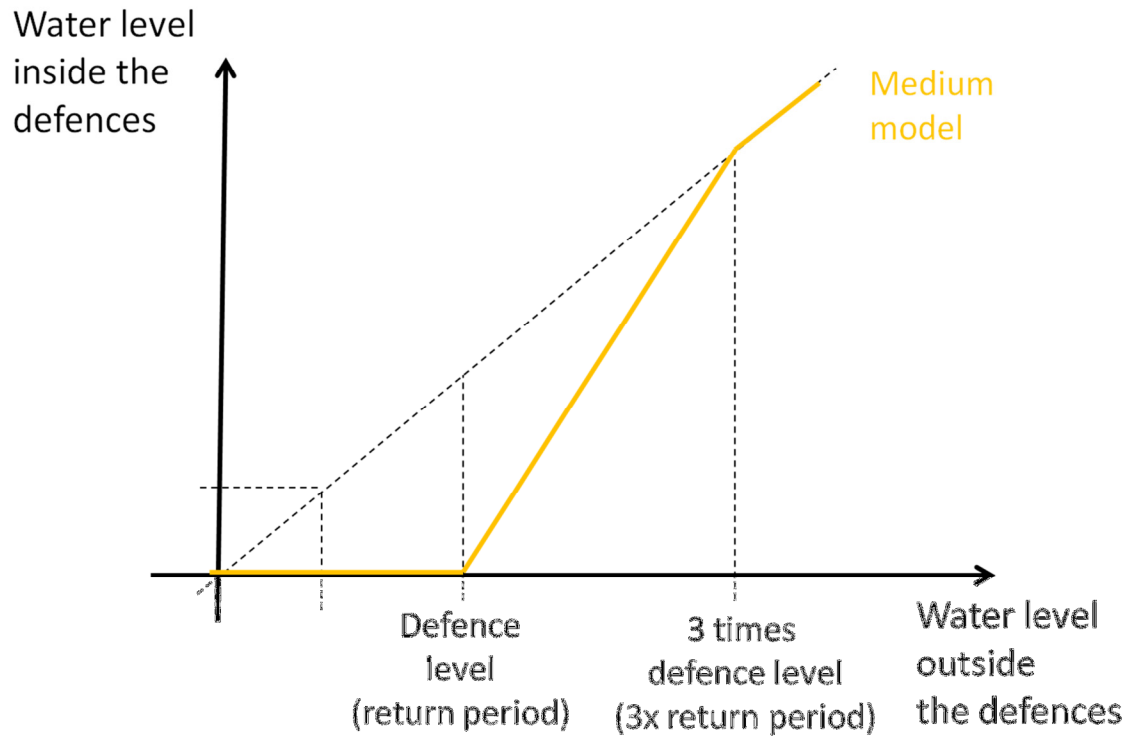
(a)

(b)





(c)



(d)

Figure S2. Representation of the relationship between the water level outside the city defenses and the water level inside the defenses, in the absence of protection (panel a), and with the three defenses failure models, i.e. the simplest and pessimistic model (panel b), the optimistic model (panel c), and the medium model (panel d).

The simplest assumption is that the defenses breaches when the design level is exceeded; in that case, there is no difference between the failed defenses and no defenses for events above the design standard. This model is also the most pessimistic.

The most optimistic assumption is that when defenses are first overtopped, this does not rapidly lead to breaching and they continue to provide some residual protection. Here, we assume that when defenses are exceeded by x cm, then the water level within the protection system is equal to x cm. In other terms, if a 2m protection experiences a 3m water level, the water level inside the protection will be reduced to 1m. This is a very simplistic assumption, but going beyond this assumption is beyond the scope of this study, and would require more detailed flood modeling more appropriate in an individual city assessment.

An intermediate assumption in which defenses progressively collapse as the water level increases until it reaches three times the design level (also expressed in return period), when total breaching is assumed.⁹ Hence, flooding increases linearly between the overtopping level and the collapse level. Above the collapse level, there is no difference between the failed defenses and no defenses for events above the design standard.

1.5. Flood losses, as a function of water level

Exposed assets as a function of water level were then translated into asset losses. To do this, assets in each elevation layer were first distributed into six categories: (1) lightweight-timber-framed dwellings; (2) masonry dwellings; (3) low-income-country dwellings; (4) dwelling contents; (5) non-residential structures; and (6) non-residential content.

Following Linham and colleagues⁷, we first distribute assets at risk in different broad categories, as shown in Table S1. The distribution of residential buildings then depends on the countries. For instance, North America and Australia are assumed to have mainly lightweight-timber-framed dwellings, while Europe and Asia have mainly masonry dwellings.

Table S1. Share of asset categories.

Asset type	% total value of net fixed assets
Non-domestic buildings and structures	42
Residential buildings	36
Equipment	14
Domestic durables	9

Then, assets are assumed to be homogenous distributed in each 50-cm elevation layer. And for each elevation (practically this is calculated using 0.5cm layers), we calculate the local water level (i.e. the water level measured against normal sea level minus the elevation, also measured against normal sea level) and the density of assets for each asset type.

Then depth-damage functions are used to calculate losses for each elevation and each asset type. Six depth-damage curves linking flood depth to the ratio of damage have been used for lightweight timber buildings, brick or concrete buildings, low-income country buildings, dwelling content, non-residential structures, and non-residential contents.⁷ The depth-damage curves for the six categories of assets are reproduced in Table S2.

Table S2. Depth-damage curves for the six asset types used in this study. The function provides the share of losses (total loss divided by the total value) as a function of flood depth (depth is zero in this table when flood depth is larger than zero, i.e. when there is a flood).

Depth (meters)	Proportion of damage by depth and asset category (%)							
	0	0.25	0.50	1.00	1.50	2.00	2.50	3.00
Dwellings: lightweight timber framed Source: Dale (2009) ¹⁰	1.6	16.9	44.5	61.8	62.9	63.3	69.4	69.4
Dwellings: Masonry Source: Yan (2005) ¹¹	0.0	1.0	2.0	5.0	8.0	11.0	22.0	35.0
Dwellings: structural, low income countries Source: Islam (1997) ¹²	0.0	3.4	5.0	7.7	10.6	13.4	15.1	15.1
Dwellings: contents Penning-Rowse et al. (2003) ¹³	0.0	31.0	34.0	36.0	38.0	38.0	38.0	38.0
Non-residential: structures Source: Penning-Rowse et al. (2003) ¹³	4.0	18.3	39.1	50.4	59.7	64.6	66.5	68.1
Non-residential: contents Source: Penning-Rowse et al. (2003) ¹³	0.6	17.0	37.4	55.0	63.2	68.9	73.3	76.8

1.6. Calculation of mean annual flood losses.

Using the flood losses for each water level, and the probability of each water level, we can estimate the mean annual flood losses in each city, taking into account the estimated level of protection following the methodology from Hallegatte and colleagues³. Results differ largely for the different models of defense failure discussed above.

This analysis provides an estimate of aggregated average annual flood losses in the 136 coastal cities, and world average losses are shown in Table S3. Results are highly dependent on the defense overtopping model. The most optimistic overtopping model gives an aggregate annual flood loss worth \$46 million with the optimistic estimate of protection levels and \$90 million with the pessimistic estimate of protection level. These numbers are clearly overoptimistic: assuming that the return period of Katrina is 400 years, as in the Interagency Performance Evaluation Taskforce report¹⁴, average annual losses for New Orleans alone would be around

\$50 million, which is more than half of our assessment for all 136 port cities with the optimistic failure model.

Table S3. Aggregated global mean annual losses due to coastal floods in the 136 port cities in 2005, depending on the protection failure model and protection standard.

Protection failure model	Aggregated global mean annual losses (million USD)	
	Protection standard	
	Minimum	Maximum
Pessimistic	8,823	5,744
Medium	5,153	3,375
Optimistic	90	46

The losses are much larger with the pessimistic and the medium overtopping models, with aggregate losses ranging from \$3 billion to \$9 billion per year, depending on the protection failure model. Using these two models thus provide some bounds for aggregate losses. Investigating how sea level rise affects these losses with these different models provide an idea of the result robustness.

In the main text, all assessments are made using the simplest (pessimistic) model that assumes that defenses fail when their protection design is exceeded. We also use the maximum protection standard (corresponding to average flood losses of \$5.7 billion in the current situation).

Table S4 ranks the most vulnerable cities in 2005 using three different metrics of vulnerability. In the left column, the table provides a ranking that is comparable to the previous exposure analysis¹, based on exposure to the 100-yr flood, i.e. the assets below the 100-yr flood irrespective of defence standard. In the central column, the table shows a ranking in terms of absolute average annual losses (AAL in million USD), taking into account all potential floods and existing protection. Some of these estimates can be compared with more sophisticated approaches. For instance, the annual losses in New Orleans are estimated at \$600 million, close to the \$650 million estimates from the Interagency Performance Evaluation Taskforce.⁸ In the right column, cities are ranked according to relative vulnerability, namely the ratio of AAL to the city's GDP. This value can be understood as the share of the city's economic output that should be saved annually to pay for future flood losses.

Ranking by exposure				Ranking by AAL (million USD)				Ranking by relative AAL (% of city GDP)						
Urban Agglomeration	100-yr exposure	AAL, with protection (millions USD)	AAL, with protection (% of GDP)	Urban Agglomeration	100-yr exposure	AAL, with protection (millions USD)	AAL, with protection (% of GDP)	Urban Agglomeration	100-yr exposure	ALL, with protection (millions USD)	AAL, with protection (% of GDP)			
1	Miami	366 421	672	0.30%	1	Guangzhou	38,508	687	1.32%	1	Guangzhou	38,508	687	1.32%
2	New York-Newark	236 530	628	0.08%	2	Miami	366,421	672	0.30%	2	New Orleans	143,963	507	1.21%
3	Osaka-Kobe	149 935	120	0.03%	3	New York-Newark	236,530	628	0.08%	3	Guayaquil	3,687	98	0.95%
4	New Orleans	143 963	507	1.21%	4	New Orleans	143,963	507	1.21%	4	Ho Chi Minh City	18,708	104	0.74%
5	Tokyo	122 910	27	0.00%	5	Mumbai	23,188	284	0.47%	5	Abidjan	1,786	38	0.72%
6	Amsterdam	83 182	3	0.01%	6	Nagoya	77,988	260	0.26%	6	Zhanjiang	2,780	46	0.50%
7	Nagoya	77 988	260	0.26%	7	Tampa-St Petersburg	49,593	244	0.26%	7	Mumbai	23,188	284	0.47%
8	Rotterdam	76 585	2	0.01%	8	Boston	55,445	237	0.13%	8	Khulna	2,073	13	0.43%
9	Virginia Beach	61 507	89	0.15%	9	Shenzen	11,338	169	0.38%	9	Palembang	1,161	27	0.39%
10	Boston	55 445	237	0.13%	10	Osaka-Kobe	149,935	120	0.03%	10	Shenzen	11,338	169	0.38%
11	Tampa-St Petersburg	49 593	244	0.26%	11	Vancouver	33,456	107	0.14%	11	Hai Phòng	6,348	19	0.37%
12	London	45 130	5	0.00%	12	Tianjin	11,408	104	0.24%	12	N'ampo	507	6	0.31%
13	Fukuoka-Kitakyushu	39 096	82	0.09%	13	Ho Chi Minh City	18,708	104	0.74%	13	Miami	366,421	672	0.30%
14	Guangzhou	38 508	687	1.32%	14	Kolkata	14,769	99	0.21%	14	Kochi	855	14	0.29%
15	Shanghai	34 306	4	0.00%	15	Guayaquil	3,687	98	0.95%	15	Tampa-St Petersburg	49,593	244	0.26%
16	Vancouver	33 456	107	0.14%	16	Philadelphia	22,132	89	0.04%	16	Nagoya	77,988	260	0.26%
17	Hong Kong	26 988	8	0.00%	17	Virginia Beach	61,507	89	0.15%	17	Surat	3,288	30	0.25%
18	Hamburg	26 260	6	0.01%	18	Fukuoka-Kitakyushu	39,096	82	0.09%	18	Tianjin	11,408	104	0.24%
19	St Peterburg	23 384	3	0.00%	19	Baltimore	14,042	76	0.08%	19	Grande_Vitória	6,738	32	0.23%
20	Hiroshima	23 331	37	0.06%	20	Jakarta	4,256	73	0.14%	20	Xiamen	4,486	33	0.22%

Table S4. City ranking by estimated exposure and risk for 2005. All monetary values are in million USD.

2. Scenarios for the future

2.1. Future cities: population, income, assets

To develop future scenarios, our analysis combines three scenarios for socio-economic changes. The first scenario (labelled NC) assumes an unchanged (or baseline) population and wealth.

The second and third scenarios start from the OECD long-term scenarios for population and GDP, and use extrapolations of UN scenarios for urbanization rate to project future city population. The OECD socio-economic baseline scenario used here are updated from those used in the previous analysis¹ and an extension of those recently published the OECD as part of the OECD Environmental Outlook to 2050.^{15,16}

The scenario is constructed using the OECD ENV-Linkages model – a recursive dynamic neo-classical general equilibrium model (GE). It is a global economic model built primarily on a database of national economies. In its current form, the model represents the world economy in 15 countries/regions, each with 22 economic sectors. The scenario creates a consistent projection of economic activity for the coming decades to 2070, applying the general framework of "conditional convergence." The assumption of "conditional convergence" assumes that there will be some gradual convergence of income levels towards those of the most developed economies. The methodology used to derive per capita GDP trend pathways on a country basis relies on a conditional convergence hypothesis for the key drivers of per capita economic growth in the long run, i.e. for population, total factor productivity, physical capital, employment and human capital.

Urbanization scenarios are similar to the ones used in the previous analysis¹ and are based on an extrapolation to 2070 of UN urbanization scenarios.

The second scenario (labelled S) assumes that all cities in a given country grow at the same rate leading by the 2070s to several coastal cities with populations exceeding 50 million people¹; the third scenario (labelled L) assumes that no city can exceed 35 million inhabitants.

The assessment is based on the assumption that the future assets (infrastructure, housing, productive capital) that will be built in coastal cities will have the elevation distribution than the assets that are already installed. Under this assumption, future assets in one elevation layer increase linearly with total assets in the city. As a result, future exposures (and losses) are proportional to current exposures (and losses) and to the increase in capital in the cities.

2.2. Taking into account climate-induced sea level rise

Considering the uncertainty on future sea level¹⁷, we make simple assumptions with optimistic and pessimistic scenarios. We assume that climate-induced sea level rise is homogeneous globally and that climate change and sea level rise do not change storm surge likelihood. The analysis combines three scenarios on sea level rise. The first one (labelled "s") assumes a stable sea level over the 21st century; the second scenario (labelled "o") is optimistic and assumes that sea level rise will reach 10 cm in 2030, 20 cm in 2050, and 30 cm in 2070; the last – and most pessimistic – scenario (labelled "p") assumes that sea level rise reaches 20 cm in 2030, 40 cm in 2050, and 70 cm in 2070.

A significant difference with the previous analysis¹ is that storminess is assumed to remain unchanged. This change makes results more conservative, considering the uncertainty on change in storm intensity.¹⁷

2.3. Taking into account local subsidence

Small magnitudes of land uplift and subsidence are almost universal, contributing to local sea-level change¹⁷. However, the magnitudes are generally small and not considered here. In addition, in susceptible locations such as deltaic areas, human-induced subsidence due to groundwater withdrawal and drainage can be significant, especially in cities built on deltas. Maximum subsidence during the 20th Century has been up to 5 metres¹⁸⁻²² and subsidence is seen as a major threat comparable to climate change in many coastal Asian cities²¹. The mean subsidence in these cities is less well measured and further, future subsidence is uncertain as it depends on human action. Hence reasonable high-end mean scenarios of human-induced subsidence are developed following Nicholls and colleagues⁴, and applied to the entire flood prone area of the cities where such subsidence may occur.

Two scenarios on subsidence are considered. The first scenario assumes no subsidence (natural or artificial) and is labelled “0”; in the second scenario, labelled “1”, natural and artificial subsidence affects susceptible cities that are mainly located wholly or partly on a delta, making local sea level rise by 20 cm more in 2030, 40 cm more in 2050, and 50 cm more in 2070. This would largely constitute human-induced subsidence. In cities potentially affected by human-induced subsidence, the local sea level can thus rise by up to 120 cm by the 2070s in the most pessimistic scenario when global sea-level rise and subsidence are combined.

2.4. Combining scenarios

Combining all these assumptions leads to $3 \times 3 \times 2 \times 3 \times 2 = 108$ scenarios. Because it would be too complex to present all results, the main paper focuses on five future scenarios summarized in Table S5. Supplementary data provide results for all scenarios.

		Scenarios				
		NC (present situation)	SEC (socio-economic change, no SLR, no subsidence)	SEC-S (socio-economic change, no SLR, with subsidence)	SLR-1 (socio-economic change, optimistic SLR, subsidence)	SLR-2 (socio-economic change, pessimistic SLR, subsidence)
Socio-economic trend	Constant (NC)	X				
	Scenario with no city limit (S)					
	Scenario with city limit (L)		X	X	X	X
Sea Level Rise	Stable (s)	X	X	X		
	Optimistic rise (o)				X	
	Pessimistic rise (p)					X
Subsidence	No (0)	X	X			
	Yes (1)			X	X	X
Defense failure model	Optimistic					
	Medium					
	Pessimistic	X	X	X	X	X
Protection levels	Min					
	Max	X	X	X	X	X

Table S5. Characteristics of the five scenarios analyzed in the main text.

3. Taking into account adaptation.

Changes in sea levels will trigger investments in new and/or reinforced coastal defenses. However, there is a large uncertainty on how adaptation will be implemented. Here, we tested three assumptions about adaptation, termed adaptation options:

- No upgrade: The most pessimistic, which is an absence of defense upgrade (Option NA).
- Maintain defense standards: The defenses will be improved to maintain coastal flooding likelihood. In practical terms, this is equivalent to assuming that dikes and seawalls will be raised by the same magnitude as relative sea level rise in each city, including subsidence as appropriate (Option PD).
- Maintain relative risk: The most optimistic assumption considered is that flood risk (i.e. the relative mean annual losses) will be maintained unchanged by raising protection by more than the relative sea level rise. In practical terms, this adaptation scenario assumes that the Standard of Protection rises appropriately to maintain risk levels and the probability of mean annual losses remains unchanged, allowing for the effect of socio-economic change. (Option PL).

To maintain constant absolute levels of risk would require that the Standard of Protection rises even more than the PL scenario, to compensate for the increase in value at risk due to economic and population growth.

Table S6 presents aggregate losses for the 136 cities, for different scenarios and different adaptation scenarios. It shows the strong increase in the absence of adaptation, with total losses largely exceeding \$1 trillion per year. It also show the increase in risk when adaptation only maintain the probability of occurrence of a flood.

	Mean annual losses (million USD) in 2050		
	Adaptation Options		
	No adaptation (NA)	Maintain present defences & constant flood probability (PD)	Maintain present average losses relative to local wealth (PL)
Scenario NC (no change – the current situation)	5,744	5,744	5,744
Scenario SEC (only socio-economic changes)	52,015	52,015	52,015
Scenario SEC-S (adds subsidence)	687,186	58,579	52,015
Scenario SLR-1 (adds optimistic sea-level rise)	1,192,785	59,767	52,015
Scenario SLR-2 (same as Scenario 1 with pessimistic sea-level rise)	1,566,856	63,273	52,015

Table S6. Change in aggregated annual losses in 2050 in the 136 cities, due to different driver Scenarios and possible adaptation options.

City	If adaptation maintains flood probability (Option PD)		Adaptation needs to maintain mean annual losses (Option PL)				Flood losses in event of defence failure (million USD – total losses for single event) (Option PL)		
	AAL (M\$)	Increase (%) (Fig. 1)	Local sea-level rise (cm)	Rise in dike height (cm)	Protection standard in 2005 (Return period (yrs))	Required Protection standard in 2050 (Return period (yrs))	Scenario SEC	Scenario SLR-1	Increase (%)
Alexandria	504	154%	60	67	100	268	16,533	50,551	206%
Barranquilla	10	116%	60	66	10	23	39	100	156%
Napoli	2	82%	20	24	50	97	39	80	105%
Sapporo	4	76%	60	64	100	179	218	417	91%
Santo Domingo	34	65%	20	23	10	17	179	325	82%
Bayrut	2	63%	20	23	100	172	91	162	78%
Houston	190	60%	60	68	50	84	5,110	9,053	77%
Istanbul	21	57%	20	23	100	167	1,120	1,972	76%
Jakarta	1,750	54%	60	63	10	16	10,513	17,276	64%
Izmir	11	51%	20	22	100	157	625	1,023	64%
Marseille-Aix-en-Provence	5	51%	20	24	100	160	266	453	70%
Athens	1	50%	20	23	100	156	48	78	63%
Shanghai	93	48%	60	66	1000	1,519	57,646	89,545	55%
Banghazi	22	46%	20	23	100	154	1,223	2,019	65%
Tel Aviv-Yafo	0	45%	20	23	100	152	7	11	57%
Fuzhou_Fujian	199	45%	60	62	20	29	2,697	3,873	44%
Ningbo	256	45%	60	62	20	29	3,397	5,001	47%
La Habana	0	42%	20	22	100	146	14	21	50%
Port-au-Prince	1	41%	20	22	10	14	6	10	67%
Algiers	9	41%	20	22	50	72	291	439	51%

Table S7. The twenty cities with the largest increase in average annual losses (from 2005 to 2050) (scenario SLR-1, adaptation option PD), if adaptation only maintains present defence standards. It provides the increase in defence height needed to maintain flood risk, and corresponding increase in protection standard. The three last columns describe the consequence of a storm that exceeds protection standards, in the case without and with sea-level rise and subsidence.

Results for all scenarios, all defense level estimates, the three overtopping model, and all time horizons (2030-2050-2070) are provided in Supplementary Data, together with the MatLab files used to produce them.

These data are organized as follows.

The directory “CODES” includes all MatLab codes. They reproduce all results. Running “City_Loop.m” produces all the information by running the risk assessment for all cities and storing results as MatLab variables.

Then, running “write_results_subs.m” writes all results in Excel format.

The main input file is located in the directory “INPUT CITY SCENARIOS”: The file “City_Scenarios_Input.xls” provides the input data, namely population and economic data and scenarios, water extreme level data, protection level data, and a marker to indicate which city is subject to subsidence. This file also includes all socio-economic and urbanization scenarios.

GIS Inputs are located in the directory “GIS DATA”. There is one file per city, and it provides the population in each 50cm elevation layer.

The results files are the following.

In the directory “RESULTS MAIN PAPER”, there are:

- The file “All_scenarios_aggregated.xls” provides the global aggregated results for all scenarios, and the five ones used in the main text are highlighted in yellow.
- The five scenarios that are described in details in the main text of the letter: “SEC Scenario.xls”, “SEC-S Scenario.xls”, “SLR-1 Scenario.xls” and “SLR-2 Scenario.xls” provides the results for these five scenarios, for the 136 cities, the two assumptions on the current protection level, and the three adaptation options. Each file has one tab for each defense failure model and for each time horizon (2005, 2030, 2050, and 2070). There is no file for the NC scenario, because it corresponds to the 2005 situation in all other scenarios.

All other scenarios (a total of 108 scenarios) are in the folder “OTHER SCENARIOS”, and they are named according to the scenario terminology (see Table S5):

First letter:

- N for no socio-economic change,
- S for socio-economic change without city limit and,
- L for socio-economic change with city limit;

Second letter:

- s for stable sea level
- o for optimistic sea level rise
- p for pessimistic sea level rise

Third letter:

- 0 for no subsidence

1 for the scenario with subsidence

Each file has then different tabs for different time horizons (2005, 2030, 2050 and 2070) and different defense failure models. And in each tab, one can find the three adaptation options.

Supplementary references

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This table provides the results of the loss analysis for the 136 cities
 In 2050, without sea level rise and with 20 cm of sea level rise and subsidence (40cm in cities prone to subsidence)
 With socio-economic change, and city population limited to 35 million inhabitants
 The protection level is taken at its optimistic bound (maximum protection).
 The protection failure model is the simplest one (model #1, panel a in Figure S2)

Urban Agglomeration	No change in sea level					20cm sea level rise and subsidence (no adaptation)		20 cm sea level rise and subsidence (adaptation at constant probability, adaptation scenario PD)			20cm sea level rise and subsidence (adaptation at constant relative risk, adaptation scenario PL)		
	100-yr exposition (M\$)	100-yr losses with no protection (M\$)	Protection level in 2005 (return period in years)	Mean annual loss (M\$)	Mean annual loss (% city GDP)	Mean annual loss (M\$)	Mean increase due to SLR and subsidence	Mean annual loss (M\$)	Mean annual loss (% city GDP)	Mean increase due to SLR and subsidence	Increase in dike height (for 20cm SLR + subsidence)	New protection level to maintain relative risk (return period in years)	New loss if protection is overtopped
Abidjan	4,017	1,328	10	826	0.72%	8,968	986%	1,023	0.89%	24%	21.3	13	9,839
Accra	190	57	10	36	0.03%	393	993%	43	0.04%	20%	20.9	12	418
Adelaide	1,278	643	100	4	0.00%	19	368%	4	0.00%	7%	20.93	107	417
Al Kuwait (Kuwait City)	1,579	549	100	9	0.00%	235	2627%	9	0.00%	5%	20.31	105	896
Al-Iskandariyah (Alexandria)	27,675	3,669	100	199	0.09%	34,621	17300%	504	0.22%	154%	67	268	50,551
Amsterdam	187,159	103,598	10000	9	0.01%	56	521%	10	0.01%	9%	63.06	10,976	93,122
Athinal (Athens)	487	113	100	1	0.00%	18	3140%	1	0.00%	50%	23	156	78
Auckland	1,119	563	100	4	0.00%	42	905%	4	0.00%	6%	20.56	107	435
Baixada Santista (Santos)	788	218	50	9	0.01%	274	3041%	9	0.01%	8%	20.45	54	463
Baltimore	31,595	15,406	50	238	0.08%	1,178	396%	271	0.09%	14%	21.76	58	12,741
Banghazi	3,048	734	100	15	0.01%	180	1112%	22	0.02%	46%	23	154	2,019
Barcelona	2,370	549	100	3	0.00%	37	1195%	4	0.00%	40%	22.93	146	372
Barranquilla	94	28	10	5	0.00%	87	1782%	10	0.01%	116%	66	23	100
Bayrut (Beirut)	336	45	100	1	0.00%	71	6658%	2	0.00%	63%	23	172	162
Belém	2,007	542	50	12	0.01%	93	698%	13	0.01%	8%	20.8	54	609
Boston	124,752	69,675	50	741	0.13%	5,557	650%	793	0.14%	7%	20.7	54	38,400
Brisbane	12,803	5,486	100	29	0.02%	178	504%	33	0.02%	11%	21.21	111	3,102
Buenos Aires	6,847	1,868	50	44	0.00%	161	268%	49	0.00%	13%	22.07	57	2,258
Cape Town	757	209	100	4	0.00%	51	1036%	5	0.00%	7%	20.59	107	471
Chennai (Madras)	3,457	966	10	825	0.12%	7,392	796%	939	0.14%	14%	21.24	11	9,001
Chittagong	4,751	1,186	20	154	0.08%	671	337%	162	0.09%	6%	20.76	21	3,138
Ciudad de Panama (Panama City)	468	200	10	42	0.06%	431	916%	44	0.06%	4%	20.23	10	437
Conakry	449	166	10	66	0.09%	716	981%	78	0.10%	18%	20.87	12	760
Dakar	177	48	10	35	0.04%	377	973%	41	0.05%	16%	20.78	12	398
Dallan	1,973	750	20	143	0.04%	1,223	757%	155	0.05%	9%	20.8	22	3,008
Dar-el-Beida (Casablanca)	940	301	100	12	0.01%	191	1458%	13	0.01%	8%	20.56	108	1,288
Dar-es-Salaam	101	41	10	62	0.07%	624	910%	65	0.08%	6%	20.43	11	642
Davao	61	22	10	5	0.01%	56	921%	6	0.01%	7%	20.4	11	57
Dhaka	10,126	2,774	20	451	0.10%	6,287	1294%	506	0.11%	12%	62.72	23	9,734
Douala	162	48	10	24	0.03%	284	1070%	31	0.04%	29%	62.62	13	304
Dubayy (Dubai)	49,574	16,861	100	286	0.11%	4,180	1362%	305	0.12%	7%	20.49	107	29,881
Dublin	6,825	1,866	70	7	0.01%	85	1046%	8	0.01%	11%	20.87	78	554
Durban	1,094	317	500	1	0.00%	38	2444%	2	0.00%	7%	20.38	531	774
El Djazair (Algiers)	363	88	50	7	0.00%	253	3755%	9	0.00%	41%	22	72	439
Fortaleza	493	160	50	2	0.00%	52	2762%	2	0.00%	23%	21.33	62	105
Fukuoka-Kitakyushu	87,966	42,913	100	177	0.09%	19,904	11134%	221	0.12%	25%	61.47	125	21,789
Fuzhou_Fujian	2,651	919	20	137	0.05%	3,525	2471%	199	0.08%	45%	62	29	3,873
Glasgow	4,365	1,757	200.00	4	0.00%	95	2243%	4	0.00%	6%	20.36	212	842
Grande_Vitoria	15,160	4,712	50	190	0.23%	2,643	1289%	211	0.26%	11%	20.82	56	10,266
Guangzhou_Guangdong	86,644	37,105	20	11,928	1.32%	254,721	2036%	13,200	1.46%	11%	60.88	22	261,495
Guayaquil	8,296	3,133	10	2,813	0.95%	31,288	1012%	3,189	1.08%	13%	60.64	11	31,645
Hai Phong	14,283	4,728	50	320	0.37%	6,209	941%	383	0.44%	30%	64	61	17,867
Hamburg	59,084	28,626	1000	14	0.01%	61	339%	15	0.01%	6%	20.79	1,060	14,225
Hangzhou	586	149	20	6	0.00%	125	2109%	7	0.00%	22%	62.17	24	134
Helsinki	2,482	936	200	3	0.00%	11	245%	3	0.00%	8%	21.35	217	645
Hiroshima	52,494	23,307	100	80	0.06%	9,456	11660%	109	0.08%	35%	62.07	137	10,696
Hong Kong	60,722	31,300	900	140	0.00%	1,269	808%	150	0.00%	7%	20.63	964	131,051
Houston	29,147	12,337	50	119	0.02%	6,088	5017%	190	0.03%	60%	68	84	9,053
Incheon	22,825	9,493	100	29	0.01%	191	553%	30	0.02%	2%	20.24	102	2,953
Istanbul	3,162	419	100	13	0.00%	327	2348%	21	0.00%	57%	23	167	1,972
Izmir	1,415	341	100	7	0.00%	314	4299%	11	0.01%	51%	22	157	1,023
Jakarta	9,577	2,553	10	1,139	0.14%	16,354	1336%	1,750	0.22%	54%	63	16	17,276
Jiddah	1,092	393	10	60	0.02%	631	943%	67	0.02%	10%	20.47	11	651
Karachi	792	260	10	121	0.02%	1,385	1040%	145	0.02%	20%	61.64	12	1,432
Khulna	4,665	1,748	20	295	0.43%	6,172	1989%	409	0.60%	39%	66.11	29	7,650
København (Copenhagen)	9,567	2,462	200	7	0.01%	36	391%	8	0.01%	15%	21.79	231	1,573
Koehi (Cochin)	1,923	505	10	430	0.29%	4,327	907%	481	0.33%	12%	20.97	11	4,648
Kolkata (Calcutta)	33,231	12,649	20	2,704	0.21%	56,303	1983%	3,350	0.26%	24%	63.76	25	64,760
Krung_Thep (Bangkok)	49,065	16,462	50	5,966	0.07%	20,778	3387%	734	0.09%	23%	63.86	63	34,145
Kuala Lumpur	19,437	6,696	100	56	0.03%	253	355%	63	0.04%	13%	21.69	114	5,897
La Habana (Havana)	31	8	100	0	0.00%	9	5939%	0	0.00%	42%	22	146	21
Lagos	2,750	728	10	287	0.15%	3,026	954%	328	0.17%	14%	20.79	11	3,196
Lima	47	14	10	4	0.00%	39	1009%	4	0.00%	26%	21.29	13	43
Lisboa (Lisbon)	4,764	1,770	100	13	0.01%	100	650%	15	0.01%	10%	20.95	110	1,406
Lomé	1,005	308	100	28	0.05%	1,017	3521%	33	0.06%	16%	20.86	117	3,169
London	101,543	36,751	1000	13	0.00%	65	384%	14	0.00%	9%	21.09	1,090	13,789
Los Angeles-Long Beach Santa Ana	35,833	15,517	50	188	0.08%	9,427	4912%	203	0.09%	8%	20.37	54	9,960
Luanda	21	7	10	9	0.00%	95	952%	10	0.00%	12%	20.62	11	99
Maceió	518	188	50	6	0.01%	54	887%	6	0.01%	10%	20.83	55	290
Manila	2,339	872	10	254	0.05%	2,846	1019%	329	0.06%	29%	63.62	13	3,122
Maputo	404	169	100	24	0.03%	184	656%	26	0.03%	7%	20.63	107	2,523
Maracaibo	775	236	100	6	0.01%	67	1086%	7	0.01%	22%	21.71	124	658
Marseille-Aix-en-Provence	3,403	788	100	3	0.00%	43	1233%	5	0.00%	51%	24	160	453
Melbourne	682	328	100	2	0.00%	10	334%	2	0.00%	9%	21.23	109	229
Miami	824,448	387,360	100	2,099	0.30%	7,340	250%	2,549	0.36%	23%	23.57	125	228,589
Montevideo	992	334	50	14	0.02%	50	258%	15	0.02%	9%	21.38	55	716
Montréal	4,235	2,482	50	14	0.00%	86	496%	15	0.00%	4%	20.4	52	729
Mumbai (Bombay)	52,173	19,827	20	6,109	0.47%	107,285	1656%	6,414	0.49%	5%	20.34	21	126,406
Murqdisho (Mogadishu)	21	8	10	13	0.04%	128	920%	13	0.04%	6%	20.37	11	131
Nagoya	175,473	99,196	100	564	0.26%	57,954	10183%	644	0.30%	14%	61.44	114	63,344
N'ampio	1,141	383	10	24	0.31%	87	255%	25	0.32%	3%	20.47	10	246
Napoli (Naples)	981	125	50	1	0.00%	35	2895%	2	0.00%	82%	24	97	80
Natal	647	250	50	9	0.02%	150	1505%	10	0.02%	7%	20.49	53	489
New Orleans	323,917	180,646	100	1,583	1.21%	161,141	10080%	1,864	1.42%	18%	61.99	118	182,592
New York-Newark	532,194	291,729	100	1,960	0.08%	7,914	304%	2,056	0.08%	5%	20.7	105	198,885
Ningbo	6,272	1,373	20	176	0.09%	4,548	2479%	256	0.13%	45%	62	29	5,001
Odessa	2,733	859	100	19	0.04%	280	1339%	22	0.05%	14%	21.04	115	2,146
Osaka-Kobe	337,354	177,054	300	261	0.03%	84,968	32516%	336	0.04%	29%	61.86	390	98,671
Palembang	2,612	934	10	418	0.39%	4,764	1040%	506	0.48%	21%	62.08	12	4,974

Perth	4,220	2,145	100	16	0.01%	65	309%	17	0.01%	8%	21.18	109	1,626
Philadelphia	49,797	27,432	50	279	0.04%	1,017	265%	294	0.04%	5%	20.83	53	14,127
Port-au-Prince	9	3	10	1	0.00%	8	1090%	1	0.00%	41%	22	14	10
Portland	3,753	1,716	50	3	0.00%	114	3965%	3	0.00%	12%	20.62	56	152
Porto	1,756	722	100	6	0.01%	34	426%	7	0.01%	7%	20.86	107	669
Porto Alegre	0	0	50	10	0.00%	71	641%	10	0.01%	8%	20.8	54	497
Providence	17,857	9,479	50	118	0.07%	525	344%	127	0.08%	7%	20.96	54	6,084
Pusan	16,852	4,523	100	30	0.01%	384	1165%	34	0.01%	10%	20.8	111	3,262
Qingdao	3,055	958	20	163	0.05%	3,260	1904%	177	0.06%	9%	20.56	22	3,461
Rabat	248	71	100	2	0.00%	60	2930%	2	0.00%	15%	20.84	115	220
Rangoon	4,177	1,387	10	163	0.17%	1,818	1017%	202	0.21%	24%	63.34	12	1,962
Recife	1,218	477	50	19	0.01%	259	1279%	20	0.01%	7%	20.49	53	977
Rio de Janeiro	4,132	1,010	50	35	0.01%	411	1088%	38	0.01%	9%	20.72	55	1,839
Rotterdam	172,316	96,071	10000	7	0.01%	256	3416%	8	0.01%	11%	61.84	11,153	79,289
Salvador	377	143	50	5	0.00%	245	4903%	5	0.00%	7%	20.34	53	257
San Diego	1,369	731	50	12	0.00%	410	3299%	13	0.00%	7%	20.39	53	634
San Francisco - Oakland	34,156	13,240	50	149	0.03%	1,703	1045%	168	0.04%	13%	21.02	57	8,071
San Jose	2,826	932	50	2	0.00%	10	551%	2	0.00%	11%	21.13	56	83
San Juan	7,342	2,235	50	68	0.02%	1,680	2365%	89	0.03%	31%	21.78	66	4,239
Sankt Peterburg (St. Petersburg)	52,615	11,899	1000	11	0.00%	187	1572%	12	0.00%	8%	20.53	1,077	11,748
Santo Domingo	636	153	10	21	0.02%	263	1166%	34	0.03%	65%	23	17	325
Sapporo	1,339	591	100	2	0.00%	346	14308%	4	0.00%	76%	64	179	417
Seattle	10,235	6,100	50	85	0.02%	545	542%	87	0.02%	3%	20.33	52	4,304
Shanghai	77,189	28,576	1000	63	0.00%	5,563	8721%	93	0.01%	48%	66	1,519	89,545
Shenzen	25,510	10,362	20	2,929	0.38%	17,553	499%	3,136	0.40%	7%	20.79	21	60,550
Singapore	3,412	2,020	2000	2	0.00%	27	1222%	2	0.00%	3%	20.26	2,068	4,208
Stockholm	517	152	100	1	0.00%	14	1613%	1	0.00%	26%	21.73	128	98
Surabaya	727	163	10	80	0.04%	1,052	1222%	110	0.06%	39%	62.05	14	1,089
Surat	7,399	3,078	10	905	0.25%	9,070	902%	928	0.26%	3%	20.21	10	9,201
Sydney	8,293	4,314	100	28	0.01%	172	509%	31	0.01%	9%	21.03	110	2,943
Taipei	2,713	1,042	20	274	0.10%	6,436	2250%	344	0.12%	26%	61.25	25	6,757
Tampa-St Petersburg	111,585	56,155	50	763	0.26%	2,997	293%	859	0.29%	13%	21.87	57	40,022
Terabulus (Tripoli)	267	64	100	2	0.00%	19	1058%	2	0.00%	37%	22.83	141	207
Tel Aviv-Yafo (Tel Aviv-Jaffa)	26	6	100	0	0.00%	1	1255%	0	0.00%	45%	23	152	11
Thành-Pho-Ho-Chi-Minh (Ho Chi Minh City)	42,093	20,216	50	1,743	0.74%	7,335	321%	1,953	0.83%	11%	65.16	57	90,365
Tianjin	25,667	9,779	20	1,810	0.24%	40,492	2137%	2,276	0.30%	26%	62.85	25	44,463
Tokyo	276,547	140,711	1000	58	0.00%	61,737	106550%	77	0.00%	33%	62	1,346	75,503
Ujung Pandang	156	33	10	11	0.01%	67	515%	12	0.02%	12%	21.29	11	116
Ulsan	1,209	368	100	2	0.00%	53	2189%	3	0.00%	30%	21.81	133	286
Vancouver	75,276	43,232	50	325	0.14%	18,912	5714%	423	0.18%	30%	61.64	65	20,674
Virginia Beach	138,390	62,671	140	278	0.15%	1,520	446%	303	0.16%	10%	21.05	153	40,549
Visakhapatnam	369	111	10	110	0.08%	1,129	926%	122	0.08%	11%	20.73	11	1,189
Washington, D C	12,326	5,972	50	74	0.01%	1,045	1321%	82	0.01%	12%	20.89	56	3,976
Wenzhou	3,187	921	20	152	0.06%	3,367	2119%	174	0.07%	15%	60.85	23	3,447
Xiamen	10,093	3,682	20	572	0.22%	12,182	2029%	729	0.29%	27%	63.67	26	13,902
Yantai	679	164	20	21	0.01%	406	1878%	24	0.01%	18%	21.16	24	461
Zhanjiang	6,256	2,865	20	806	0.50%	16,709	1973%	891	0.55%	11%	61.24	22	17,440

This table provides the results of the loss analysis for the 136 cities
 In 2050, without sea level rise and with 40 cm of sea level rise and subsidence (40cm in cities prone to subsidence)
 With socio-economic change, and city population limited to 35 million inhabitants
 The protection level is taken at its optimistic bound (maximum protection).
 The protection failure model is the simplest one (model #1, panel a in Figure S2)

Urban Agglomeration	No change in sea level					40cm sea level rise and subsidence (no adaptation)		40 cm sea level rise and subsidence (adaptation at constant probability, adaptation scenario PD)			40cm sea level rise and subsidence (adaptation at constant relative risk, adaptation scenario PL)		
	100-yr exposition (M\$)	100-yr losses with no protection (M\$)	Protection level in 2005 (return period in years)	Mean annual loss (M\$)	Mean annual loss (% city GDP)	Mean annual loss (M\$)	Mean increase due to SLR and subsidence	Mean annual loss (M\$)	Mean annual loss (% city GDP)	Mean increase due to SLR and subsidence	Increase in dike height (for 40cm SLR + subsidence)	New protection level to maintain relative risk (return period in years)	New loss if protection is overtopped
Abidjan	4,017	1,328	10	826	0.72%	10,836	1213%	1,187	1.03%	44%	42.18	15	11,623
Accra	190	57	10	36	0.03%	458	1174%	49	0.05%	36%	41.52	14	480
Adelaide	1,278	643	100	4	0.00%	88	2086%	5	0.00%	14%	41.73	114	446
Al Kuwait (Kuwait City)	1,579	549	100	9	0.00%	892	10242%	9	0.00%	10%	40.55	110	936
Al-Iskandariyah (Alexandria)	27,675	3,669	100	199	0.09%	44,877	22455%	581	0.25%	192%	87.88	304	58,470
Amsterdam	187,159	103,598	10000	9	0.01%	102	1042%	10	0.01%	13%	84.13	11,340	96,240
Athinal (Athens)	487	113	100	1	0.00%	73	13246%	1	0.00%	98%	44.18	207	107
Auckland	1,119	563	100	4	0.00%	419	9914%	5	0.00%	13%	41.1	114	463
Baixada Santista (Santos)	788	218	50	9	0.01%	467	5256%	10	0.01%	15%	40.82	58	493
Baltimore	31,595	15,406	50	238	0.08%	5,841	2359%	299	0.10%	26%	43.03	64	14,367
Banghazi	3,048	734	100	15	0.01%	1,588	10595%	28	0.02%	89%	45.56	200	2,748
Barcelona	2,370	549	100	3	0.00%	307	10731%	5	0.00%	75%	44.71	183	484
Barranquilla	94	28	10	5	0.00%	102	2106%	11	0.01%	143%	86.94	25	113
Bayrut (Beirut)	336	45	100	1	0.00%	164	15583%	2	0.00%	136%	44.37	251	246
Belém	2,007	542	50	12	0.01%	586	4955%	13	0.01%	15%	41.41	58	654
Boston	124,752	69,675	50	741	0.13%	37,206	4924%	849	0.15%	15%	41.4	58	41,249
Brisbane	12,803	5,486	100	29	0.02%	1,076	3552%	36	0.02%	22%	42.35	124	3,459
Buenos Aires	6,847	1,868	50	44	0.00%	592	1257%	56	0.00%	28%	44.13	65	2,602
Cape Town	757	209	100	4	0.00%	453	9998%	5	0.00%	15%	41.15	115	501
Chennai (Madras)	3,457	966	10	825	0.12%	9,347	1033%	1,028	0.15%	25%	42.07	13	10,024
Chittagong	4,751	1,186	20	154	0.08%	2,934	1811%	171	0.09%	11%	41.5	22	3,288
Ciudad de Panama (Panama City)	468	200	10	42	0.06%	451	962%	47	0.06%	10%	40.51	11	459
Conakry	449	166	10	62	0.09%	831	1155%	89	0.12%	34%	41.51	14	872
Dakar	177	48	10	35	0.04%	429	1121%	45	0.05%	29%	41.32	13	446
Dallan	1,973	750	20	143	0.04%	3,012	2010%	166	0.05%	16%	41.43	23	3,241
Dar-el-Beida (Casablanca)	940	301	100	12	0.01%	1,256	10159%	14	0.01%	16%	41.13	117	1,395
Dar-es-Salaam	101	41	10	62	0.07%	660	959%	69	0.08%	11%	40.8	11	677
Davao	61	22	10	5	0.01%	60	995%	6	0.01%	16%	40.94	12	62
Dhaka	10,126	2,774	20	451	0.10%	9,219	1944%	524	0.11%	16%	83.55	23	10,154
Douala	162	48	10	24	0.03%	311	1179%	34	0.04%	40%	83.43	14	333
Dubayy (Dubai)	49,574	16,861	100	286	0.11%	29,215	10114%	326	0.13%	14%	41.01	115	31,900
Dublin	6,825	1,866	70	7	0.01%	532	7114%	9	0.01%	20%	41.53	84	606
Durban	1,094	317	500	1	0.00%	746	27710%	2	0.00%	14%	40.81	569	826
El Djazair (Algiers)	363	88	50	7	0.00%	452	6805%	12	0.00%	76%	43.26	91	566
Fortaleza	493	160	50	2	0.00%	108	5814%	3	0.00%	62%	43.15	85	141
Fukuoka-Kitakyushu	87,966	42,913	100	177	0.09%	21,434	11998%	235	0.12%	33%	81.87	133	23,251
Fuzhou Fujian	2,651	919	20	137	0.05%	4,148	2926%	237	0.09%	73%	82.89	35	4,637
Glasgow	4,365	1,757	200.00	4	0.00%	824	20293%	5	0.01%	12%	40.71	224	890
Grande_Vitoria	15,160	4,712	50	190	0.23%	10,096	5208%	227	0.28%	20%	41.38	60	11,163
Guangzhou_Guangdong	86,644	37,105	20	11,928	1.32%	262,207	2098%	13,537	1.49%	13%	81.1	23	268,090
Guayaquil	8,296	3,133	10	2,813	0.95%	32,267	1047%	3,278	1.11%	17%	80.79	12	32,555
Hai Phong	14,283	4,728	50	320	0.37%	16,029	2482%	418	0.48%	40%	85.97	67	19,432
Hamburg	59,084	28,626	1000	14	0.01%	168	1825%	15	0.01%	11%	41.49	1,116	15,064
Hangzhou	586	149	20	6	0.00%	233	2252%	7	0.00%	27%	82.68	26	141
Helsinki	2,482	936	200	3	0.00%	38	1093%	4	0.00%	17%	42.76	237	703
Hiroshima	52,494	23,307	100	80	0.06%	10,421	12860%	117	0.08%	46%	82.57	147	11,584
Hong Kong	60,722	31,300	900	140	0.00%	11,514	6067%	159	0.00%	14%	41.19	1,026	140,038
Houston	29,147	12,337	50	119	0.02%	7,246	5990%	214	0.04%	80%	89.45	95	10,389
Inchon	22,825	9,493	100	29	0.01%	1,248	4166%	31	0.02%	5%	40.55	105	3,030
Istanbul	3,162	419	100	13	0.00%	1,746	12980%	29	0.00%	119%	45.31	234	2,890
Izmir	1,415	341	100	7	0.00%	997	13880%	14	0.01%	101%	43.9	209	1,411
Jakarta	9,577	2,553	10	1,139	0.14%	17,852	1467%	1,872	0.23%	64%	83.32	17	18,540
Jiddah	1,092	393	10	60	0.02%	702	1062%	75	0.02%	24%	41.06	12	733
Karachi	792	260	10	121	0.02%	1,451	1095%	151	0.03%	24%	81.97	12	1,489
Khulna	4,665	1,748	20	295	0.43%	6,851	2219%	459	0.67%	56%	88.15	32	8,788
København (Copenhagen)	9,567	2,462	200	7	0.01%	177	2308%	9	0.01%	28%	43.24	259	1,784
Koehi (Cochin)	1,923	505	10	430	0.29%	4,837	1026%	521	0.36%	21%	41.64	12	5,096
Kolkata (Calcutta)	33,231	12,649	20	2,704	0.21%	60,930	2154%	3,515	0.27%	30%	84.56	26	68,537
Krung_Thep (Bangkok)	49,065	16,462	50	5,966	0.07%	30,827	5073%	818	0.10%	37%	85.93	71	38,153
Kuala Lumpur	19,437	6,696	100	56	0.03%	1,153	1971%	69	0.04%	24%	42.96	125	6,607
La Habana (Havana)	31	8	100	0	0.00%	21	13660%	0	0.00%	80%	42.99	185	28
Lagos	2,750	728	10	287	0.15%	3,407	1087%	360	0.19%	26%	41.33	13	3,549
Lima	47	14	10	4	0.00%	48	1254%	5	0.00%	48%	42.15	15	51
Lisboa (Lisbon)	4,764	1,770	100	13	0.01%	747	5521%	16	0.01%	18%	41.7	119	1,530
Lomé	1,005	308	100	28	0.05%	3,148	11112%	36	0.06%	29%	41.45	130	3,562
London	101,543	36,751	1000	13	0.00%	313	2246%	16	0.00%	17%	42.14	1,184	15,010
Los Angeles-Long Beach Santa Ana	35,833	15,517	50	188	0.08%	10,158	5301%	217	0.10%	15%	40.72	58	10,697
Luanda	21	7	10	9	0.00%	105	1061%	11	0.00%	21%	41.04	12	108
Maceió	518	188	50	6	0.01%	283	5025%	7	0.01%	22%	41.85	62	323
Manila	2,339	872	10	254	0.05%	3,123	1128%	365	0.06%	44%	85.11	15	3,489
Maputo	404	169	100	24	0.03%	1,389	3289%	27	0.03%	13%	41.15	112	2,672
Maracaibo	775	236	100	6	0.01%	588	10238%	8	0.01%	40%	42.84	142	773
Marseille-Aix-en-Provence	3,403	788	100	3	0.00%	358	10971%	6	0.01%	100%	45.86	214	637
Melbourne	682	328	100	2	0.00%	42	1784%	3	0.00%	18%	42.43	120	249
Miami	824,448	387,360	100	2,099	0.30%	25,674	1123%	2,964	0.42%	45%	46.15	147	277,610
Montevideo	992	334	50	14	0.02%	180	1181%	17	0.02%	18%	42.85	60	785
Montréal	4,235	2,482	50	14	0.00%	510	3451%	15	0.00%	8%	40.84	54	757
Mumbai (Bombay)	52,173	19,827	20	6,109	0.47%	128,081	1997%	6,664	0.51%	9%	40.61	22	131,802
Murqdisho (Mogadishu)	21	8	10	13	0.04%	136	982%	14	0.04%	13%	40.77	11	140
Nagoya	175,473	99,196	100	564	0.26%	60,738	10677%	666	0.31%	18%	81.81	118	65,731
N'ampo	1,141	383	10	24	0.31%	245	906%	26	0.33%	6%	40.88	11	253
Napoli (Naples)	981	125	50	1	0.00%	81	6216%	3	0.00%	188%	46.27	155	133
Natal	647	250	50	9	0.02%	487	5100%	11	0.02%	15%	41.05	58	527
New Orleans	323,917	180,646	100	1,583	1.21%	171,210	10716%	1,940	1.48%	23%	82.47	123	190,749
New York-Newark	532,194	291,729	100	1,960	0.08%	31,949	1530%	2,159	0.09%	10%	41.43	110	209,043
Ningbo	6,272	1,373	20	176	0.09%	5,137	2813%	282	0.14%	60%	83.08	32	5,561
Odessa	2,733	859	100	19	0.04%	2,030	10333%	24	0.06%	26%	41.75	126	2,391
Osaka-Kobe	337,354	177,054	300	261	0.03%	92,559	35430%	366	0.05%	41%	82.47	425	107,860
Palembang	2,612	934	10	418	0.39%	5,016	1100%	526	0.49%	26%	82.49	13	5,183

Perth	4,220	2,145	100	16	0.01%	265	1575%	18	0.01%	17%	42.34	118	1,762
Philadelphia	49,797	27,432	50	279	0.04%	3,713	1232%	309	0.04%	11%	41.66	56	14,908
Port-au-Prince	9	3	10	1	0.00%	11	1482%	1	0.00%	77%	42.81	18	12
Portland	3,753	1,716	50	3	0.00%	156	5455%	4	0.00%	28%	41.39	65	175
Porto	1,756	722	100	6	0.01%	179	2667%	7	0.01%	13%	41.57	114	715
Porto Alegre	0	0	50	10	0.00%	483	4918%	12	0.01%	21%	42	61	550
Providence	17,857	9,479	50	118	0.07%	2,333	1872%	135	0.08%	14%	41.82	57	6,515
Pusan	16,852	4,523	100	30	0.01%	3,109	10127%	36	0.01%	18%	41.36	119	3,529
Qingdao	3,055	958	20	163	0.05%	3,546	2079%	189	0.06%	16%	41	23	3,720
Rabat	248	71	100	2	0.00%	217	10837%	3	0.00%	34%	41.77	135	257
Rangoon	4,177	1,387	10	163	0.17%	1,942	1093%	211	0.22%	30%	84.05	13	2,062
Recife	1,218	477	50	19	0.01%	970	5063%	21	0.01%	14%	41.04	57	1,047
Rio de Janeiro	4,132	1,010	50	35	0.01%	1,803	5108%	40	0.01%	17%	41.28	59	1,971
Rotterdam	172,316	96,071	10000	7	0.01%	840	11417%	8	0.01%	15%	82.34	11,489	81,871
Salvador	377	143	50	5	0.00%	262	5248%	6	0.00%	16%	40.75	58	277
San Diego	1,369	731	50	12	0.00%	641	5215%	14	0.00%	13%	40.72	57	674
San Francisco - Oakland	34,156	13,240	50	149	0.03%	7,834	5166%	185	0.04%	24%	41.84	63	8,966
San Jose	2,826	932	50	2	0.00%	67	4133%	2	0.00%	22%	42.22	62	92
San Juan	7,342	2,235	50	68	0.02%	4,238	6118%	107	0.03%	56%	42.92	80	5,202
Sankt Peterburg (St. Petersburg)	52,615	11,899	1000	11	0.00%	3,119	27857%	13	0.01%	17%	41.13	1,173	12,643
Santo Domingo	636	153	10	21	0.02%	410	1880%	50	0.04%	141%	44.62	26	499
Sapporo	1,339	591	100	2	0.00%	402	16647%	5	0.00%	95%	84.19	198	464
Seattle	10,235	6,100	50	85	0.02%	3,499	4026%	90	0.02%	6%	40.66	53	4,439
Shanghai	77,189	28,576	1000	63	0.00%	24,763	39168%	102	0.01%	62%	86.82	1,664	99,775
Shenzen	25,510	10,362	20	2,929	0.38%	59,948	1947%	3,338	0.43%	14%	41.5	23	64,947
Singapore	3,412	2,020	2000	2	0.00%	359	17364%	2	0.00%	7%	40.48	2,128	4,339
Stockholm	517	152	100	1	0.00%	90	10941%	1	0.00%	48%	42.86	150	118
Surabaya	727	163	10	80	0.04%	1,126	1316%	119	0.06%	50%	82.55	15	1,170
Surat	7,399	3,078	10	905	0.25%	9,298	927%	949	0.27%	5%	40.4	10	9,403
Sydney	8,293	4,314	100	28	0.01%	1,046	3609%	34	0.01%	20%	42.11	121	3,240
Taipei	2,713	1,042	20	274	0.10%	7,003	2458%	375	0.13%	37%	81.74	28	7,390
Tampa-St Petersburg	111,585	56,155	50	763	0.26%	11,777	1444%	948	0.32%	24%	43.39	63	45,042
Terabulus (Tripoli)	267	64	100	2	0.00%	169	10365%	3	0.00%	68%	44.56	175	265
Tel Aviv-Yafo (Tel Aviv-Jaffa)	26	6	100	0	0.00%	9	10931%	0	0.00%	87%	45.18	196	15
Thành-Pho-Ho-Chi-Minh (Ho Chi Minh City)	42,093	20,216	50	1,743	0.74%	11,842	579%	2,032	0.86%	15%	86.96	59	94,788
Tianjin	25,667	9,779	20	1,810	0.24%	43,488	2303%	2,383	0.31%	32%	83.4	26	46,759
Tokyo	276,547	140,711	1000	58	0.00%	67,958	117297%	85	0.00%	47%	82.65	1,482	83,432
Ujung Pandang	156	33	10	11	0.01%	118	990%	13	0.02%	21%	42.21	12	127
Ulsan	1,209	368	100	2	0.00%	269	11584%	4	0.00%	56%	42.98	159	350
Vancouver	75,276	43,232	50	325	0.14%	20,765	6284%	466	0.20%	43%	82.24	72	22,858
Virginia Beach	138,390	62,671	140	278	0.15%	8,304	1773%	328	0.17%	19%	42.02	166	44,202
Visakhapatnam	369	111	10	110	0.08%	1,242	1029%	131	0.09%	19%	41.23	12	1,289
Washington, D C	12,326	5,972	50	74	0.01%	3,914	5225%	91	0.02%	23%	41.63	62	4,410
Wenzhou	3,187	921	20	152	0.06%	3,488	2199%	180	0.08%	19%	81.06	24	3,557
Xiamen	10,093	3,682	20	572	0.22%	13,216	2210%	793	0.31%	39%	84.89	28	15,322
Yantai	679	164	20	21	0.01%	484	2257%	29	0.01%	40%	42.36	28	553
Zhanjiang	6,256	2,865	20	806	0.50%	17,287	2045%	926	0.57%	15%	81.72	23	18,128