Sea Level Damage Risk with Probabilistic Weighting of IPCC Scenarios: An Application to Major Coastal Cities

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Abstract

In some coastal cities there is an urgent need to decide on adaptation investments given the long periods needed to complete the relevant infrastructures. However such decisions are usually made under significant uncertainty due to local climate change and socio-economic impacts. The Intergovernmental Panel on Climate Change (IPCC) has developed four global scenarios according to different representative concentration pathways (RCPs); however, using these scenarios directly is equivalent to using incomplete information in the decision-making process because they do not provide information on what sea level rise behavior is most probable. In this study, I propose a model which assigns probabilities to IPCC scenarios with Local Sea Level Rise (LSLR) information. I obtain expected damage and risk measures for the world’s 120 major coastal mega-cities at specific moments in time. That is, I consider uncertainty in both scenario selection and within each scenario. With this information it is possible to make adaptation investment decisions under uncertainty with a criterion of not exceeding certain risk levels in the future. The paper shows that in the year 2100 for the equal probability mixed scenario (25% RCP 2.6, 50% RCP 4.5 and 25% RCP 8.5) the expected damage is US$ 1,251,732 millions for New Orleans and US$ 1,196,517 millions for Guangzhou. The risk measurements show that in that year the damage in the 5% of worse cases will be US$ 2,800,756 millions for Guangzhou and US$ 1,832,466 millions for New Orleans. However, not all countries have sufficient resources to make the necessary adaptation investments, so we analyze expected damage and risk according to World Bank country income groups. The paper shows that the USA and China will need to make major adaptation investments in the future. The coastal LSLR risk in lower-income cities is also calculated.

Key words

Adaptation, stochastic modeling, climate change, risk measure, uncertainty, country income groups

1 Introduction

In this century coastal cities are being exposed to significant damage from sea level rise (SLR) caused by climate change. This damage may be exacerbated by socio-economic effects such as population and asset growth in those cities (Hallegatte et al 2013). IPCC (IPCC, 2014) global sea level rise (GSLR) information is insufficient because impact effects are not uniform and may affect cities differently as a result of the net contribution of several factors (Kopp et al. 2014). Differences in local sea level rise (LSLR) between cities can be significant, so it is critical for decision-making to work with regionalized data.

The aggregation of negative SLR effects and high-growth socio-economic effects generates the greatest risks, and those risks are increasing over time (Abadie et al., 2107).

Estimations of expected LSLR and the corresponding damage clearly suffer from insufficient information for financial decision-making because of the absence of probabilities assigned to the Representative Concentration Pathway (RCP) scenarios.

In financial economics expected value is not an adequate risk measure (Hull, 2012) (Wilmott, 2014). Risk measures are associated with worst-case events. In this paper we use Expected Shortfall (ES)[1] as a risk measure. This is a mean value of the worst damage cases which has better properties than other risk measures such as Value at Risk (Hull, 2012) (Rockafellar and Uryasev, 2002).

A recent editorial in *Nature Climate Change* reminds us that special attention should be paid to the socio-economic impacts of significant but less likely climate events (Editorial, 2016). These low-probability, high-damage impacts have frequently been discussed in earlier climate change economics literature (Weitzman, 2007, 2009, 2013; Nordhaus, 2011) and are very important due to the huge magnitude of the potential damage from them (Pindyck, 2011). Hinkel et al. (2015) also argue in favor of providing estimates of low confidence situations as they are greatly needed for risk-adverse decision making, especially considering that the IPCC scenarios focus on central distribution rather than the high-risk tail and considering the presence of deep uncertainty. Hinkel et al., (2015) argue that the IPCC's global mean sea-level rise scenarios do not necessarily provide the right information for coastal decision-making and risk management.

In this context, decisions on investing in adaptation to mitigate LSLR need to deal with uncertainty. This uncertainty regarding the future climate makes it financially incorrect to directly use the output of a single RCP scenario directly as an input for infrastructure design, unless that scenario is considered to have a 100% probability. The first step towards dealing with uncertainty is to calculate local percentile information (Kopp et al. 2014). In summary, to assess investments in LSLR adaptation it must be acknowledged that there will be some sources of uncertainty such as RCP probabilities, climate modeling, impact damage modeling, adaptation costs, socio-economic scenarios, etc. Accordingly, Hunt and Watkiss, (2010) provide an overview of the state of the art in the quantification and valuation of climate risks at city scale. They conclude that many of the decisions relating to future urban development require information on climate change risks to cities.

Uncertainty is addressed in the fifth and latest IPCC Assessment Report (AR5) (IPCC, 2014) with the communication of the degree of certainty in assessment findings. In the case of global sea level rise (GSLR) the qualifier assigned is “likely”. The IPCC GSLR information is clearly insufficient because (i) it is global in nature; (ii) there is no GSLR that is only expected because of the failure to weigh up the four scenarios; and (iii) the term “likely” covers a range of 66-100%, making it difficult to use in standard stochastic models to obtain risk measures.

There are relatively few applications that cover adaptation alternatives or investment projects. One of the few is Kontogianni et al. (2014), which explores modern management tools for assessing the economic impacts of SLR and the effectiveness of proactive coastal adaptation under uncertain conditions on the Greek coast. A second example is the paper by Woodward et al., (2011) on flood risk management in the Thames Estuary.

[1] This measure is also known as C-VaR or tail loss.

Without adaptation, 0.2–4.6% of the world's population is expected to be flooded annually in 2100 under 25–123 cm of global mean sea-level rise and the associated annual costs could reach 0.3-9.3% of global GDP (Hinkel et al., 2014). The impacts of sea-level rise (SLR) in 83 developing countries are assessed by Dasgupta et al., (2009), whose results show a loss of global GDP ranging from 1.3% to 6.05% for projected sea-level rises of 1 m and 5 m respectively. An assessment of the risks of coastal extremes for the coast of California (Heberger et al., 2011) estimates that 480,000 people, a wide range of critical infrastructures, vast areas of wetlands and other natural ecosystems, and nearly $100 billion in property along the California coast are at increased risk from flooding from a 1.4-meter sea-level rise if no adaptation actions are taken.

Risk management is a fundamental policy response to climate change: Robust approaches that consider flexibility and the time dimension can be very valuable in supporting decision-making under uncertainty (Chambwera et al., 2014).

Abadie et al. (2016) calculate the risks for major European coastal cities under the RCP2.6, RCP4.5, and RCP 8.5 scenarios using local information. Their results show that in the worst cases, despite their low probability of occurrence, the scale of the damage is huge in comparison to annual average figures. More recently, Abadie et al. (2017) analyze expected damage and risk measures for 120 major coastal world cities under the same scenarios and the need for adaptation investments when the risk is greater than a given percentage of city-level GDP. In both studies their results depend on the fulfillment of the corresponding scenarios. Both papers use stochastic diffusion models.

Other studies have developed frameworks to account for the expected losses from sea-level rise and coastal extreme events using a different methodologies. For instance, Boettle et al. (2013) use extreme value theory with the block-maxima approach for two Danish cities: Copenhagen and Kalundborg. They analyze expected damage and the standard deviation as a function of varying location and scale parameters of the generalized extreme value distribution (GEV). Boettle et al. (2016) likewise use a Generalized Pareto Distribution (GPD) to assess the impact of sea-level rise as well as potential protection measures against flood damage for the aforesaid two cities. They assume that a rise in mean levels results in a shift of today's sea level distribution without using future expected RCP information.

In this study I use a stochastic diffusion model to assess the expected damage and risk measures for 120 major world coastal cities due to climate and socio-economic effects under uncertainty. The model is based on regionalized IPCC RCP scenarios for each city. I use stochastic SLR values rather than the fixed values used in many studies, as this enables risk measures to be calculated. The paper essentially makes three contributions: (i) As a novelty I propose a methodology based on a stochastic diffusion model together with Monte Carlo simulation for building a global stochastic scenario to assign probabilities on three RCPs (2.6, 4.5 and 8.5). This methodology enables the adaptation decision-making process based on the probability assigned to the IPCC scenarios ; (ii) I apply that methodology to 120 coastal cities for certain combinations of the RCPs scenario probabilities and obtain expected damage and risk measurements using Expected Shortfall(ES) along with their changes over time from the present to the year 2100; and (iii) I analyze expected damage and risks for World Bank income groups. The paper highlights the high economics risk that will be faced in the future by some mega-cities in China and the United States (USA).

The paper is organized as follows: Section 2 is dedicated to Material and Methods, and describes the stochastic diffusion model, its calibration, the Monte Carlo simulation process, the risk measure, and the damage function. Section 3 describes the calculation of the combined scenario for assigning probabilities to the three RCP scenarios. Section 4 presents the results at the following levels: (i) city; (ii) continent; (iii) Word Bank income group; and (iv) some relevant countries (USA and China). Section 5 contains a discussion and section 6 concludes.

2 Material and Methods

2.1 A stochastic approach to modeling global sea-level rise

The IPCC report (2013) provides a range of estimates of global sea level rise (GSLR) for every decade from 2007 until the end of the century, according to different representative concentration pathways (RCPs). However this information is insufficient to analyze the risk in coastal cities because local SLR can differ significantly from global levels. Working with regionalized data is therefore critical for making decisions on adaptation investments.

Regionalized means and percentiles are calculated by Kopp et al., (2014) for three representative concentration paths. They do not consider RCP 6.0 in their projections because the figures for this pathway are nearly identical to those for RCP 4.5. The calculations of Koop et al. (2014) take into account changes in ocean dynamics, static equilibrium effects, glacial isostatic adjustments, and other local non-climatic drivers such as groundwater depletion, sediment compaction, and tectonic processes.

Using the data on medians and percentiles from Kopp et al. (2014), a continuous stochastic Geometric Brownian Motion (GBM)[2] model was calibrated to obtain the probability distribution of relative SLR at each moment in time for each coastal city analyzed in each scenario (for three of the latest IPCC emission scenarios or Representative Concentration Pathways: RCPs 2.6, 4.5 and 8.5). This means 120 coastal cities and three scenarios for each city, entailing 360 GBM models with different parameters. The stochastic diffusion models derived and the corresponding uncertainties formed the basis for assessing different actions, as shown below. These GBM models have enabled an LSLR distribution function to be drawn up that is log-normal at all times. The expected LSLR drift was obtained by minimizing the sum of the square of the differences with the theoretical median values (2030, 2050 and 2100). The volatility was calculated with the 95th percentile from 2100 using log-normal distribution properties.

The detailed parameter calculation process is shown in Appendix. Figure 1 shows a diagram of the calculation process. The stored values are used to build mixed scenarios resulting from the probabilistic combination of the three basic scenarios.

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[2] The Geometric Brownian Motion (GBM) diffusion model is a very common model defined as "a stochastic process often assumed for asset prices where the logarithm of the underlying variable follows a generalized Wiener process" (Hull, 2012). Note that in a GBM stochastic process the median is not equal to the mean.

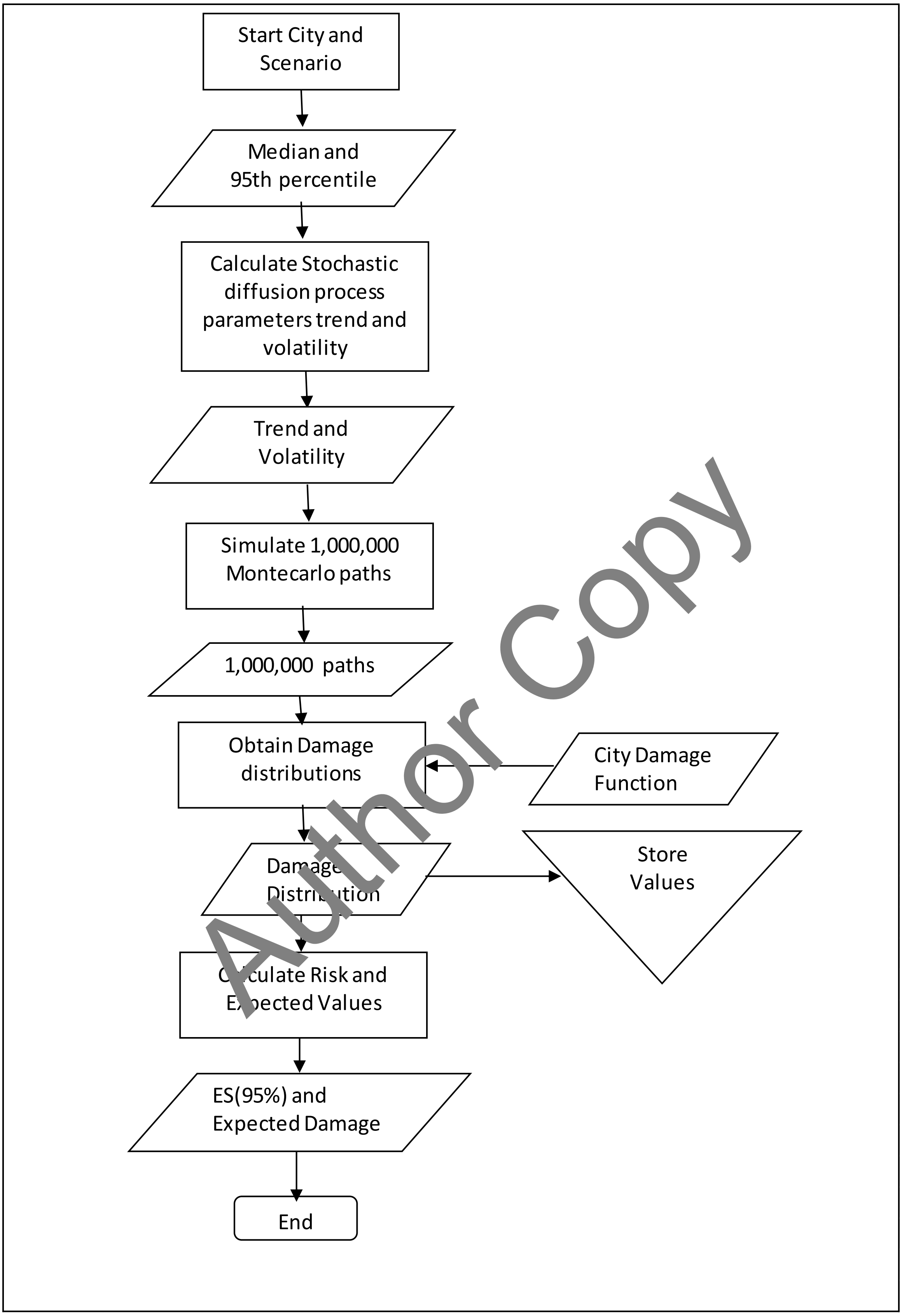

Figure 1. Diagram of the calculation process

2.2 Monte Carlo Simulation

In this study I used 1,000,000 Monte Carlo simulations for each case, i.e. the combination of the climate-induced SLR scenario (RCP2.6, RCP4.5, RCP8.5) and time (2020 - 2100 with five year intervals), which was linked to socio-economic development and to each city. The number of simulations enabled me to approximate almost exactly the theoretical distribution of SLR for each city at time *t*. The detailed Monte Carlo simulation process is shown in the supplementary material.

Table 1 shows the SLR mean, median and 95th percentile for 2011 for the three RCP scenarios in selected cities. RCP 2.6 provides the most optimistic SLR for any time, while RCP 8.5 presents the most pessimistic values. The figures for RCP 4.5 are very close to each other, showing a middle-of-the-road path (Abadie et al., 2017).

The Table 1 median and percentille 95th figures are almost exactly the same as those calculated by Kopp et al. (2014). However, note that I now have a stochastic diffusion process that generates a log-normal distribution for any time *t*.

Table 1 shows that in 2100 the most risky scenario (RCP 8,5) for some cities expects a mean SLR of more than one meter, with the case of Bangkok standing out with an expected SLR of more than two meters. The 95th percentile shows that in the 5% of worse cases the SLR could rise more than one and a half meters in some cities, such as Guangzhou, New Orleans, Bangkok, Calcutta, Osaka, Shanghai, New York, Zhanjiang, Surat, Hirosima, Houston, and Virginia Beach.

Table 1: Median, Mean and 95% Percentile Simulated Values for 2100 (centimeters).

no.	City	RCP 2.6			RCP 4.5			RCP 8.5		
		Median	Mean	P95	Median	Mean	P95	Median	Mean	P95
1	GUANGZHOU GUANGDONG	51.6	55.8	111.9	61.3	65.4	111.9	83.0	87.1	150.0
2	NEW ORLEANS	121.6	122.2	160.7	131.5	132.1	160.7	149.0	149.9	199.0
3	MUMBAI	44.5	46.7	81.7	55.4	57.6	81.7	76.0	78.7	124.0
4	KRUNG THEP (BANGKOK)	170.8	[illegible]	206.8	180.7	181.1	206.8	202.0	202.6	249.0
5	KOLKATA (CALCUTTA)	100.6	101.6	137.8	111.3	112.3	137.8	129.0	130.3	176.0
6	OSAKA	90.6	91.6	131.7	100.4	101.6	131.7	124.0	125.5	177.0
7	ALEXANDRIA	45.4	49.8	107.6	56.3	58.0	107.6	74.0	76.4	123.0
8	GUAYAQUIL	40.2	42.7	78.3	49.2	51.7	78.3	69.0	71.8	117.0
9	SHENZEN	39.4	42.6	82.7	50.4	53.3	82.7	71.0	74.3	123.0
10	SHANGHAI	75.6	77.3	119.7	87.4	89.3	119.7	109.0	111.3	165.0
11	TIANJIN	49.5	52.5	101.7	62.3	64.9	101.7	84.0	86.9	142.0
12	TOKYO	46.3	48.7	88.5	57.3	59.6	88.5	81.0	83.9	136.0
13	HAI PHONG	51.3	53.4	91.5	61.3	63.3	91.5	81.0	83.4	131.0
14	NAGOYA	11.2	16.5	53.5	21.2	26.2	53.5	45.0	50.3	102.0
15	THÀNH-PHO-HO-CHÍ-MINH	61.6	63.9	107.8	72.3	74.5	107.8	92.0	94.5	146.0
16	ABIDJAN	29.4	32.0	66.6	39.1	41.7	66.6	60.0	62.9	108.0
17	VISAKHAPATNAM	39.4	41.8	77.6	49.2	51.5	77.6	67.0	69.9	116.0
18	BOSTON	57.7	60.1	103.1	70.4	72.7	103.1	91.0	93.9	149.0
19	NEW YORK	62.9	65.1	107.3	75.6	77.8	107.3	96.0	98.8	154.0
20	ZHANJIANG	65.3	67.3	111.4	75.2	77.3	111.4	96.0	98.4	151.0
21	SURAT	77.5	79.3	121.7	88.4	90.1	121.7	109.0	111.0	161.0
22	MIAMI	54.3	55.9	93.4	64.3	65.8	93.4	84.0	85.9	132.0
23	GRANDE VITORIA	50.4	52.4	90.6	60.2	62.2	90.6	80.0	82.5	132.0
24	KHULNA	65.5	67.7	110.7	76.4	78.6	110.7	94.0	96.5	148.0

25	XIAMEN	51.4	53.7	92.6	61.2	63.5	92.6	83.0	85.8	137.0
26	FUKUOKA-KITAKYUSHU	47.4	49.9	88.6	57.4	60.0	88.6	81.0	84.1	135.0
27	CHENNAI	41.3	43.9	79.6	51.4	54.0	79.6	71.0	73.9	119.0
28	LOMÉ	61.6	63.1	99.8	71.4	72.9	99.8	91.0	93.0	140.0
29	VANCOUVER	26.1	29.4	64.1	33.0	35.9	64.1	46.0	49.0	88.0
30	HIROSHIMA	75.6	77.1	116.7	85.5	87.2	116.7	109.0	111.1	163.0
31	HOUSTON	95.7	96.7	135.8	105.4	106.3	135.8	123.0	124.4	173.0
32	SAN FRANCISCO	50.4	52.3	88.6	58.2	60.2	88.6	75.0	77.2	122.0
33	TAIPEI	49.4	51.9	93.7	59.2	61.8	93.7	82.0	85.1	139.0
34	KOCHI (COCHIN)	52.4	54.7	91.7	62.3	64.7	91.7	84.0	86.7	134.0
35	TAMPA-ST. PETERSBURG	59.6	61.3	98.8	68.4	70.0	98.8	88.0	90.2	138.0
36	SAN JUAN	51.6	53.6	89.9	59.3	61.3	89.9	78.0	80.4	126.0
37	HONG KONG	41.3	44.0	83.5	51.1	53.8	83.5	72.0	75.0	124.0
38	WASHINGTON DC	62.7	64.1	104.9	74.3	75.7	104.9	93.0	94.9	146.0
39	NINGBO	53.3	55.5	96.5	64.2	66.4	96.5	86.0	88.7	141.0
40	VIRGINIA BEACH	71.6	73.2	114.8	83.6	85.1	114.8	102.0	104.0	156.0

2.3 Risk Measuring

The central distribution measures (mean and median) of the SLR projections do not provide all the information that needs to be considered from a coastal risk management perspective: information is required on the “upper-tail end” of the probability distribution, i.e. the worst-case scenario (Hinkel et al., 2015). Risk measures are very useful analytical tools in situations of uncertainty and have often been used in economics to account for uncertainties of prices or other other variables in investment projects (Abadie and Chamorro, 2013). In this paper we use Expected Shortfall (ES) as a coherent[3] measure of risk (Artzner et al., 1999). ES is a good risk measure and in particular makes it possible to perform many large-scale calculations and show their numerical efficiency and stability (Rockafellar and Uryasev, 2002).

Expected Shortfall (ES) is the mean expected loss in the (1-α)% worse cases, so ES (95%) is the mean expected loss in the worst 5% of cases. The GBM distribution model enables the risk corresponding to any value of α to be estimated, but in this study I focus only on the worst 5% of cases, so 1-α=95%, although the model can be calculated with other values.

With a stochastic model it is possible to generate a large number of scenarios using Monte Carlo simulation methods and to calculate ES(1-α) fairly accurately. That is the numerial method approach followed in this paper.

2.4 The Damage Function

A recent study by Hallegatte et al. (2013) estimates the cost of annual average damage due to the combined effect of sea-level rise and extreme events in 136 major mega-cities. The authors define a damage function in which flood losses depend on the following variables: global sea-level rise (*S*), the level of protection in place in coastal cities (*P*), subsidence (*SUB*)[4], extreme events (*E)*, the socio-economic scenario (*SE)*, the defense failure model, and the characteristics of defenses (*DF)*.

[3] It is considered that a coherent risk measure R(D), in which D represents damage, must meet the following four conditions: monotonicity, sub-additivity, positive homogeneity and translation invariance.
[4] Defined as the sum of subsidence and land-uplift.

$$D = f(S, P, SUB, E, SE, DF) \tag{1}$$

The cost function provided in their paper, which relates damage to SLR, served as an input for the study presented in this paper. However Hallegatte et al. (2013) follow a deterministic approach to SLR, while I model it in a stochastic way to account for uncertainty at local level. The modeling is done following the latest IPCC scenarios RCP2.6, RCP4.5 and RCP8.5 regionalized by Kopp et al. (2014). In addition, I use the risk measure defined above to develop a risk-based assessment of potential damage. Only 120 of the cities analyzed by Hallegatte et al., (2013) are considered in the study by Kopp et al., (2014), so I limit my study to the 120 mega-cities that appear in both papers.

The damage function is based on two main components: The first is local sea-level rise at each city, which is estimated using the stochastic GBM model as described in Section 2.1. The three LSLR scenarios are distinguished via the index *i*, so that at a time *t* the local SLR in scenario RCP2.6 and city k is $S_t^{i,k}$, assuming the stochastic behavior defined as laid out. The subsidence in each city is not considered in my damage function as it is taken into account together with other local determinants in the SLR regionalization process developed by Kopp et al. (2014).

The second component of the damage function is represented by the socio-economic development of each city in the future, as defined by Hallegatte et al. (2013)[5]. Accordingly, damage also varies with time *t* in a deterministic way, due to the effect of the socio-economic scenario. Note that the function does not include extreme events as a variable. However, the original values from Hallegatte et al. (2013) used in this paper incorporate the probability of extreme events obtained from the DIVA model. This DIVA model information is also used because it enables homogeneous comparisons to be made between cities. The model proposed could be used in a city with more damage information if such information is obtained in the future.

In areas where there are coastal defenses I assume that they fail to provide any protection once they are overcome by flooding. This means that the damage function for each local SLR scenario *i* and for each city *k* at each time *T* is defined as follows:

$$D_t^{i,k} = f(S_t^{i,k}, t) \tag{2}$$

At time *t* the function has the following form:

$$D_t^{i,k} = f^1(S_t^{i,k}) + f^2(t) \tag{3}$$

where $f^1(S_t^{i,k})$ represents the impact of sea-level rise in city *k* at time t in scenario *i*, including subsidence, while $f^2(t)$ shows the socio-economic impacts in the absence of SLR.

In this way, following the data from Hallegatte et al. (2013), I calibrate a continuous damage function for each city using discontinuous data. The main factor that increases damage is found to be $f^1(S_t^{i,k})$, followed by socio-economic development over the years. Obviously, both factors contribute to increasing the risk over time.

[5] Hallegatte et al. (2013) develop three possible socio-economic scenarios: a constant scenario, a scenario with no city limit (every city within a country grows at the same rate), and a scenario with city limits assuming that no city will exceed 35 million inhabitants. In this study I use the data for this last scenario.

3 Calculations

3.1 Building a combination of IPCC SLR scenarios

Now, if probabilities p_i are assigned to the three IPCC scenerios used here with $p_1 + p_2 + p_3 = 1$, the expected sea level rise for city *k* emerges, as shown in equation (4)

$$E_0(S_t^k) = V_0^k(p_1 e^{\alpha^{1,k}t} + p_2 e^{\alpha^{2,k}t} + p_2 e^{\alpha^{2,k}t}) - (p_1 B_0^{1,k} + p_2 B_0^{2,k} + p_2 B_0^{3,k}) \qquad (4)$$

The total variance $Var(S_t^k) = Var(V_t^k)$ for city k is shown in Equation (5).

$$\sum_{i=1}^{3} p_i \left[Var(V_t^{i,k}) + (E_0(S_t^{i,k}))^2 \right] - (E_0(S_t^k))^2 \qquad (5)$$

An infinite number of scenario combinations are possible. The methodology proposed enables any combination to be calculated. However I calculate three additional scenarios:

A) An equal probability scenario where RCP6.0 is represented by the RCP4.5 scenario values (p_1=25.00%, p_2=50.00% and p_3=25.00%).
B) An equal probability scenario discarding the possibility of the RCP2.6 scenario (p_1=0.00%, p_2=66.67% and p_3=33.33%).
C) A scenario with equal probability for RCP4.5 and RCP8.5 (p_1=0.00%, p_2=50.00% and p_3=50.00%).

The results for the case of New Orleans are shown in Table 2, where the theoretical values are compared with the Monte Carlo simulated values for the original IPCC scenarios and equal probability scenario A) in the year 2100.

Table 2: New Orleans Mean and Variance Scenario 25% RCP2.6, 50% RCP4.5, 25% RCP8.5 in 2100 (SLR in centimeters).

Scenario	no. Simulations	Probability	V_0	B_0	alpha	sigma	Theoretical Mean	MC Mean	Theoretical Variance	MC Variance
RCP2.6	1,250,000	25%	[illegible]	[illegible]20.9	0.0030	0.0053	122.23	122.22	519.75	519.42
RCP4.5	2,500,000	50%	[illegible]33.8	324.6	0.0034	0.0053	132.08	132.09	546.51	546.87
RCP8.5	1,250,000	25%	33[illegible]	327.5	0.0038	0.0063	149.88	149.87	840.06	839.52
Total	5,000,000	100%					**134.06**	**134.07**	**712.70**	**712.60**

Table 2 shows that the Monte Carlo method, using 5,000,000 simulations in this case, is a good procedure for obtaining an SLR distribution because the mean and variance values are almost identical to the theoretical ones.

Observe that in the combined scenario the mean is the weighted figure for three RCP means, while the variance is higher than the weighted values, which is due to the influence of the more volatile scenarios in the risk, which is greater than the probability for this scenario.

3.2 Obtaining the mean and risk of damage with a combination of IPCC SLR scenarios

After obtaining the 1,000,000 Monte Carlo simulations of SLR for each city and each scenario I selected a path depending on the probabilities. For example, in the case of equal probability scenario A) I took path 250,000 from RCP2.6, path 500,000 from RCP4.5 and path 250,000 from RCP8.5. Now with this total of 1,000,000 paths I used the damage function to obtain the corresponding damage distribution. With this distribution I calculated the mean value and the ES(95%), in the latter case with the mean of the 50,000 worst values. Figure 2 shows the ES(95%) in the case of New Orleans as a function of the probability of the IPCC scenarios.

Of the three additional scenarios it is the most pessimistic ones which have most influence on the value of ES(95%).

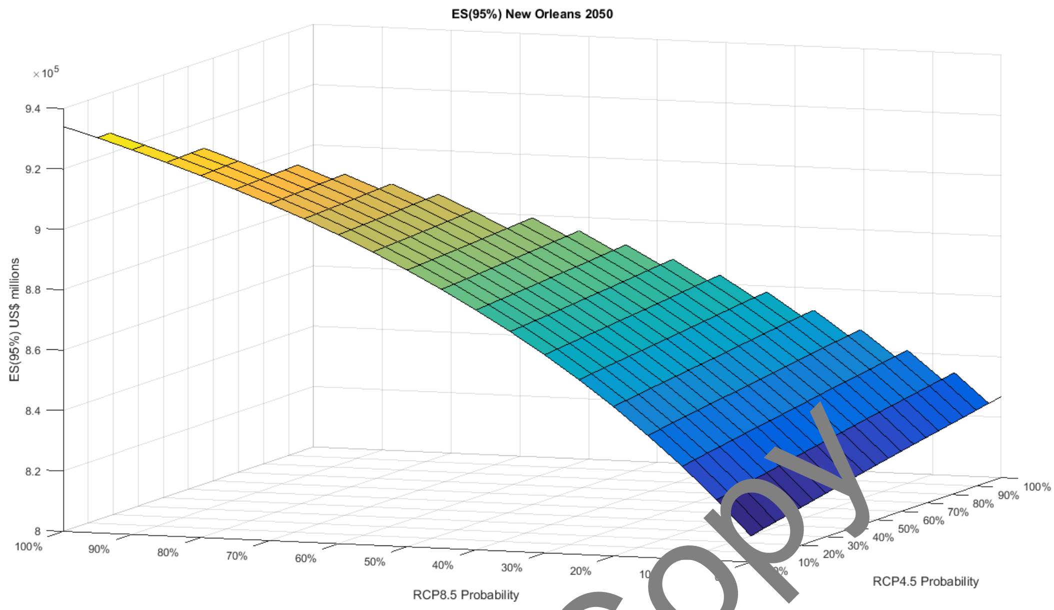

Figure 2. New Orleans 2100 ES(95%) as a function of the IPCC scenario probability.

Figure 2 also shows the greater impact on risk measuring of the probability of the RCP 8.5 scenario. Some probability combinations are not possible because they must add up to one.

4 Results

4.1 Results for weighted scenarios

Table 3 shows the expected damage in the 15 most strongly affected cities in 2100 in the equal probability scenario (25% RCP 2.6, 50% RCP 4.5 and 25% RCP 8.5). The table includes many Asian cities, but New Orleans is the city with the greatest expected damage. It can be seen that the expected damage grows rapidly with time, so if mitigation measures are insufficient there will need to be substantial investment in adaptation in many coastal cities. New Orleans, Guangzhou, Bangkok, Mumbai and Calcutta are the five cities with the greatest expected damage in 2100. In the case of New Orleans the expected damage in that year is US$ 1,251,732 millions.

This mean measurement is important but insufficient, because it does not show the extreme effects of low-probability but high damage. The ES(95%) risk measure is presented in Table 4, and shows that the risk is greater in Guangzhou than in New Orleans. This is because the variance in samage is greater in Guangzhou, i.e. there is greater uncertainty there. This differentiated behavior can be seen in Figure 3.

Table 3: Ranking of cities considering expected damage in 2025-2100 under the 25% RCP2.6, 50% RCP4.5 and 25% RCP8.5 scenario (millions of US$)

no.	CITY	Continent	2025	2050	2075	2100
1	NEW ORLEANS	North America	259,129	563,210	892,664	1,251,732
2	GUANGZHOU GUANGDONG	Asia	136,512	388,171	743,593	1,196,517

3	KRUNG THEP (BANGKOK)	Asia	124,674	339,300	575,793	835,836
4	MUMBAI	Asia	24,707	143,895	337,767	594,853
5	KOLKATA (CALCUTTA)	Asia	74,326	214,021	377,679	567,378
6	OSAKA	Asia	83,276	192,192	309,534	442,660
7	ALEXANDRIA	Africa	12,482	71,246	170,358	296,610
8	SHANGHAI	Asia	10,186	74,122	163,979	272,600
9	GUAYAQUIL	South America	7,668	45,824	138,752	271,363
10	SHENZEN	Asia	4,215	33,965	108,926	219,958
11	TIANJIN	Asia	19,304	65,712	127,227	201,709
12	TOKYO	Asia	16,013	70,683	130,379	200,311
13	HAI PHONG	Asia	2,327	29,442	83,092	152,770
14	THÀNH-PHO-HO-CHÍ-MINH	Asia	4,148	28,732	69,156	118,874
15	NEW YORK	North America	7,643	30,262	61,809	100,239

Table 4: Ranking of cities considering the 2100 ES(95%) under the 25% RCP2.6, 50% RCP4.5 and 25% RCP8.5 scenario (millions of US$).

no.	CITY	Continent	2025	2050	2075	2100
1	GUANGZHOU GUANGDONG	Asia	388,103	[illegible]	1,780,975	2,800,756
2	NEW ORLEANS	North America	[illegible]	[illegible]	1,326,645	1,832,466
3	MUMBAI	Asia	[illegible]	384,399	774,892	1,310,529
4	KRUNG THEP (BANGKOK)	Asia	205,528	486,422	793,745	1,133,409
5	KOLKATA (CALCUTTA)	Asia	147,772	355,130	596,635	881,334
6	OSAKA	Asia	158,224	321,041	507,388	723,781
7	ALEXANDRIA	Africa	65,633	235,066	443,006	705,048
8	GUAYAQUIL	South America	25,554	162,699	371,707	661,637
9	SHENZEN	Asia	16,046	138,429	320,346	577,702
10	SHANGHAI	Asia	52,401	181,598	338,425	532,281
11	TIANJIN	Asia	65,756	167,634	292,293	447,426
12	TOKYO	Asia	71,616	161,165	275,361	423,355
13	HAI PHONG	Asia	16,568	103,580	212,364	350,530
14	NAGOYA	Asia	9,588	74,543	146,773	268,807
15	THÀNH-PHO-HO-CHÍ-MINH	Asia	20,351	79,188	152,876	244,446

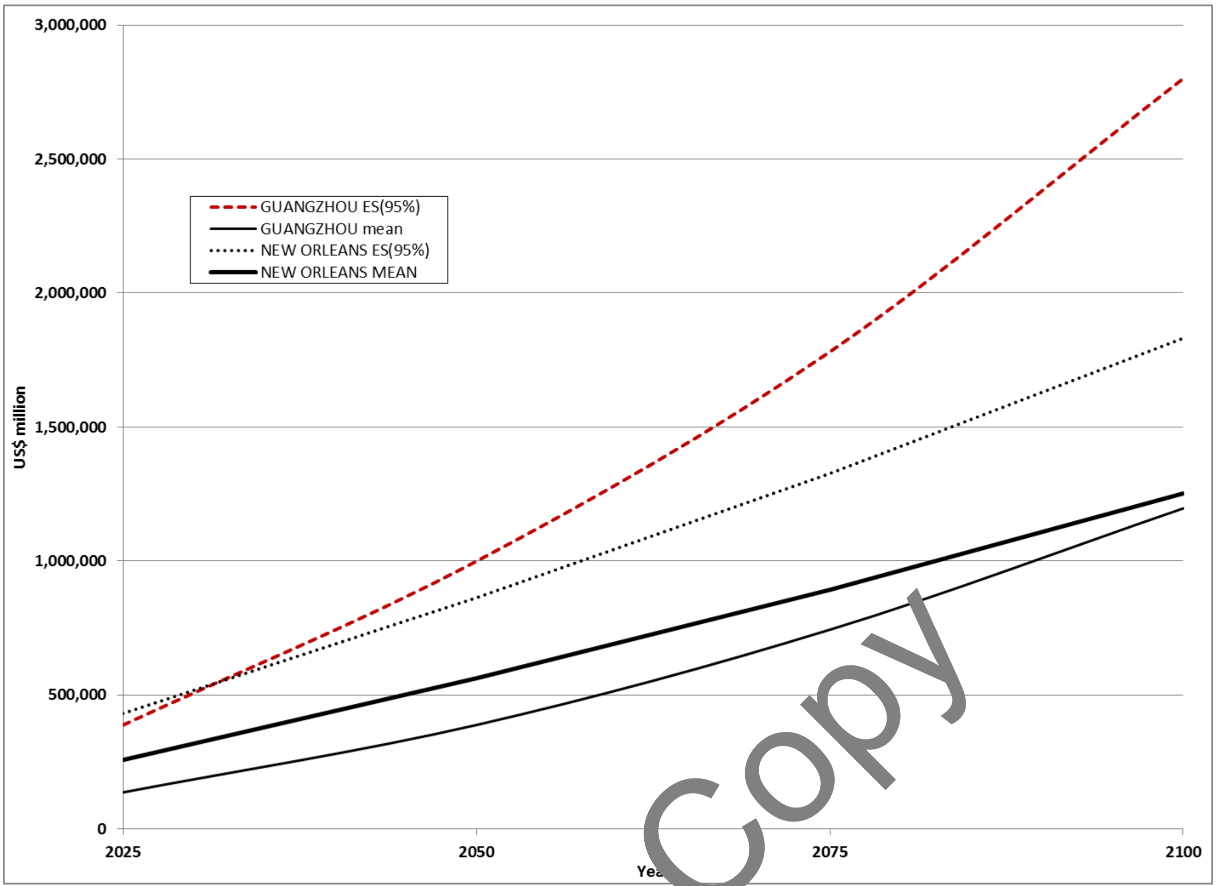

Figure 3. Differentiated behavior between New Orleans and Guangzhou in 2100 in the equal probability scenario.

Table 4 shows that in the case of Guangzhou in 2100 the ES(95%) is US$ 2,800,756 millions, i.e. in the 5% of worse cases that is the amount of the mean damage expected. Table 4 shows that the damage in the 5% of worse cases in 2100 will exceed US$ 500,000 millions in ten cities, eight of them in Asia.

Table 5 shows the five cities at most risk on each continent under the three IPCC and the three combined scenarios. In general the scenarios can be classified from lowest to highest risk as RCP 2.6, RCP 4.5, A), B), C), RCP 8.5. This is not the case in Alexandria, where the 95% percentile gives a higher figure in RCP2.6 than RCP4.5 using the data in Kopp et al. (2014). Asian and North American cities are at most risk while European cities are at least risk. The African cities stand at an intermediate level of risk and the risk level in the mega-cities of Oceania is low. Table 5 also shows that in calculating risk levels the probability assigned to the riskiest scenario has a significant impact.

Table 5: Cities ranked by high 2100 ES(95%) on each continent and for some scenarios (millions of US$).

RCP 2.6		100.00%	0.00%	0.00%	25.00%	0.00%	0.00%
RCP 4.5	Continent	0.00%	100.00%	0.00%	50.00%	66.67%	50.00%
RCP 8.5		0.00%	0.00%	100.00%	25.00%	33.33%	50.00%
GUANGZHOU		2,429,580	2,627,065	3,175,214	2,800,756	2,879,034	2,970,759
MUMBAI		998,779	1,154,451	1,536,325	1,310,529	1,359,216	1,419,409
KRUNG THEP (BANGKOK)	Asia	996,605	1,058,297	1,220,816	1,133,409	1,152,718	1,177,355
KOLKATA (CALCUTTA)		750,658	821,505	971,920	881,334	901,406	925,577
OSAKA		603,567	655,707	808,968	723,781	742,248	765,869
ISTANBUL		29,675	29,945	33,649	30,925	31,290	31,914
GLASGOW	Europe	2,775	3,264	4,424	3,667	3,829	4,021
LISBON		2,691	2,963	3,834	3,293	3,404	3,546

LONDON		941	1,040	1,493	1,245	1,296	1,366
HAMBURG		930	1,072	1,438	1,233	1,277	1,334
NEW ORLEANS	North America	1,607,000	1,712,759	2,002,232	1,832,466	1,869,115	1,915,497
BOSTON		172,121	197,229	256,750	219,865	227,817	237,474
NEW YORK		162,396	188,821	238,983	207,126	214,281	222,466
MIAMI		114,417	128,001	164,879	143,039	147,729	153,592
VANCOUVER		80,057	84,744	104,359	91,344	93,750	97,026
BRISBANE	Oceania	3,669	4,215	5,773	4,914	5,099	5,336
SYDNEY		3,312	3,878	5,316	4,521	4,693	4,910
PERTH		1,063	1,200	1,580	1,358	1,405	1,466
ADELAIDE		340	386	497	431	446	463
MELBOURNE		159	178	229	198	205	213
GUAYAQUIL	South America	511,478	585,778	780,811	661,637	687,194	718,394
GRANDE VITORIA		103,789	118,477	158,389	134,366	139,496	145,891
RIO DE JANEIRO		14,278	16,736	22,933	19,408	20,175	21,134
RECIFE		9,702	11,210	15,160	12,785	13,296	13,927
NATAL		4,724	5,454	[illegible]	6,216	6,464	6,769
ALEXANDRIA	Africa	739,968	571,386	[illegible]	[illegible]	693,597	728,853
ABIDJAN		159,191	187,815	[illegible]	219,933	229,823	242,200
LOMÉ		90,613	[illegible]	[illegible]	115,073	118,999	123,873
LAGOS		39,049	43,738	55,790	48,661	50,204	52,119
DAR-EL-SALAM		14,695	[illegible]	22,201	18,971	19,667	20,519

Tables 6, 7, and 8 show the trend over time in the risk of damage for 25 mega-cities from 2050 to 2075 and 2100. These tables show high levels of risk for more remote dates. The risk level rises over time. The top five cities most at risk are the same ones at all times.

Table 6: Cities ranked by 2050 ES(95%) damage in some scenarios (millions of US$).

no.							
	RCP 2.6	100.00%	0.00%	0.00%	25.00%	0.00%	0.00%
	RCP 4.5	0.00%	100.00%	0.00%	50.00%	66.67%	50.00%
	RCP 8.5	0.00%	0.00%	100.00%	25.00%	33.33%	50.00%
1	GUANGZHOU GUANGDONG	966,539	976,248	1,061,446	999,324	1,008,713	1,023,708
2	NEW ORLEANS	808,642	826,795	934,071	863,057	876,241	894,819
3	KRUNG THEP (BANGKOK)	449,846	467,128	523,386	486,422	494,117	503,760
4	MUMBAI	348,064	354,191	438,366	384,399	393,354	407,731
5	KOLKATA (CALCUTTA)	325,955	341,546	386,322	355,130	361,646	369,404
6	OSAKA	297,271	305,837	350,882	321,041	326,707	334,466
7	ALEXANDRIA	283,555	192,951	241,864	235,066	214,094	222,625
8	SHANGHAI	161,599	173,014	203,424	181,598	186,224	191,501
9	GUAYAQUIL	147,096	155,097	183,419	162,699	166,686	171,622
10	TIANJIN	162,009	162,128	180,091	167,634	169,205	172,346
11	TOKYO	146,901	152,672	179,323	161,165	164,568	169,169
12	SHENZEN	127,400	129,923	156,933	138,429	141,272	145,963
13	HAI PHONG	91,314	97,367	118,651	103,580	106,550	110,242
14	THÀNH-PHO-HO-CHÍ-MINH	73,192	75,794	87,645	79,188	80,730	82,792
15	BOSTON	67,840	71,179	85,337	75,457	77,310	79,768

16	NEW YORK	65,136	70,117	82,059	73,330	75,223	77,299
17	NAGOYA	74,304	71,874	78,311	74,543	74,524	75,660
18	ZHANJIANG	65,489	68,183	75,619	70,018	71,181	72,478
19	SURAT	54,989	55,940	63,469	58,299	59,170	60,477
20	VISAKHAPATNAM	45,433	48,497	62,440	52,712	54,505	56,923
21	ABIDJAN	47,202	49,796	61,910	53,292	54,836	56,944
22	MIAMI	47,567	49,724	58,333	52,231	53,389	54,887
23	FUKUOKA-KITAKYUSHU	43,097	44,962	51,391	46,889	47,787	48,898
24	KHULNA	42,673	44,738	50,942	46,362	47,290	48,371
25	XIAMEN	40,266	42,542	49,182	44,344	45,339	46,494

Table 7: Cities ranked by 2075 ES(95%) damage in some scenarios (millions of US$).

no.	RCP 2.6 RCP 4.5 RCP 8.5	100.00% 0.00% 0.00%	0.00% 100.00% 0.00%	0.00% 0.00% 100.00%	25.00% 50.00% 25.00%	0.00% 66.67% 33.33%	0.00% 50.00% 50.00%
1	GUANGZHOU GUANGDONG	1,624,758	1,706,259	1,967,180	1,780,975	1,819,102	1,862,802
2	NEW ORLEANS	1,196,100	1,254,373	[illegible]	1,326,645	1,351,607	1,383,166
3	MUMBAI	637,604	700,903	[illegible]	774,892	800,514	832,281
4	KRUNG THEP (BANGKOK)	712,839	750,472	[illegible]	793,745	807,149	823,919
5	KOLKATA (CALCUTTA)	525,039	564,504	654,773	596,635	609,470	624,355
6	OSAKA	443,021	470,777	563,126	507,388	519,176	534,081
7	ALEXANDRIA	492,717	[illegible]	485,079	443,006	425,256	445,065
8	GUAYAQUIL	[illegible]	341,431	431,328	371,707	384,487	399,301
9	SHANGHAI	284,001	315,030	383,807	338,425	348,548	359,909
10	SHENZEN	[illegible]	293,961	371,905	320,346	330,913	343,769
11	TIANJIN	[illegible]	275,425	327,324	292,293	299,212	307,870
12	TOKYO	230,114	250,915	315,981	275,361	283,877	294,446
13	HAI PHONG	175,297	194,922	245,824	212,364	219,609	228,003
14	THÀNH-PHO-HO-CHÍ-MINH	133,314	143,663	172,203	152,876	156,987	161,739
15	NAGOYA	127,639	135,538	167,495	146,773	150,683	155,881
16	BOSTON	115,965	128,152	160,611	139,266	143,809	149,186
17	NEW YORK	110,105	123,941	151,368	132,780	137,008	141,565
18	ABIDJAN	98,371	111,098	148,477	124,342	129,418	135,531
19	VISAKHAPATNAM	100,135	112,735	147,489	124,504	129,375	135,122
20	ZHANJIANG	105,277	113,378	133,111	119,595	122,572	125,861
21	SURAT	91,883	97,732	115,147	103,732	106,141	109,021
22	MIAMI	79,349	86,392	106,984	93,726	96,530	99,922
23	KHULNA	75,633	82,409	97,048	86,763	89,076	91,528
24	GRANDE VITORIA	67,853	75,274	96,607	82,732	85,668	89,192
25	XIAMEN	68,033	74,953	92,997	81,206	83,761	86,731

Table 8: Cities ranked by 2100 ES(95%) damage in some scenarios (millions of US$).

no.	RCP 2.6 RCP 4.5 RCP 8.5	100.00% 0.00% 0.00%	0.00% 100.00% 0.00%	0.00% 0.00% 100.00%	25.00% 50.00% 25.00%	0.00% 66.67% 33.33%	0.00% 50.00% 50.00%
1	GUANGZHOU GUANGDONG	2,429,580	2,627,065	3,175,214	2,800,756	2,879,034	2,970,759

2	NEW ORLEANS	1,607,000	1,712,759	2,002,232	1,832,466	1,869,115	1,915,497
3	MUMBAI	998,779	1,154,451	1,536,325	1,310,529	1,359,216	1,419,409
4	KRUNG THEP (BANGKOK)	996,605	1,058,297	1,220,816	1,133,409	1,152,718	1,177,355
5	KOLKATA (CALCUTTA)	750,658	821,505	971,920	881,334	901,406	925,577
6	OSAKA	603,567	655,707	808,968	723,781	742,248	765,869
7	ALEXANDRIA	739,968	571,386	795,073	705,048	693,597	728,853
8	GUAYAQUIL	511,478	585,778	780,811	661,637	687,194	718,394
9	SHENZEN	451,676	514,913	682,551	577,702	599,841	626,951
10	SHANGHAI	426,315	484,663	608,278	532,281	549,145	569,078
11	TIANJIN	374,051	410,173	512,348	447,426	460,927	477,671
12	TOKYO	328,220	371,249	494,771	423,355	438,562	457,877
13	HAI PHONG	274,395	313,814	409,051	350,530	363,255	378,593
14	NAGOYA	202,510	234,059	325,401	268,807	280,302	294,837
15	THÀNH-PHO-HO-CHÍ-MINH	203,573	225,272	278,496	244,446	251,801	260,533
16	ABIDJAN	159,191	187,815	266,455	219,933	229,823	242,200
17	VISAKHAPATNAM	168,026	195,853	264,507	221,585	230,787	241,929
18	BOSTON	172,121	197,229	2[illegible],750	219,865	227,817	237,474
19	NEW YORK	162,396	188,821	238,9[illegible]3	207,126	214,281	222,466
20	ZHANJIANG	151,165	166,85[illegible]	20[illegible],313	180,553	185,755	191,872
21	SURAT	134,639	147,43[illegible]	179,022	159,561	163,787	168,894
22	MIAMI	114,417	128,0[illegible]	164,879	143,039	147,729	153,592
23	GRANDE VITORIA	103,789	118,4[illegible]7	158,389	134,366	139,496	145,891
24	KHULNA	115,0[illegible]9	128,793	156,107	137,884	141,974	146,513
25	XIAMEN	101,3[illegible]7	115,225	150,982	129,514	134,149	139,843

Table 9 shows the differences between the maximum and the minimum risks measured by ES (95%), where the RCP8.5 scenario is usually the maximum and the RCP2.6 the minimum. These differences grow substantially over time. Table 9 shows that they could be between 22.5% and 60.7% in 2100 for the cities selected. There are major differences, so it is necessary to form an opinion as to the likelihood of the scenarios. Without scenario probabilities all the calculations are contingent on scenario realization. In the case of New York in 2100 the difference is 67.4%, which translates into a substantial figure of US$107,264 millions. The biggest difference is found for Guangzhou, at US$ 745,633 millions, an increase of 30.7%.

Table 9: ES(95%) Maximum and Minimum Scenario Damage (millions of US$)

no.	Cities	2050		2075		2100	
		Max-Min	% Max-Min	Max-Min	% Max-Min	Max-Min	% Max-Min
1	GUANGZHOU GUANGDONG	94,907	9.8%	342,422	21.1%	745,633	30.7%
2	NEW ORLEANS	125,430	15.5%	249,764	20.9%	395,231	24.6%
3	KRUNG THEP (BANGKOK)	73,540	16.3%	259,555	40.7%	537,546	53.8%
4	MUMBAI	90,302	25.9%	142,594	20.0%	224,210	22.5%
5	KOLKATA (CALCUTTA)	60,366	18.5%	129,734	24.7%	221,262	29.5%
6	OSAKA	53,611	18.0%	120,106	27.1%	205,401	34.0%
7	ALEXANDRIA	90,604	47.0%	127,926	35.1%	223,687	39.1%
8	SHANGHAI	41,824	25.9%	122,963	39.9%	269,332	52.7%
9	GUAYAQUIL	36,322	24.7%	99,806	35.1%	230,875	51.1%

10	TIANJIN	18,083	11.2%	102,599	38.1%	181,963	42.7%
11	TOKYO	32,422	22.1%	66,446	25.5%	138,297	37.0%
12	SHENZEN	29,534	23.2%	85,867	37.3%	166,551	50.7%
13	HAI PHONG	27,338	29.9%	70,526	40.2%	134,656	49.1%
14	THÀNH-PHO-HO-CHÍ-MINH	14,454	19.7%	38,888	29.2%	122,891	60.7%
15	BOSTON	17,497	25.8%	39,856	31.2%	74,923	36.8%
16	NEW YORK	16,922	26.0%	44,646	38.5%	107,264	67.4%
17	NAGOYA	6,437	9.0%	41,263	37.5%	96,481	57.4%
18	ZHANJIANG	10,130	15.5%	50,106	50.9%	84,629	49.2%
19	SURAT	8,480	15.4%	47,354	47.3%	76,587	47.2%
20	VISAKHAPATNAM	17,007	37.4%	27,834	26.4%	53,148	35.2%
21	ABIDJAN	14,708	31.2%	23,264	25.3%	44,383	33.0%
22	MIAMI	10,766	22.6%	27,635	34.8%	50,462	44.1%
23	FUKUOKA-KITAKYUSHU	8,294	19.2%	21,414	28.3%	54,600	52.6%
24	KHULNA	8,269	19.4%	28,754	42.4%	41,059	35.7%
25	XIAMEN	8,917	22.1%	24,964	36.7%	49,606	48.9%

4.2 Results for cities summarized by income group and continent

The following results per income group are obtained using the World Bank classification of December 2016 (World Bank, 2016).

Table 10 shows the short-term expected damage in 2025 by income group and continent. Table 10 also shows the impact on US and Chinese mega-cities. It can be seen that with 16 cities, the United States accounts for close to 32% of total expected damage and China with 13 cities accounts for nearly 22%. Between them the US and China account for more than 50% of the expected damage in major coastal cities. Other lower-middle income countries account for nearly 16% of total expected damage. Some of these countries may have problems funding investment in adaptation, and the same may happen in the case of the six cities from low income countries.

Table 10: 2025 Expected Damage per income group and continent (millions of US$)

Continent and Income Group	no. cities							
		RCP 2.6	100.00%	0.00%	0.00%	25.00%	0.00%	0.00%
		RCP 4.5	0.00%	100.00%	0.00%	50.00%	66.67%	50.00%
		RCP 8.5	0.00%	0.00%	100.00%	25.00%	33.33%	50.00%
Africa	10		22,173	16,436	14,496	17,376	15,786	15,474
Low income	4		1,642	1,421	1,637	1,529	1,492	1,530
Lower-middle income	6		20,531	15,015	12,859	15,847	14,294	13,943
Asia	47		605,526	560,621	569,392	572,843	563,621	570,271
Low income	1		41	39	37	39	38	38
Lower-middle income	14		134,301	120,356	130,041	126,266	123,589	125,241
Upper-middle income	17		335,431	315,753	314,157	319,051	315,271	320,138
. *China*	13		208,493	191,556	190,244	194,212	191,145	196,051
High income	15		135,753	124,472	125,157	127,487	124,722	124,854
Europe	18		760	671	554	664	632	613
Lower-middle income	1		108	82	56	82	74	69
Upper-middle income	2		212	236	146	207	206	191
High income	15		440	353	351	374	352	352
North America	23		314,789	295,213	294,682	300,047	295,098	295,045
Low income	1		4	4	4	4	4	4

Upper-middle income	3	348	330	320	332	326	325
High income	19	314,437	294,880	294,358	299,711	294,768	294,716
. United States	16	308,955	289,760	290,835	294,898	290,179	290,392
Oceania	6	211	215	208	212	213	212
High income	6	211	215	208	212	213	212
South America	16	10,750	9,940	9,037	9,916	9,638	9,493
Upper-middle income	15	10,734	9,923	9,022	9,899	9,622	9,477
High income	1	16	17	16	16	16	16
Total 120 mega-cities	120	954,209	883,097	888,370	901,058	884,987	891,107
Low income	6	1,687	1,465	1,678	1,572	1,535	1,572
Lower-middle income	21	154,941	135,453	142,957	142,195	137,956	139,254
Upper-middle income	37	346,725	326,242	323,645	329,490	325,425	330,131
High income	56	450,856	419,937	420,090	427,801	420,072	420,150
Total 120 mega-cities (%)	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Low income	5.0%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%
Lower-middle income	17.5%	16.2%	15.3%	16.[illegible]%	15.8%	15.6%	15.6%
Upper-middle income	30.8%	36.3%	36.9%	36.4%	36.6%	36.8%	37.0%
. China	10.8%	21.8%	21.7%	21.4%	21.6%	21.6%	22.0%
High income	46.7%	47.2%	47.6%	47.3%	47.5%	47.5%	47.1%
. United States	13.3%	3[illegible].4%	[illegible]2.8%	32.7%	32.7%	32.8%	32.6%

Table 11 is similar to Table 10, but shows risk measured by ES(95%) on the assumption of perfect correlation between risks in cities, i.e. when the worst happens in one city the worst also happens in other cities. The United States accounts for nearly [illegible]6% and China nearly 28%. This figure is lower than that for expected damage in the United States because of its lower damage distribution volatility. By contrast the figure for ES(95%) in China is higher.

Lower-middle income countries account for nearly 20% of risk, a figure higher than that for expected damage. Asia and North America between them account for 97% of the expected damage in 2025.

Table 11: 2025 Expected Shortfall ES(95%) per income group and continent (millions of US$)

Continent and Income Group	no. cities							
		RCP 2.6	100.00%	0.00%	0.00%	25.00%	0.00%	0.00%
		RCP 4.5	0.00%	100.00%	0.00%	50.00%	66.67%	50.00%
		RCP 8.5	0.00%	0.00%	100.00%	25.00%	33.33%	50.00%
Africa	10		125,657	69,625	71,892	90,371	70,438	70,903
Low income	4		11,356	10,185	11,662	10,892	10,710	10,975
Lower-middle income	6		114,301	59,440	60,231	79,479	59,728	59,927
Asia	47		1,515,173	1,396,967	1,441,695	1,438,065	1,414,473	1,441,467
Low income	1		122	117	107	116	113	112
Lower-middle income	14		366,673	331,284	365,453	350,803	344,199	350,305
Upper-middle income	17		848,101	782,834	783,271	796,969	783,762	802,787
. China	13		645,269	580,716	566,786	590,484	576,216	592,692
High income	15		300,277	282,733	292,864	290,177	286,399	288,263
Europe	18		5,553	5,021	3,721	4,978	4,662	4,461
Lower-middle income	1		943	761	481	743	670	626
Upper-middle income	2		2,044	2,573	1,370	2,243	2,239	2,050
High income	15		2,565	1,687	1,869	1,992	1,752	1,786
North America	23		571,555	546,151	585,249	564,291	561,298	568,343

Low income	1	17	16	16	16	16	16
Upper-middle income	3	1,069	1,017	1,054	1,040	1,029	1,036
High income	19	570,469	545,118	584,178	563,235	560,252	567,291
. *United States*	16	553,754	529,827	570,919	547,826	545,446	552,775
Oceania	6	750	716	723	727	718	720
High income	6	750	716	723	727	718	720
South America	16	41,318	37,252	35,342	37,951	36,658	36,388
Upper-middle income	15	41,274	37,206	35,296	37,906	36,612	36,342
High income	1	44	46	46	45	46	46
Total 120 mega-cities	120	2,260,005	2,055,732	2,138,622	2,136,384	2,088,246	2,122,283
Low income	6	11,494	10,317	11,785	11,024	10,839	11,103
Lower-middle income	21	481,918	391,485	426,166	431,025	404,597	410,858
Upper-middle income	37	892,489	823,629	820,991	838,158	823,643	842,215
High income	56	874,104	830,301	879,681	856,177	849,168	858,106
Total 120 mega-cities (%)	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Low income	5.0%	0.5%	0.5%	0.6%	0.5%	0.5%	0.5%
Lower-middle income	17.5%	21.3%	19.0%	19.9%	20.2%	19.4%	19.4%
Upper-middle income	30.8%	39.5%	40.1%	3[illegible].4%	39.2%	39.4%	39.7%
. *China*	10.8%	28.6%	28.2%	26.5%	27.6%	27.6%	27.9%
High income	46.7%	38.7%	40.[illegible]%	41.1%	40.1%	40.7%	40.4%
. *United States*	13.3%	24.5%	25.8%	26.7%	25.6%	26.1%	26.0%

Table 12 shows the expected damage figures for 2050. There is a major increase in expected damage compared to the 2025 figures.

Table 12: 2050 Expected Damage per income group and continent (millions of US$)

Continent and Income Group	no. cities							
		RCP 2.6	100.00%	0.00%	0.00%	25.00%	0.00%	0.00%
		RCP 4.5	0.00%	100.00%	0.00%	50.00%	66.67%	50.00%
		RCP 8.5	0.00%	0.00%	100.00%	25.00%	33.33%	50.00%
Africa	10		98,227	102,035	133,403	108,905	112,487	117,755
Low income	4		13,860	16,090	22,149	17,048	18,111	19,126
Lower-middle income	6		84,366	85,945	111,255	91,857	94,376	98,629
Asia	47		1,660,949	1,772,837	2,141,581	1,832,598	1,895,950	1,981,849
Low income	1		124	144	184	149	157	164
Lower-middle income	14		451,056	491,539	618,621	513,239	533,952	555,220
Upper-middle income	17		905,660	955,799	1,130,851	982,469	1,014,243	1,067,735
. *China*	13		581,231	619,528	765,003	641,722	668,072	716,625
High income	15		304,109	325,355	391,925	336,741	347,597	358,731
Europe	18		4,424	5,048	5,877	5,096	5,320	5,464
Lower-middle income	1		872	816	836	834	822	826
Upper-middle income	2		1,582	2,050	1,977	1,913	2,023	2,014
High income	15		1,970	2,182	3,064	2,349	2,475	2,624
North America	23		679,457	711,934	796,712	725,113	740,296	754,475
Low income	1		17	18	23	19	20	21
Upper-middle income	3		1,160	1,298	1,648	1,351	1,415	1,473
High income	19		678,281	710,618	795,040	723,743	738,862	752,981

. United States	16	662,861	693,575	775,313	706,433	720,922	734,591
Oceania	6	964	1,209	1,695	1,269	1,371	1,452
High income	6	964	1,209	1,695	1,269	1,371	1,452
South America	16	52,564	61,018	82,742	64,323	68,248	71,902
Upper-middle income	15	52,495	60,933	82,622	64,233	68,151	71,799
High income	1	69	86	120	90	97	103
Total 120 mega-cities	120	2,496,584	2,654,081	3,162,010	2,737,303	2,823,672	2,932,897
Low income	6	14,000	16,252	22,356	17,216	18,288	19,310
Lower-middle income	21	536,294	578,300	730,712	605,930	629,150	654,675
Upper-middle income	37	960,896	1,020,079	1,217,098	1,049,965	1,085,832	1,143,021
High income	56	985,393	1,039,450	1,191,844	1,064,192	1,090,402	1,115,891
Total 120 mega-cities (%)	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Low income	5.0%	0.6%	0.6%	0.7%	0.6%	0.6%	0.7%
Lower-middle income	17.5%	21.5%	21.8%	23.1%	22.1%	22.3%	22.3%
Upper-middle income	30.8%	38.5%	38.4%	38.5%	38.4%	38.5%	39.0%
. China	10.8%	23.3%	23.3%	24.2%	23.4%	23.7%	24.4%
High income	46.7%	39.5%	39.2%	37.7%	38.9%	38.6%	38.0%
. United States	13.3%	26.6%	26.1%	2[illegible].5%	25.8%	25.5%	25.0%

Table 13 shows the ES(95%) risk figures for 2050. There is also a major increase in risks compared to the 2025 figures. Note that the risk can only be summarized if there is perfect correlation.

Table 13: 2050 Expected Shortfall ES(95%) per income group and continent (millions of US$)

Continent and Income Group	no. cities							
		RCP 2.6	100.00%	0.00%	0.00%	25.00%	0.00%	0.00%
		RCP 4.5	0.00%	100.00%	0.00%	50.00%	66.67%	50.00%
		RCP 8.5	0.00%	0.00%	100.00%	25.00%	33.33%	50.00%
Africa	10		396,428	312,447	388,155	362,558	345,140	358,319
Low income	4		45,061	47,874	58,185	51,018	52,429	54,215
Lower-middle income	6		351,366	264,573	329,970	311,540	292,710	304,105
Asia	47		3,795,490	3,855,630	4,401,446	4,026,082	4,093,336	4,244,830
Low income	1		392	432	500	447	459	471
Lower-middle income	14		1,067,379	1,108,420	1,313,273	1,174,379	1,200,112	1,235,424
Upper-middle income	17		2,090,670	2,091,541	2,334,319	2,163,831	2,193,414	2,292,628
. China	13		1,634,411	1,619,464	1,804,887	1,671,689	1,693,894	1,783,274
High income	15		637,048	655,237	753,354	687,426	699,350	716,307
Europe	18		24,308	26,128	26,439	26,371	26,527	26,626
Lower-middle income	1		5,350	5,450	5,281	5,368	5,378	5,355
Upper-middle income	2		9,834	12,448	10,810	11,724	11,994	11,748
High income	15		9,123	8,229	10,348	9,279	9,156	9,524
North America	23		1,175,000	1,209,079	1,381,194	1,264,622	1,286,371	1,316,222
Low income	1		53	54	62	56	57	59
Upper-middle income	3		3,099	3,272	3,887	3,453	3,538	3,645
High income	19		1,171,849	1,205,753	1,377,246	1,261,113	1,282,775	1,312,518
. United States	16		1,128,298	1,162,165	1,329,798	1,216,318	1,237,682	1,266,744
Oceania	6		3,285	3,558	4,400	3,821	3,938	4,083
High income	6		3,285	3,558	4,400	3,821	3,938	4,083

South America	16	200,896	212,623	253,623	223,874	229,645	236,784
Upper-middle income	15	200,660	212,359	253,288	223,588	229,349	236,475
High income	1	237	264	335	286	296	308
Total 120 mega-cities	120	5,595,407	5,619,464	6,455,257	5,907,329	5,984,956	6,186,864
Low income	6	45,506	48,360	58,746	51,521	52,946	54,744
Lower-middle income	21	1,424,096	1,378,443	1,648,525	1,491,287	1,498,200	1,544,883
Upper-middle income	37	2,304,263	2,319,621	2,602,303	2,402,596	2,438,295	2,544,496
High income	56	1,821,541	1,873,040	2,145,683	1,961,925	1,995,515	2,042,740
Total 120 mega-cities (%)	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Low income	5.0%	0.8%	0.9%	0.9%	0.9%	0.9%	0.9%
Lower-middle income	17.5%	25.5%	24.5%	25.5%	25.2%	25.0%	25.0%
Upper-middle income	30.8%	41.2%	41.3%	40.3%	40.7%	40.7%	41.1%
. *China*	10.8%	29.2%	28.8%	28.0%	28.3%	28.3%	28.8%
High income	46.7%	32.6%	33.3%	33.2%	33.2%	33.3%	33.0%
. *United States*	13.3%	20.2%	20.7%	20.6%	20.6%	20.7%	20.5%

5 Discussion

5.1 Discussion of Results

Even if mitigation policies prove extremely successful, many climate impacts are already occurring and will continue to occur due to the inertia of the processes, so adaptation investments will be necessary. In this paper I calculate the expected damage and the ES(95%) risk measures for major coastal cities around the world.

The means and above all the risks calculated above are relevant values for investment decision-making. Policy-makers and stakeholders need to be aware of risks and procedures need to be drawn up for jointly defining with stakeholders how much risk each city can accept. In each country and in each city there may be a different level of risk aversion.

However, possible adaptation measures depend on the economic possibilities of each city and country: Some low-income, lower-middle income and upper-middle income countries may find it difficult to undertake the investments needed to adapt to SLR.

Without sufficient adaptation measures there may be population displacement in some cities, especially in mega-cities in low-income and middle-income countries. International financial support may be needed by some of these cities.

The ES(95%) risk indicator is useful and relatively easy for many stakeholders to understand. It can be compared with other figures such as city GDP as in Abadie et al. (2017). The adaptation plans of cities should be consistent with expected damage and risks and should be implemented earlier in some cities than in others.

However, flexible adaptation investment may be a good option for immediate investment decisions taking into account the risk of SLR in the coming decades, as it may avoid adaptation investment that proves unnecessary if future SLR turns out to be lower than currently expected. This option of incremental investment in the future can be achieved with an initial incremental cost, for example by building dikes with larger foundations so that the dike height can be increased in the future. These flexible adaptations may be useful if certain risks materialize, such as more melting of ice in the Arctic than expected. In the context of adaptation economics, it can be said that “Real Option Analysis quantifies the investment risk with uncertain future outcomes” (Watkiss et al., 2015). This is very useful when considering the value of flexibility of investments. “This includes the flexibility over the timing of the capital investment, but also the flexibility to adjust the investment as it progresses over time, i.e. allowing a project to adapt, expand or scale-back in response to unfolding events. The approach can therefore assess whether it is better to invest now or to wait – or whether it is better to invest in options that offer greater flexibility in the future." (Watkiss and Hunt, 2013), It can therefore justify options (or decisions) that would not be taken forward under a conventional economic analysis" (Watkiss and Hunt, 2013).

Determining specific adaptation measures for each city calls for an ad hoc analysis that lies outside the scope of this study. Each city will need to define its portfolio of adaptation measures considering not just hazard but also its risk aversion, geography, social and cultural values, institutional and financial resources, etc.

Nevertheless, potential measures that would need to be adapted to each city's context could include:

- Urban planning measures such as not urbanising the low-lying areas most at risk. In some cases this may necessitate reallocation of properties. Other construction measures such as building codes are also relevant.
- Protection infrastructures: improvement and building of new protection infrastructures (walls, embankments, barriers, gates, culverts, larger dikes).
- If possible, reservation of space for future adaptation infrastructures.
- Soft or behavioral measures such as early warning systems.
- Financial measures: insurance, reinsurance, bonds, etc. However, financial measures may not be effective (e.g. due to insurance firms charging higher premiums as the perceived risk becomes greater).

Each city must choose its portfolio of adaptation measures considering its risks and costs.

The countries with the greatest expected damage and risks in their mega-cities are the USA and China. This is consistent with recent US history, as the last 10 years have seen two of the most catastrophic coastal extreme events in the country's recent history. In 2005 the city of New Orleans was hit by hurricane Katrina, which caused damage estimated at US$147 billion (2010), the highest costs ever recorded for a coastal extreme event (Nicholls and Kebede, 2012). Other direct damage included disruption of the electrical system infrastructure, which affected up to 2.7 million people. Three nuclear plants were also affected and were forced to run at a reduced level during the storm. The death of almost 1,800 people should be added to this number (Graumann et al. 2005). In 2012, Hurricane Sandy killed 43 people in New York, left thousands homeless, caused an estimated $US19 billion in public and private losses and crippled the financial district. The New York Stock Exchange closed for the first time since 1888 and the storm surge flooded New York City's subway tunnels and inundated the runways at La Guardia and Kennedy airports (Steffen et al., 2014).

Some cities in lower-middle income countries face high risks of damage in the coming decades, and how they will fund the necessary adaptation investments remains to be seen.

5.2 Comparison with other studies

Other papers have analyzed expected damage in some coastal cities, e.g. Hallegatte et al. (2013). Table 14 shows a comparison between the expected damage results obtained by Hallegatte et al. (2013) and those found in the present study. Note that the results of Hallegatte et al. (2013) are for an SLR of 20 cm.

Table 14. Comparison of damage in 2050 with Hallegatte et al. (2013)

Expected damage costs (millions of US$) per IPCC RCP				**Expected damage costs (millions of US$) for an optimistic sea level rise scenario from Hallegatte et al. (2013)**	
Urban Agglomeration	**RCP2.6**	**RCP4.5**	**RCP8.5**	**Urban Agglomeration**	**SLR 20 cm**
1 New Orleans	539,200	554,973	603,350	1 Guangzhou (S)	254,721
2 Guangzhou	346,032	375,053	456,394	2 New Orleans (S)	161,141
3 Krung Thep (Bangkok)	323,092	334,940	364,059	3 Mumbai	107,285
4 Kolkata (Calcutta)	198,283	210,923	235,809	4 Osaka (S)	84,968
5 Osaka	180,943	187,319	213,040	5 Tokyo (S)	61,737
6 Mumbai	121,190	132,452	189,435	6 Nagoya (S)	57,954
7 Alexandria	67,683	66,586	84,194	7 Kolkata (Calcutta) (S)	56,303

8 Shanghai	62,792	71,576	90,486	8 Tianjin (S)	40,492
9 Tokyo	59,531	67,795	87,524	9 Alexandria (S)	34,621
10 Tianjin	56,895	64,084	77,751	10 Guayaquil (S)	31,288
11 Guayaquil	37,635	43,459	58,784	11 Krung Thep (Bangkok) (S)	20,778
12 Zhanjiang	29,990	32,569	37,833	12 Fukuoka-Kitakyushu (S)	19,904
13 Shenzen	26,850	31,261	46,543	13 Vancouver (S)	18,912
14 Surat	26,445	27,957	33,221	14 Shenzen	17,553
15 New York	25,743	29,389	36,509	15 Zhanjiang (S)	16,709
16 Thành-Pho-Ho-Chí-Minh	24,349	27,544	35,487	16 Jakarta (S)	16,354
17 Hai Pòng	23,077	27,478	39,758	17 Xiamen (S)	12,182
18 Boston	23,059	26,746	34,725	18 Hiroshima (S)	9,456
19 Fukuoka-Kitakyushu	22,334	23,995	28,496	19 Los Angeles-Long Beach Santa Ana	9,427
20 Houston	18,573	19,225	21,500	20 Surat	9,070

* (S) indicates that the city is subject to significant subsidence.

Table 14 shows a comparison between the expected damage results obtained by Hallegatte et al. (2013) and those found in present study. Note that the Hallegatte et al. (2013) results are for an SLR of 20 cm.

However, in my study I use the regionalized percentiles from Kopp et al. (2014), which incorporate specific subsidence for each city. The median SLR for Kopp et al. (2014) in the three scenarios is greater than 20 cm in many cases, as can be seen in Table 1. The columns for the three RCPs in Table 14 are the same as in Abadie et al. (2017).

The damage calculated in this paper, depending on the RCP scenario, varies between 1.2 and 3.7 times that found by Hallegatte at al. (2013).

Table 15 shows the mean SLR and the expected damage for the equal probability scenario, compared with Hallegatte et al. (2013).

Table 15. Comparison of damage in 2050 in the equal probability scenario case (millions of US$).

Equal Probability Scenario			**Expected damage costs for an optimistic sea level rise scenario from Hallegatte et al. (2013)**	
Urban Agglomeration	**Expected SLR (cm)**	**Expected Damage**	**Urban Agglomeration**	**SLR 20 cm**
1 New Orleans	62.1	563,210	1 Guangzhou (S)	254,721
2 Guangzhou	26.1	388,171	2 New Orleans (S)	161,141
3 Krung Thep (Bangkok)	84.2	339,300	3 Mumbai	107,285
4 Kolkata (Calcutta)	22.4	143,895	4 Osaka (S)	84,968
5 Osaka	49.4	214,021	5 Tokyo (S)	61,737
6 Mumbai	45.6	192,192	6 Nagoya (S)	57,954
7 Alexandria	24.0	71,246	7 Kolkata (Calcutta) (S)	56,303
8 Shanghai	38.2	74,122	8 Tianjin (S)	40,492
9 Tokyo	19.8	45,824	9 Alexandria (S)	34,621
10 Tianjin	20.1	33,965	10 Guayaquil (S)	31,288
11 Guayaquil	27.0	65,712	11 Krung Thep (Bangkok) (S)	20,778
12 Zhanjiang	24.2	70,683	12 Fukuoka-Kitakyushu (S)	19,904
13 Shenzen	25.7	29,442	13 Vancouver (S)	18,912
14 Surat	30.7	28,732	14 Shenzen	17,553
15 New York	34.5	30,262	15 Zhanjiang (S)	16,709

Table 15 shows the impact of a greater expected SLR in the present study.

However, the comparison above is limited to the expected value, because calculation of risk measures as expected shortfall usually applied in financial economics is seldom applied in the evaluation of SLR risk.

Some recent papers have calculated that expected future SLR will be higher than previously estimated, e.g. Grinsted et al., (2013) and DeConto and Pollard, (2016). This justifies greater risks and expected values.

6 Conclusions

This work proposes a methodology for coastal adaptation decision-making using regionalized sea level rise distributions and a cost function for each city. When making decisions it is necessary to assign probabilities to the RCP scenarios. With this model the expected damage and the Expected Shortfall (ES) risk measure can be calculated. Adaptation investment decisions should be taken considering the levels of risk both before and after investment.

High levels of risk in some cities will in the future reach values unacceptable to policy-makers and stakeholders, so major adaptation investment will be necessary. That investment should be decided in advance because of the time lag in the construction of adaptations.

The methodology is applied to 120 coastal mega-cities around the world. The calculations highlight that there are high risk levels in some Asian and North American cities. The study also shows that risk increases rapidly over time, and depending on each city may reach unacceptable levels in few decades.

Some cities in lower and middle income countries may experience financial problems in making adaptation investments. If adaptation investments are not made in some cities, some coastal areas could experience population migrations and abandonment.

The methodology can be useful for both adaptation investment and city planning decision-making, for example for planning the expansion of a city.

The methodology could also be used with more up-to-date cost function for each city. However the cost criterion used in this study is the same for all cities, which enables cities to be sorted for both expected damage and for the expected shortfall risk measure.

7 Appendix

7.1 List of abbreviations

Table A.1: List of Abbreviations

Abbreviation	Description
AR5	Fifth IPCC Assesment Report
DIVA	Dynamic Interactive Vulnerability Assessment
ES	Expected Shortfall
GBM	Geometric Brownian Motion
GDP	Gross Domestic Product
GEV	Generalized Extreme Value
GPD	Generalized Pareto Distribution
GSLR	Global Sea Level Rise
IIASA	International Institute for Applied System Analysis

IPCC	Intergovernmental Panel on Climate Change
LSLR	Local Sea Level Rise
RCPs	Representative Concentration Pathways
SLR	Sea Level Rise

7.2 Parameters Calculations

I use the GBM stochastic process defined as follows:

$$dV_t^{i,k} = \alpha^{i,k} V_t^{i,k} + \sigma^{i,k} V_t^{i,k} dZ_t^{i,k} \text{ where } i \in \{1,2,3\} \tag{A.1}$$

I calculate the parameters $\alpha^{i,k}$ and V_0^k that best fit the regionalized IPCC scenarios, where $\alpha^{i,k}$ is the growth rate and V_0^k is an initial value, which is the same for the three scenarios of city *k*. Note that initially I add V_0^k to the median of each city in each scenario for a better fit with the three median values (2030, 2050 and 2100).

This value V_0^k grows at a rate $\alpha^{i,k}$; the term $\sigma^{i,k}$ is the instantaneous volatility, and $dZ_t^{i,k}$ denotes the increment to a standard Wiener process. The effective sea-level rise in city *k* at time *t*, $S_t^{i,k}$ is then estimated as the difference between $V_t^{i,k}$ and $B_0^{i,k}$, where $B_0^{i,k}$ is the value that ensures that the 2030 median is met.

$$S_t^{i,k} = V_t^{i,k} - B_0^{i,k} \tag{A.2}$$

The values of $\alpha^{i,k}$ and X_o^k are estimated using Equation (A.3) for median values, so the best fit is obtained by minimizing the sum on the square of the differences between the theoretical value in Equation (A.3) and the median values of Kopp et al. (2014). The value of $\sigma^{i,k}$ is calculated by adjusting a log-normal distribution to the top percentile (95% percentile for 2100).

$$S_t^{i,k} = V_0^k e^{(\alpha^{i,k} - \frac{(\sigma^{i,k})^2}{2})t} - B_0^{i,k} \tag{A.3}$$

Figure A.1 shows this calculation for New Orleans in the 8.5 scenario. The $S_t^{i,k}$ sea level rise median fits almost perfectly with the median values of Kopp et al., 2014. Note that this is now a stochastic diffusion model. The dashed line shows the fit with median values plus V_0^k after the calculation of $\alpha^{i,k}$ and V_0^k according to Equation (A.1). Te continuous line shows the real mean values after subtracting $B_0^{i,k}$, according to Equation (A.3), compared to the median of Kopp et al., 2014. The results show the good fit of the median for the calibrated GBM diffusion model. This model has a mean that is somewhat different from the median.

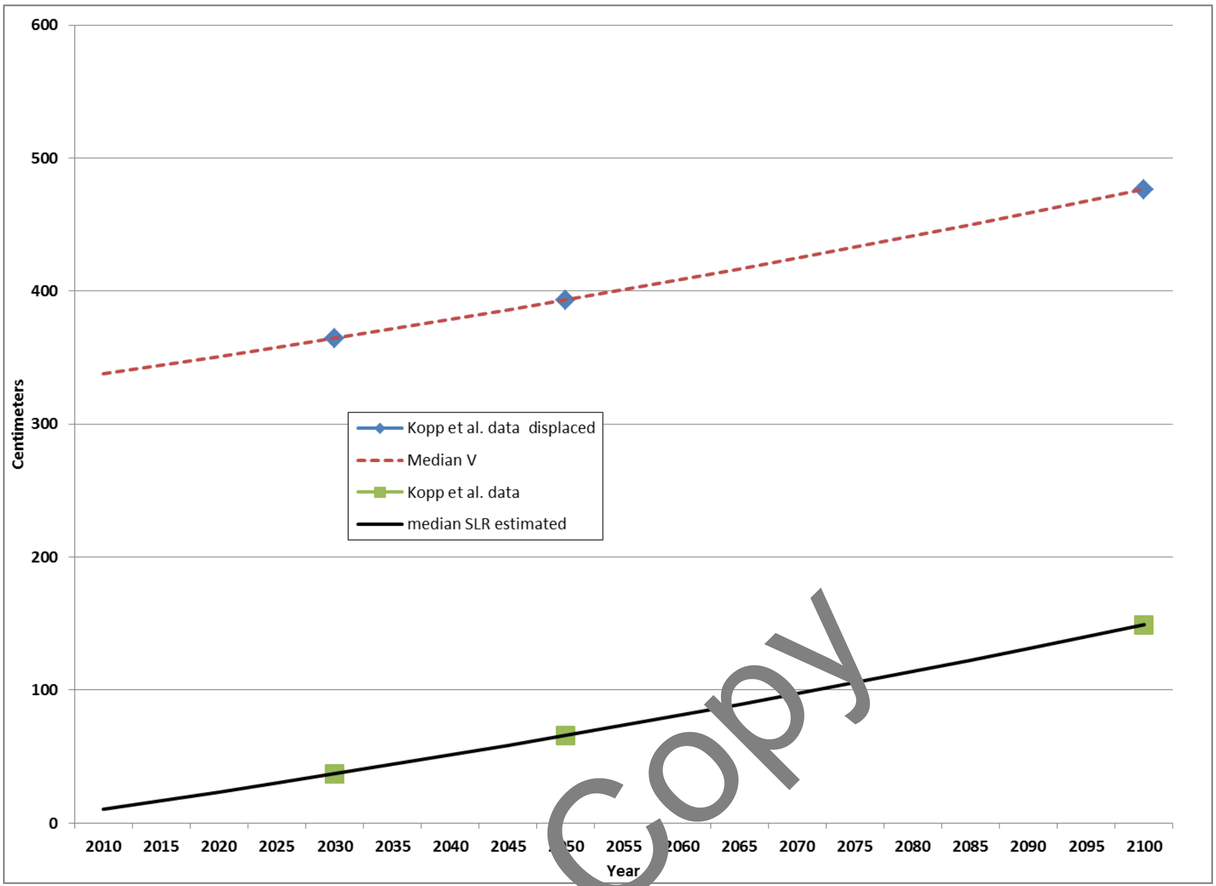

Figure A.1. Tend and initial value stochastic diffusion model estimation with median values (New Orleans 8.5 scenario)

At a time t this distribution process generates a log normal distribution where the initial time is defined as in Equation (A.4). This is the expected value at the initial time of LSLR for city k at future time t:

$$E_0(S_t^{i,k}) = E_0(V_t^{i,k}) - B_0^{i,k} = V_0^k e^{\alpha^{i,k} t} - B_0^{i,k} \qquad (A.4)$$

The variance is expressed for scenario i as in Equation (A.5).

$$Var(V_t^{i,k}) = (V_0^k)^2 e^{2\alpha^{i,k} t}(e^{(\sigma^{i,k})^2 t} - 1) \qquad (A.5)$$

Defining $X_t^{i,k} = \ln(V_t^{i,k})$ then $X_t^{i,k}$ still follows a normal distribution, with the following moments:

$$E_0(X_t^{i,k}) = X_o^k + (\alpha^{i,k} - \frac{(\sigma^{i,k})^2}{2})t \qquad (A.6)$$

$$Var(X_t^{i,k}) = (\sigma^{i,k})^2 t \qquad (A.7)$$

$$\ln(V_t^{i,k}) : \phi\left[\ln(V_0^k) + (\alpha^{i,k} - \frac{(\sigma^{i,k})^2}{2})t, (\sigma^{i,k})^2 t\right] \qquad (A.8)$$

Where $X_0^k = \ln(V_0^k)$.

Table A.1 shows the parameters calculated for the stochastic diffusion process for selected cities.

Table A.1: Calibrated parameters for selected cities

no.	City	V_0	RCP 2.6		RCP 4.5		RCP 8.5	
			Trend	Volatility	Trend	Volatility	Trend	Volatility
1	GUANGZHOU GUANGDONG	52.69	0.0074	0.0297	0.0085	0.0275	0.0105	0.0253

2	NEW ORLEANS	333.78	0.0030	0.0053	0.0034	0.0053	0.0038	0.0063
3	MUMBAI	36.57	0.0082	0.0250	0.0100	0.0228	0.0122	0.0226
4	KRUNG THEP (BANGKOK)	407.19	0.0035	0.0039	0.0037	0.0040	0.0042	0.0048
5	KOLKATA (CALCUTTA)	144.96	0.0053	0.0092	0.0059	0.0092	0.0067	0.0102
6	OSAKA	167.14	0.0043	0.0096	0.0049	0.0096	0.0060	0.0106
7	ALEXANDRIA	59.16	0.0062	0.0303	0.0071	0.0175	0.0090	0.0196
8	GUAYAQUIL	31.90	0.0086	0.0278	0.0101	0.0258	0.0127	0.0244
9	SHENZEN	29.94	0.0090	0.0319	0.0107	0.0282	0.0134	0.0263
10	SHANGHAI	93.02	0.0060	0.0153	0.0069	0.0150	0.0083	0.0156
11	TIANJIN	72.11	0.0054	0.0233	0.0067	0.0206	0.0086	0.0198
12	TOKYO	56.42	0.0063	0.0223	0.0076	0.0209	0.0099	0.0211
13	HAI PHONG	60.68	0.0064	0.0199	0.0075	0.0189	0.0093	0.0190
14	NAGOYA	9.85	0.0106	0.0695	0.0144	0.0559	0.0199	0.0436
15	THÀNH-PHO-HO-CHÍ-MINH	73.28	0.0064	0.0192	0.0073	0.0180	0.0089	0.0179
16	ABIDJAN	34.27	0.0066	0.0301	0.0084	0.0272	0.0114	0.0255
17	VISAKHAPATNAM	36.63	0.0079	0.0262	0.0094	0.0243	0.0116	0.0242
18	BOSTON	66.91	0.0061	0.0209	[illegible]	0.0195	0.0091	0.0202
19	NEW YORK	73.28	0.0061	0.0189	0.0073	0.0184	0.0089	0.0190
20	ZHANJIANG	85.53	0.0058	[illegible]	[illegible]	0.0169	0.0082	0.0167
21	SURAT	93.02	0.0061	[illegible]	0.0070	0.0144	0.0083	0.0146
22	MIAMI	93.51	0.0045	[illegible]	0.0054	0.0147	0.0069	0.0152
23	GRANDE VITORIA	65.57	0.0059	[illegible]	0.0069	0.0186	0.0088	0.0192
24	KHULNA	68.46	[illegible]	0.0190	0.0080	0.0181	0.0093	0.0183
25	XIAMEN	52.69	[illegible]	0.0219	0.0082	0.0212	0.0104	0.0211
26	FUKUOKA-KITAKYUSHU	41.43	[illegible]	0.0252	0.0092	0.0240	0.0118	0.0233
27	CHENNAI	[illegible]	[illegible]	0.0281	0.0108	0.0263	0.0133	0.0246
28	LOMÉ	[illegible]	0.0055	0.0151	0.0064	0.0147	0.0079	0.0156
29	VANCOUVER	[illegible]	0.0107	0.0405	0.0123	0.0349	0.0151	0.0312
30	HIROSHIMA	93.02	0.0060	0.0143	0.0068	0.0143	0.0083	0.0151
31	HOUSTON	159.13	0.0046	0.0096	0.0052	0.0089	0.0060	0.0105
32	SAN FRANCISCO	59.16	0.0064	0.0194	0.0073	0.0189	0.0090	0.0189
33	TAIPEI	56.42	0.0066	0.0227	0.0077	0.0219	0.0099	0.0217
34	KOCHI (COCHIN)	36.88	0.0091	0.0242	0.0104	0.0232	0.0128	0.0222
35	TAMPA-ST. PETERSBURG	78.13	0.0056	0.0166	0.0065	0.0158	0.0080	0.0169
36	SAN JUAN	50.62	0.0072	0.0209	0.0082	0.0202	0.0101	0.0201
37	HONG KONG	41.80	0.0074	0.0266	0.0087	0.0249	0.0111	0.0236
38	WASHINGTON DC	132.03	0.0038	0.0128	0.0046	0.0125	0.0057	0.0134
39	NINGBO	66.91	0.0060	0.0201	0.0071	0.0191	0.0091	0.0193
40	VIRGINIA BEACH	116.39	0.0047	0.0137	0.0056	0.0129	0.0067	0.0142

7.3 Monte Carlo Simulation

For a GBM it is possible to find a discretization algorithm which is both exact and simple, i.e. the differential equation can be integrated exactly; the result is as follows:

$$V_t^{i,k} = V_0^k e^{(\alpha^{i,k} - \frac{(\sigma^{i,k})^2}{2})t + \sigma^{i,k} \int_0^t dZ_t^{i,k}} \tag{A.9}$$

Now, over a time step Δt the following emerges:

$$V_{t+\Delta t}^{i,k} = V_t^{i,k} + \Delta V_t^{i,k} = V_t^{i,k} e^{(\alpha^{i,k} - \frac{(\sigma^{i,k})^2}{2})\Delta t + \sigma^{i,k}\sqrt{\Delta t}\varepsilon} \tag{A.10}$$

Where $\Delta V_t^{i,k}$ denotes the change in $V_t^{i,k}$ over Δt, and ε stands for a random sample from a *N(0,1)* distribution. With this simulation it is possible to obtain the SLR values using Equation A.2. This can be seen in (Abadie and Chamorro, 2013) using the Monte Carlo Method together with stochastic diffusion models.

Note that Equation (A.10) is an exact expression. Therefore, Δt need not be small. Indeed, if there is just one risk value which depends only on the terminal value of the asset then the latter can be simulated in a great leap using a time step of length *T*. However there remains a minor error that can arise from using a finite number of random numbers.

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