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Low-Probability Flood Risk Modeling for New York City

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The devastating impact by Hurricane Sandy (2012) again showed New York City (NYC) is one of the most vulnerable cities to coastal flooding around the globe. The low-lying areas in NYC can be flooded by nor'easter storms and North Atlantic hurricanes. The few studies that have estimated potential flood damage for NYC base their damage estimates on only a single, or a few, possible flood events. The objective of this study is to assess the full distribution of hurricane flood risk in NYC. This is done by calculating potential flood damage with a flood damage model that uses many possible storms and surge heights as input. These storms are representative for the low-probability/high-impact flood hazard faced by the city. Exceedance probability-loss curves are constructed under different assumptions about the severity of flood damage. The estimated flood damage to buildings for NYC is between US$59 and 129 millions/year. The damage caused by a 1/100-year storm surge is within a range of US$2 bn–5 bn, while this is between US$5 bn and 11 bn for a 1/500-year storm surge. An analysis of flood risk in each of the five boroughs of NYC finds that Brooklyn and Queens are the most vulnerable to flooding. This study examines several uncertainties in the various steps of the risk analysis, which resulted in variations in flood damage estimations. These uncertainties include: the interpolation of flood depths; the use of different flood damage curves; and the influence of the spectra of characteristics of the simulated hurricanes.

KEY WORDS: Catastrophe model; flood risk; hurricane; New York City; uncertainty

1. INTRODUCTION

The devastating impact by Hurricane Sandy (2012) again showed New York City (NYC) is one of the most vulnerable cities to coastal flooding around the globe, in terms of both the probability of being hit by a major storm surge and the potential consequences.(1) Storm surges and related coastal flooding are mainly caused by strong winds that pile up water along the shore and generate large waves. A large proportion of NYC and the surrounding region lie less than ∼3–4 m (10–13 ft) above mean sea level, while some floodwalls are even lower than 1.5 m (∼3.3 ft).(2) Both houses and infrastructure in these low-lying areas are vulnerable to coastal flooding from nor'easter storms in winter or North Atlantic hurricanes in the summer period. While hurricanes are much less frequent than nor'easters on the eastern seaboard of the United States, they can be more destructive, and it has been recorded that 15 hurricanes have struck NYC since the year 1815 with a strength of category 3 and above on the Saffir-Simpson scale.(2)

Flood risk for NYC may be quantified by the probabilities of flood events (or return periods) and their potential consequences,(3,4) and is usually expressed in monetary terms (e.g., US$/year). The risk indicator resulting from the product of the probability and damage of a single flood event is the expected annual event damage (EAED). This

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indicator has, for instance, been calculated for the NYC-Newark region by Nichols,[(5)] who estimates the current risk from flooding to be US$3.2 bn/year. However, this risk estimate is not very informative because it only considers one event: namely, a 1/100-year storm. Other events may result in different estimates of the EAED, and events with lower and higher return periods than 1/100 also contribute to the overall risk.[(6–10)] The importance of addressing the full distribution of possible hurricane storm surge events is illustrated by Lin *et al.*,[(11,12)] who apply simulation methods to assess the probability distribution of storm surges in NYC, and find a heavy tail for low-probability extreme events. With such a full distribution of events, the expected annual damage (EAD)—which is often referred to as "risk"—can be calculated more accurately than it has been in existing studies that have used the standard (often idealized) flood events and their impact areas, as mapped in the United States by the Federal Emergency Management Agency (FEMA).[4(1,13)] The complete distribution of risk can be calculated in two steps: (1) flood damage for different events is estimated and used to establish what is called an annual exceedance probability-loss (EPL) curve, which gives for different return periods the corresponding flood damage estimate; (2) the EAD is then calculated by estimating the area (i.e., the integral) under the EPL curve.[(14)] Such EPL curves and corresponding estimates of EAD are of particular importance to insurance companies for their financial risk management, and for deriving premiums.[(15–17)] In addition, policymakers who plan to invest in flood management measures need to consider the EAD when assessing current risk levels and calculating the benefits (expressed as "the reduced EAD") of flood risk management strategies.

The main objective of this article is to develop a new methodology to assess the full distribution of flood risk, as represented by EPL curves and EAD, and to apply this methodology to NYC. To construct the EPL curves, we combine several models and apply a digital elevation model (DEM) and a flood damage model to estimate the damage from a series of representative low-probability storm surge events. This set of extreme surge events is selected from a large database of synthetic surge events for NYC that has been generated by Lin *et al.*[(11)] Each surge event shows surge heights for the NYC coastline, which need to be converted into a map with inundation depths by using a DEM for the NYC area. The set of inundation maps is subsequently used as input for the flood damage model developed by Aerts and Botzen.[(13)] The model output is a series of surge flood damage estimations, which are used for constructing the surge EPL curves. The effect of the astronomical tide is approximately accounted for by shifting the surge EPL curves towards higher probabilities by a magnitude that has been estimated by Lin *et al.*[(11)] Finally, the obtained flood EPL curves are used to calculate the EAD for the NYC area.

The remainder of this article is organized as follows. Section 2 gives background information on coastal storm surges in the NYC area. Section 3 describes the method, models, and data used for this study. Section 4 presents the results. Section 5 compares the results with existing research, and discusses the uncertainties in the flood risk analysis, which provides insights for possible users of the EPL and EAD information. Section 6 concludes.

2. HURRICANES AND FLOOD DAMAGE IN NEW YORK CITY

Hurricanes are major tropical cyclones or low-pressure systems whose destructiveness derives from very high winds (minimum wind speeds of 120 km/hour), flooding due to high storm surges and waves, and heavy rainfall. The surge flood height is amplified if the surge coincides with the astronomical high tide; waves breaking on the shoreline can also add to the flooding. A period characterized by many severe Atlantic hurricanes (Saffir-Simpson categories 3–5) in the 1940s to 1960s was followed by a relatively quiet period during the 1970s up to the early 1990s, and again by a very active period since the late 1990s. In addition, Atlantic hurricanes are affected by climate variations, including the El Niño-Southern Oscillation (ENSO, a warming of the ocean surface off the western coast of South America that occurs every 4–12 years). During the El Niño phase, tropical vertical shear increases due to stronger upper-atmosphere westerly winds, inhibiting the development and growth of Atlantic hurricanes. Therefore, Atlantic tropical cyclones are 36% more frequent and 6% more intense during the La Niña phase of ENSO than during the El Niño phase.[(18)]

Hurricanes strike the NY region infrequently, but when they do strike, generally between July and October, they can produce large storm surges as well as wind and rain damage. A direct hit of a hurricane in NYC may cause huge economic

[4]For more information, see http://msc.fema.gov/.

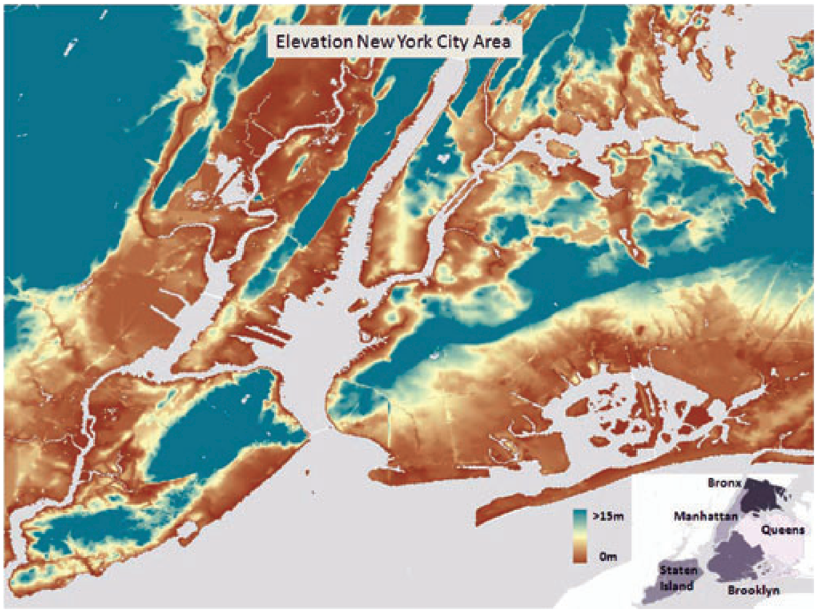

Fig. 1. Elevation of NYC and the New Jersey area with the low-lying areas shown in various shades of brown.

losses,[19] and the Hurricane Evacuation Zones provided by the NYC Office of Emergency Management show that large parts of the city are low lying and potentially vulnerable to surge flooding (Fig. 1). Several studies exist that provide rough estimates of potential flood losses and flood exposure due to hurricanes and winter storms in NYC. Nicholls *et al.*[5] used a relatively simple method to estimate the exposure of population and assets to floods in 135 port cities around the globe, including the NYC-Newark region. They estimated the current exposure for the NYC-Newark region from a 100-year flood event to be at US$320 bn. In addition, nor'easters can have high wind speed and cause considerable damage, as demonstrated by, for example, the nor'easter in December 1992 with damage of over US$1 bn in NYC, and the consequent flooding of lower Manhattan.[19] Furthermore, a report on climate change and adaptation by NYS[20] estimated the combined direct and indirect losses from a 100-year flood to be at US$58 bn, of which US$48 bn can be attributed to indirect economic losses, which were calculated as the cost for economic losses as opposed to direct material damage. The most recent study by Aerts and Botzen[13] used a detailed flood damage model to estimate direct flood damage in NYC. They showed that, for a category 1–3 hurricane, the total value of exposed assets including houses and infrastructure varies between ~US$18 bn and 34 bn, and the maximum potential damage to these assets varies between ~US$6 bn and 11 bn.

3. METHODS USED TO ESTIMATE FLOOD RISK

Fig. 2 outlines the method we used to construct the annual EPL curves and calculate the EAD, which follows five main steps. First, low-probability surge events for NYC are selected from the synthetic data set by Lin *et al.*[11] (Section 3.1). Second, for each selected event, the coastal surge heights are interpolated inland, and a DEM is used to create the inundation map (Section 3.2). Third, the inundation maps are combined with information on the exposed assets to generate a set of flood damage maps using different stage damage functions, which produce high, medium, and low estimates of damage. Fourth, this information is used to construct flood EPL curves, which show the potential damage for different return periods. Finally, the EAD is obtained by the numerical integration of the EPL curve (Section 3.3).

3.1. Low-Probability Storm Surge Scenarios

Historical data on hurricanes making landfall in a local area are very limited. Therefore, hurricane risk assessment, which involves the statistical quantification of hurricane effects at local scales, often relies on Monte Carlo simulations of synthetic storms. This study applies a set of low-probability synthetic hurricane surge events generated by Lin *et al.*[11] for NYC with a coupled system composed of a statistical-deterministic hurricane model and surge

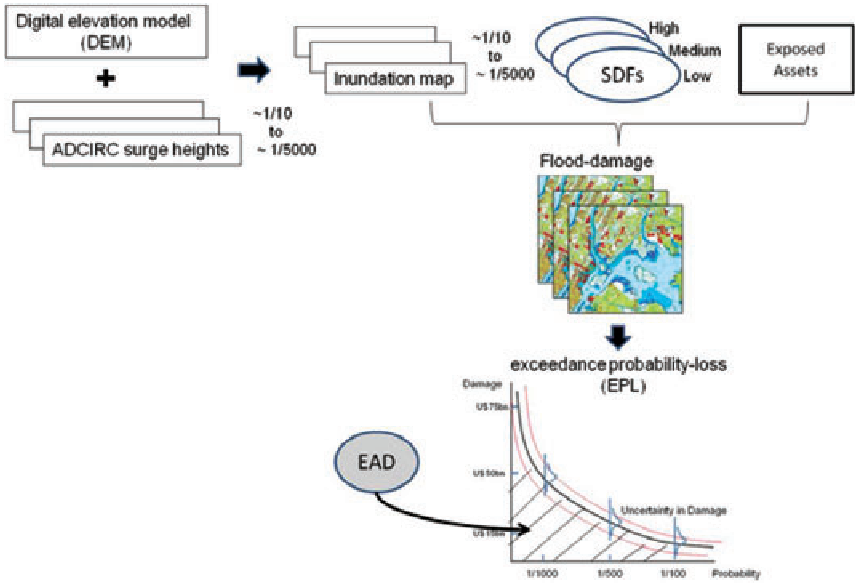

Fig. 2. Methodology followed to calculate expected annual damage (EAD) using the area under the exceedance probability loss (EPL) curve.

hydrodynamic models. The hurricane model[21] generates synthetic tropical cyclones under given large-scale atmospheric and ocean environments for various climate conditions; the synthetic storms for the current climate condition are in statistical agreement with the (albeit limited) observations.[21] The hydrodynamic models used include the Advanced Circulation Model (ADCIRC)[22,23] and the Sea, Lake, and Overland Surges from Hurricanes (SLOSH)[24] model; the SLOSH model with a low-resolution numerical grid is used to select (from very large synthetic storm sets) surge events with return periods, in terms of the surge height at the Battery in lower Manhattan, NYC, greater than 10 years. The ADCIRC model with higher resolution grids is used to further analyze the selected events and estimate the surge probabilities. The 1/1,000 (exceedance probability $p = 0.001$), 1/500 ($p = 0.002$), 1/100 ($p = 0.01$), and 1/50 ($p = 0.02$) storms at the Battery (with the effect of the astronimical tide accounted for) result in storm-tide heights of 3.48, 3.12, 2.30, and 1.61 m, respectively.

To carry out this flood risk assessment for NYC, we select low-probability extreme surge events from Lin *et al.*'s[11] ADCIRC-model-simulated surge events, under the current climate condition estimated from the National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis data.[25] To save computational resources, one may select a relatively small set of storms that represent a number of return periods. For example, Merz and Thieken[26] used seven return periods to produce EPL curves for flood damage caused by the river Rhine in Germany. Ward *et al.*[10] show, however, that selecting a limited number of return periods to create an EPL curve results in considerable deviations from the "true" risk. Therefore, we apply the entire storm set of the tail of the surge distribution to construct reliable EPL curves. Considering that most of the sea walls that protect lower Manhattan are about 1.5 m high,[2] we select all events from the original 5,000-event set of Lin *et al.*[11] that have surge heights greater than 1.5 m at the Battery. The selected event set is composed of 214 extreme events (all simulated with the ADCIRC model) that will be used to estimate, for the current climate conditions, the potential damage of floods with return periods of 40 years and longer, with the effect of the astronomical tide accounted for in accordance with Lin *et al.*[11] The data for each event include the surge height at each simulation grid point along the coast, as shown in Fig. 3.

3.2. Flood Extent and Inundation Depth

To calculate inundation levels, the simulated surge heights (Section 3.1) along the coast need to be interpolated and applied to terrain elevation. A simple nearest neighbor method is used, which was successfully applied for calculating flood depths and damage in the Netherlands.[13] The elevation data

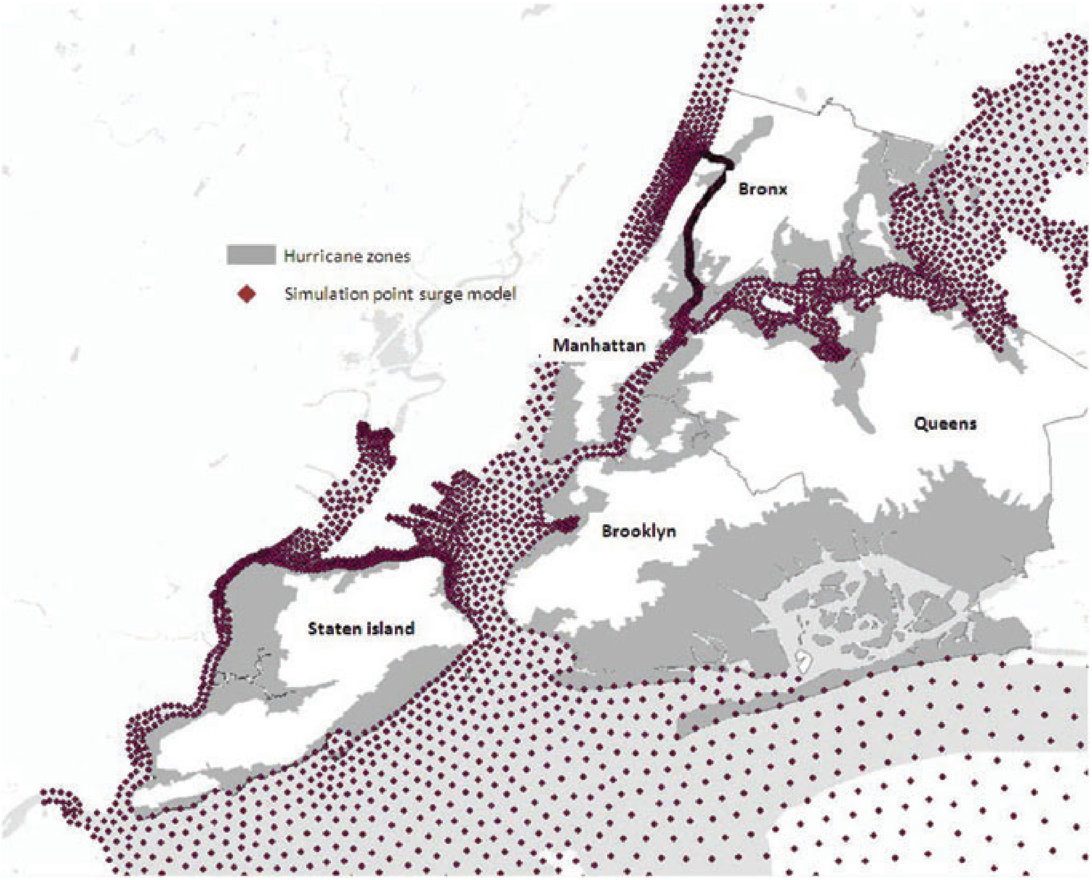

Fig. 3. Hurricane 1, 2, and 3 evacuation zones, and ADCIRC surge simulation grid points in New York City with its five boroughs.

are extracted from the USGS database[5] of the National Elevation Data (NED) with a resolution of ~1/3 arc second (~10 × 10 m^2). For each NED cell, we determine via a nearest neighbor procedure which coastline point of the simulated surge height (Section 3.1) should be used for determining the inundation depth. This is done using the grid tool of the Geospatial Data Abstraction Library.[6] Next, by subtracting the elevation level from the surge level of a particular cell, an estimate for the flood depth in each cell is obtained. Negative results, for places where land elevation exceeded maximum expected water height, are zeroed to indicate that no flooding can take place. The analysis process is applied for all the NED cells for each of the 214 surge event scenarios, resulting in 214 inundation maps. As an example, an inundation map for NYC in the event of an extreme low-probability storm (~ 1/1,000 event) is depicted in Fig. 4. Note that this procedure does not address existing levees or dunes that protect areas from inundation or lower water levels during storm events. This pertains, for example, to the Jamaica Bay area, where the Rockaways lower water levels during storm events.[(27)]

3.3. Flood Risk Modeling

A raster-based flood damage modeling approach has been applied to estimate the direct economic damage. For each grid cell (~10 × 10 m^2), the model combines the information on exposed individual buildings with the information on inundation depth (Section 3.2), using stage-damage functions (SDFs), which describe the relation between flood depth and potential damage. In this approach, other physical characteristics of the storm surge are neglected, such as flow velocity or duration of the

[5]For more information, see: http://www.topodepot.com/10MeterUSGSDem.aspx.
[6]For more information, see: www.gdal.org.

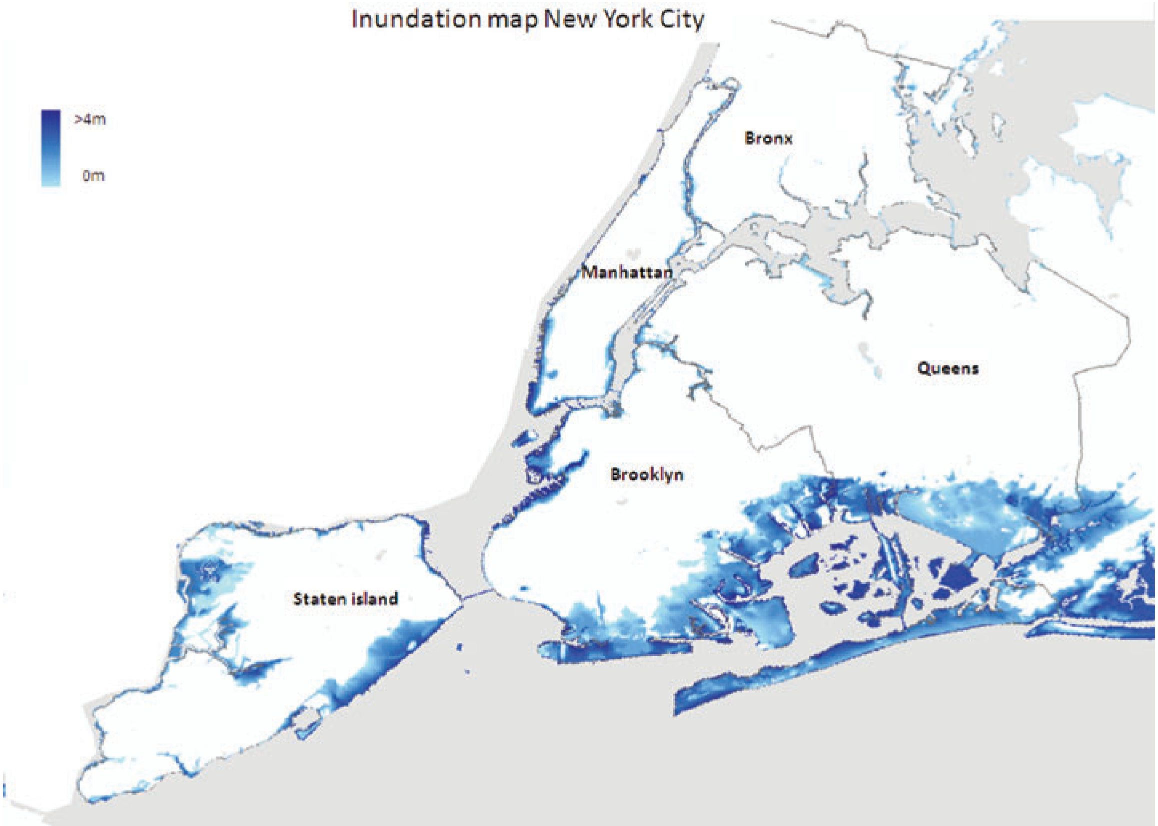

Fig. 4. Example of an inundation map for NYC for a ∼1/1,000 storm.

inundation, as is common practice in many similar studies.[8,13,28–31]

3.3.1. Exposure Data and Classification of Damage Categories

Data on the exposure of the 1.05 million buildings and infrastructure objects in NYC (airports, naval bases, etc.) have been derived from the MapPLUTO database of the NYC Department of City Planning.[32] This database contains data by tax lot and information about the principal buildings on it. For example, MapPLUTO has information on: the number of stories; the building class; the estimated year of construction; the year(s) of renovation; the building's assessed value; and the square footage for all structures on the lot. To classify building types for the purpose of determining the potential flood damage, we follow the method described by Aerts and Botzen[13] to assign individual buildings on a tax lot to a dominant zoning type listed in the MapPLUTO database. If a lot contains mixed zoning classes, such as a mix of residential, industrial, and commercial buildings, then all buildings on a lot are assigned to the class that most likely uses the ground floor. Table I lists all 16 reclassed building types and their reference to the MapPLUTO database.[13]

3.3.2. Flood Damage Estimation

Flood damage is estimated for a given inundation depth for each of the 16 building types (represented by different stage damage functions) for each grid cell. To account for uncertainty in the maximum damage estimates,[9,34] we use three SDFs (see Table II) for high, medium, and low estimates of the maximum damage, based on the multicolored manual (MCM).[33] The three function types represent a range of possible flood damages that might occur to properties. The maximum damage values for each of the SDFs are provided in US$ per m^2. Maximum damage for each of the 16 building types can be calculated by multiplying the footprint of the building by the maximum damage values for each SDF. The area

Table I. The 16 Building Classifications Used in the Flood Damage Model and the Reference to the MapPLUTO Database (3rd Column) and the Number in the Multicoloured Manual (MCM)[33] (The Last Three Columns Provide High, Medium, and Low Estimates of the Maximum Damage per Square Meter [in US$/m^2])

Name	Class	#MapPLUTO	#MCM	MaxDam High [US$/M^2]	MaxDam Med [US$/M^2]	MaxDam Low [US$/M^2]
Residential bungalow	1	A en B	Bungalow	1,900	1,550	1200
Residential flat	2	C, D, L, N, R, S	Flat	2,900	2,300	1800
Warehouses	3	E	410	850	650	450
Industry	4	F	221	1,100	850	600
Garages	5	G	221	1,100	850	600
Hotels	6	H	511	2,600	1,450	2,050
Hospitals	7	I	620	1,400	1,400	1,400
Theatres	8	J	518	3,400	2,750	2,100
Stores	9	K	211	2,500	2,100	1,600
Churches	10	M	630	700	700	700
Offices	11	O, Y, Z	310	2,100	1,650	1,100
Museum	12	P7	630	700	700	700
Library	13	P8	640	3,150	2,650	2,150
Clubs	14	P (others)	234	2,300	1,850	1,300
Recreation	15	Q	523	2,100	1,650	1,100
Education	16	W	610	4,300	3,300	2,100

in square meters of the building footprints has been derived from the MapPLUTO database. For inundation levels higher than 3 m, we assume that maximum damage occurs. In addition, the MCM provides detailed SDFs for various building types and infrastructure, which have been derived from a large number of interviews.[35]

3.3.3. *Estimation of EPL and EAD*

The last step in the calculation is to derive an estimate of the flood risk for the extreme events by conducting a statistical analysis of the calculated flood damage data. The set of the extreme surge events used for the analysis includes events with an estimated annual frequency of ~1/50 per year down to ~1/10,000 per year (with 40-year and longer return periods when the tidal effect is included), based on the estimation of the water level at the Battery in NYC made by Lin *et al.*[11] To derive the overall risk from this set of individual storms, an EPL curve is created using the approach described by Grossi and Kunreuther.[16] This method relates potential flood loss to the exceedance probability of that loss (i.e., the probability that a certain level of flood damage will be exceeded). This exceedance probability is derived from the annual frequency (adjusted to account for the tidal effect) associated with the set of the selected storm events from Lin *et al.*,[11] which are reordered in order of descending damage estimates, after which the cumulative probabilities are recalculated, resulting in exceedance probabilities. The resulting EPL curves are subsequently used to calculate the EAD as the area (integral) under the EPL curve.

4. RESULTS

Fig. 5 displays the EPL curves for potential flood damage in NYC based on the three SDFs (low, medium, high as in Table II). For the most extreme storms (probability <1/5,000), the total damage varies roughly between US$14 bn and 26 bn. The EPL curves show an abrupt increase in damage estimates for extreme low-probability storms with probability <1/3,000 (<0.00033). Apparently, a significantly larger area will be inundated under such extreme conditions that includes relatively expensive infrastructure, such as JFK airport. The total damage caused by a 1/100 year storm surge, which corresponds to the standard for defining flood zones in the United States, lies within a range of US$ ~2 bn and 5 bn. For a 1/500 storm surge, this estimate lies between US$ ~ 5 bn and 11 bn.

Flood damage and exceedance probabilities are also investigated for each of the five boroughs of NYC. It appears that Brooklyn and Queens are the most vulnerable and can potentially expect the largest flood damage (e.g., maximum damage for Brooklyn is US$ 10.18 bn in Table III). Both

Table II. Stage Damage Functions (SDFs) Representing the Fraction of the Maximum Flood Damage That Can Occur Due to a Certain Inundation Depth (m); These Functions Represent High (HIGH SDF), Medium (MEDIUM SDF), and Low (LOW SDF) Estimates of Flood Damage Based on the MCM[33] (The MCM Reference Number is Listed Along the Row Labeled "#MCM," and the Building Types Refer to the Reclassed Buildings Listed in Table I)

	#MCM nr.																	
	Building type			410	221	221	511	620	518	211	630	310	630	640	234	523	610	0
HIGH SDF	Depth (m)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.25	0.45	0.51	0.49	0.34	0.34	0.40	0.29	0.45	0.52	0.18	0.42	0.18	0.29	0.47	0.42	0.42	0.00
	0.50	0.58	0.65	0.58	0.54	0.54	0.50	0.41	0.57	0.62	0.34	0.55	0.34	0.40	0.56	0.57	0.55	0.00
	0.75	0.64	0.72	0.68	0.67	0.67	0.62	0.49	0.68	0.72	0.48	0.67	0.48	0.56	0.66	0.68	0.65	0.00
	1.00	0.69	0.76	0.75	0.76	0.76	0.75	0.57	0.80	0.83	0.61	0.78	0.61	0.67	0.74	0.77	0.71	0.00
	1.25	0.74	0.80	0.79	0.81	0.81	0.79	0.70	0.86	0.86	0.69	0.81	0.69	0.74	0.79	0.81	0.80	0.00
	1.50	0.77	0.82	0.83	0.86	0.86	0.83	0.77	0.89	0.88	0.78	0.85	0.78	0.81	0.83	0.85	0.84	0.00
	1.75	0.83	0.87	0.86	0.89	0.89	0.87	0.81	0.91	0.91	0.85	0.88	0.85	0.87	0.87	0.88	0.87	0.00
	2.00	0.86	0.89	0.90	0.92	0.92	0.90	0.85	0.94	0.93	0.93	0.92	0.93	0.93	0.91	0.92	0.90	0.00
	2.25	0.88	0.90	0.93	0.94	0.94	0.93	0.89	0.96	0.95	0.98	0.94	0.98	0.95	0.93	0.94	0.93	0.00
	2.50	0.92	0.93	0.96	0.97	0.97	0.97	0.92	0.98	0.98	0.98	0.97	0.98	0.97	0.97	0.97	0.96	0.00
	2.75	0.99	0.99	0.98	0.99	0.99	0.98	0.96	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.00
	3.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00
MEDIUM SDF	#MCM nr.																	
	Building type	625	625	410	221	221	511	620	518	211	630	310	630	640	234	523	610	0
	Depth (m)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.25	0.43	0.49	0.23	0.19	0.19	0.22	0.29	0.25	0.21	0.18	0.24	0.18	0.17	0.28	0.25	0.23	0.00
	0.50	0.53	0.62	0.35	0.38	0.38	0.33	0.41	0.39	0.37	0.34	0.38	0.34	0.29	0.39	0.39	0.37	0.00
	0.75	0.58	0.67	0.50	0.53	0.53	0.49	0.49	0.55	0.52	0.48	0.53	0.48	0.47	0.54	0.54	0.51	0.00
	1.00	0.62	0.71	0.60	0.63	0.63	0.65	0.57	0.67	0.64	0.61	0.65	0.61	0.59	0.64	0.66	0.61	0.00
	1.25	0.67	0.74	0.68	0.71	0.71	0.72	0.70	0.75	0.72	0.69	0.72	0.69	0.69	0.71	0.73	0.70	0.00
	1.50	0.71	0.76	0.76	0.78	0.78	0.78	0.77	0.81	0.78	0.78	0.78	0.78	0.78	0.78	0.79	0.76	0.00
	1.75	0.77	0.83	0.82	0.83	0.83	0.83	0.81	0.85	0.83	0.85	0.83	0.85	0.85	0.83	0.84	0.81	0.00
	2.00	0.82	0.86	0.87	0.87	0.87	0.87	0.85	0.89	0.88	0.93	0.87	0.93	0.92	0.88	0.89	0.86	0.00
	2.25	0.85	0.87	0.90	0.90	0.90	0.91	0.89	0.92	0.91	0.98	0.91	0.98	0.94	0.91	0.92	0.90	0.00
	2.50	0.90	0.91	0.94	0.94	0.94	0.94	0.92	0.95	0.95	0.98	0.94	0.98	0.96	0.94	0.95	0.94	0.00
	2.75	0.98	0.99	0.97	0.97	0.97	0.97	0.96	0.98	0.97	0.99	0.97	0.99	0.98	0.97	0.97	0.97	0.00
	3.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00
LOW SDF	#MCM nr.																	
	Building type	625	625	410	221	221	511	620	518	211	630	310	630	640	234	523	610	0
	Depth (m)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	0.25	0.37	0.47	0.00	0.02	0.02	0.06	0.29	0.00	0.00	0.18	0.04	0.18	0.07	0.08	0.11	0.05	0.00
	0.50	0.46	0.60	0.03	0.14	0.14	0.10	0.41	0.14	0.04	0.34	0.10	0.34	0.15	0.15	0.18	0.13	0.00
	0.75	0.51	0.65	0.24	0.32	0.32	0.31	0.49	0.37	0.20	0.48	0.32	0.48	0.37	0.36	0.34	0.29	0.00
	1.00	0.55	0.68	0.39	0.43	0.43	0.50	0.57	0.48	0.29	0.61	0.44	0.61	0.50	0.48	0.45	0.42	0.00
	1.25	0.60	0.72	0.53	0.55	0.55	0.62	0.70	0.58	0.45	0.69	0.57	0.69	0.63	0.60	0.59	0.55	0.00
	1.50	0.64	0.74	0.68	0.67	0.67	0.73	0.77	0.70	0.56	0.78	0.69	0.78	0.75	0.72	0.73	0.67	0.00
	1.75	0.72	0.81	0.76	0.75	0.75	0.80	0.81	0.77	0.65	0.85	0.77	0.85	0.84	0.80	0.81	0.75	0.00
	2.00	0.77	0.85	0.83	0.81	0.81	0.86	0.85	0.84	0.75	0.93	0.84	0.93	0.92	0.87	0.87	0.82	0.00
	2.25	0.81	0.87	0.88	0.87	0.87	0.90	0.89	0.89	0.86	0.98	0.88	0.98	0.95	0.91	0.91	0.88	0.00
	2.50	0.87	0.91	0.93	0.91	0.91	0.94	0.92	0.93	0.90	0.98	0.93	0.98	0.97	0.94	0.94	0.93	0.00
	2.75	0.95	0.97	0.96	0.96	0.96	0.97	0.96	0.97	0.95	0.99	0.96	0.99	0.98	0.97	0.97	0.97	0.00
	3.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00

boroughs are estimated to contribute between 38% and 41% to the total damage for NYC in the case of either a 1/100- or 1/500-year flood event. Queens and Brooklyn are followed by Manhattan, Staten Island, and the Bronx with the damage per borough, respectively, 11%, 9%, and 1–2% of the total damage for 1/100 and 1/500 flood events (Table III; Fig. 6).

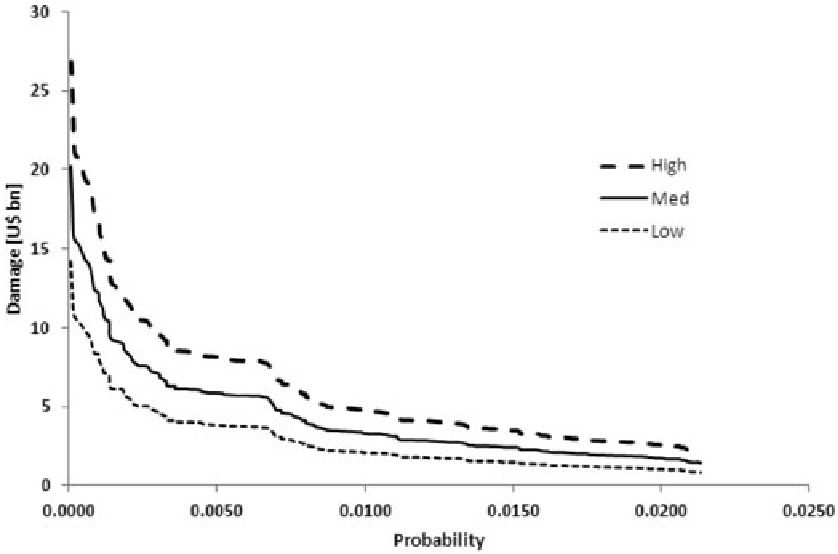

Fig. 5. Exceedance probability loss (EPL) curves for NYC according to three different stage damage functions (low, medium, high; Table II).

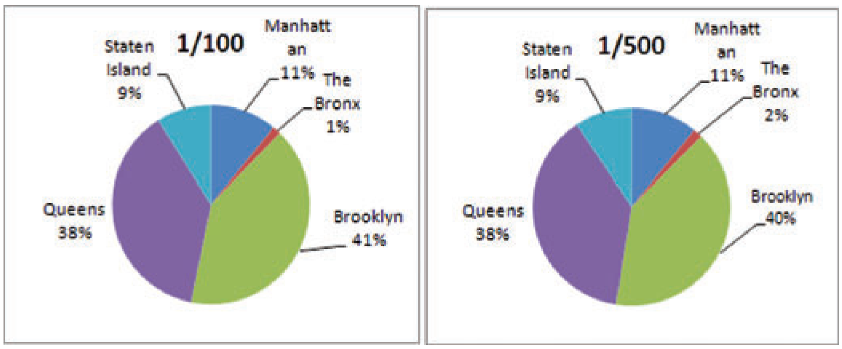

Fig. 6. Distribution of flood damage over the five boroughs for 1/100 and 1/500 flood events (using the medium stage damage functions from Section 3.3).

With the three EPL curves shown in Fig. 5, the EAD can be calculated by estimating the area under the curves. The results of these EAD calculations are presented in Table IV. The total EAD for NYC lies between US$ 59 and 129 million/year, depending on the SDFs used (see Section 3.3). If the EAD is calculated separately for each of the five boroughs, then Brooklyn shows the highest values (~US$ 23–52 million/year), followed by Queens (~US$21–44 million/year). In terms of the EAD per borough expressed as a percentage of the total EAD, the EAD calculations are relatively stable when applying the different stage damage function. For example, the EAD for Brooklyn is ~40% of the total EAD for the three SDFs.

Fig. 7 shows the potential flood damage in the five NYC boroughs for both the official FEMA 1/100 and 1/500 flood zones. On the left side of the 1/100 boundary, the damage values of, in particular, Queens and Brooklyn increase relatively quickly compared with the other boroughs. This implies that

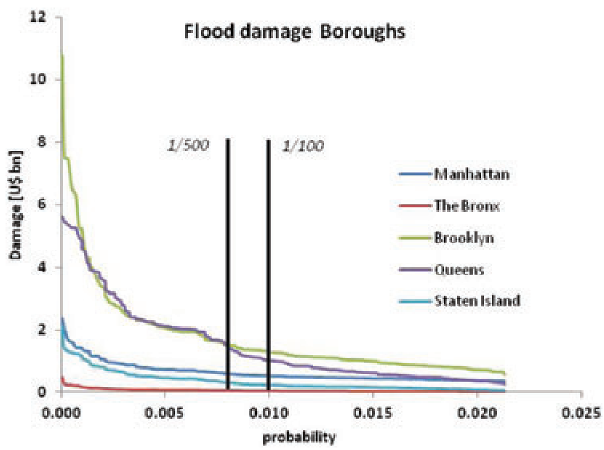

Fig. 7. Flood damage in US$ bn per borough for different exceedance probabilities, using high stage-damage functions (SDFs).

quite a few buildings in these boroughs are located in the potential vulnerable flood zones that may become the future 1/100 flood zone under climate

Table III. Total Damage and the Exceedance Probability Estimated Using Three Stage Damage Functions (Low, Medium, High) for NYC and for Each of the Five Boroughs

Return Period	Total damage [U$ bn]			Damage per Borough [U$ bn] Manhattan			The Bronx			Brooklyn			Queens			Staten Island		
	High	Med	Low	High	Med	Low	High	Med	Low	High	Med	Low	High	Med	Low	High	Med	Low
1/5,000	21.08	15.70	10.83	2.71	1.99	1.36	0.39	0.26	0.15	10.18	7.48	5.05	7.07	5.44	3.95	1.88	1.40	0.96
1/3,000	20.65	15.26	10.40	2.28	1.67	1.13	0.34	0.22	0.13	10.10	7.44	5.02	6.99	5.35	3.85	1.82	1.32	0.86
1/2,000	16.44	12.14	8.29	2.20	1.61	1.09	0.33	0.22	0.13	8.92	6.49	4.32	6.89	5.25	3.78	1.72	1.27	0.86
1/1,000	15.41	11.23	7.52	1.97	1.43	0.96	0.31	0.21	0.12	8.63	6.26	4.15	6.86	5.23	3.72	1.71	1.24	0.82
1/500	11.55	8.43	5.65	1.96	1.43	0.96	0.30	0.20	0.12	7.30	5.25	3.43	6.56	4.98	3.54	1.69	1.23	0.81
1/200	8.07	5.83	3.81	1.96	1.43	0.95	0.27	0.17	0.09	7.24	5.20	3.40	6.46	4.89	3.48	1.58	1.17	0.79
1/100	4.69	3.31	2.06	1.91	1.38	0.92	0.26	0.17	0.09	7.24	5.19	3.39	6.35	4.79	3.39	1.54	1.13	0.76
1/70	3.61	2.52	1.53	1.89	1.37	0.91	0.25	0.16	0.09	7.07	5.08	3.31	6.12	4.59	3.22	1.50	1.08	0.70
1/50	2.50	1.70	0.98	1.83	1.32	0.87	0.24	0.16	0.09	6.32	4.52	2.96	6.03	4.52	3.17	1.45	1.06	0.70

Table IV. Expected Annual Damage (EAD) for NYC and for Each of its Five Boroughs (in US$ million/year and as a Percentage of the Total EAD); High, Medium, and Low Refer to the Different Stage-Damage Functions (Section 3.3)

	High	Med	Low
Total EAD [million US$/year]	129.3	92.6	59.7
EAD Borough [million US$/year]	High	Med	Low
Manhattan	18.6	13.1	8.3
The Bronx	1.6	1.0	0.5
Brooklyn	52.5	37.1	23.3
Queens	44.7	32.7	22.0
Staten Island	9.8	7.1	4.6
% of total EAD	High	Med	Low
Manhattan	14.4	14.2	14.0
The Bronx	1.2	1.1	0.8
Brooklyn	40.6	40.0	39.1
Queens	34.6	35.3	36.8
Staten Island	7.6	7.7	7.8

change since this is approximately the current 1/500 flood zone.[11] Flood-risk management policies could be first prioritized to these areas.

5. DISCUSSION

Estimates from existing research on potential flood damage in NYC vary considerably. Possible reasons for these differences will be discussed in this section. Since storm surge height simulations for NYC and their probability have been extensively discussed by Lin *et al.*,[11,12] we focus here on differences in flood damage calculations.

Studies by Nicholls *et al.*[5] show the potential flood exposure to flooding is US$320 bn, while Leblanc and Linkin[19] and NYS[20] provide flood damage estimates for a category 3 hurricane event in the NYC area of, respectively, US$200 bn and US$58 bn. These estimates are much higher than the damage of a comparable extreme event in our simulations, which result in a maximum amount of flood damage of ~US$21 bn for an extreme hurricane with a return period of ~1/5,000 (see Table III; Section 4.2). The EAD for a 1/100 flood by Aerts and Botzen[13] was estimated at ~US$18 million/year, which is lower than our lowest estimate.

The most recent and detailed information on direct flood damage to buildings in NYC is described by Aerts and Botzen.[13] They estimate flood damage for different FEMA flood zones (1/100 and 1/500), as well as for four Hurricane Evacuation Zones. Aerts and Botzen[13] calculate flood damage using the total replacement value of the ground floor and its contents. The total ground floor value in the flood zones is estimated at between US\$6.26 bn and US\$7.44 bn for buildings in, respectively, the 1/100 and 1/500 flood zones. Our range of flood damage that can be caused by a 1/100 storm is estimated somewhat lower at between US\$2.06 bn and 4.69 bn. For a 1/500 storm, the estimate by Aerts and Botzen[13] of US\$7.4 bn is well within our range of US\$5.65 bn–11.55 bn. Our range of estimates of the maximum damage for an extreme low-probability hurricane (US\$ ~14–26 bn; Fig. 5) is close to the most recent estimates by Aerts and Botzen[13] for a category 4 hurricane event (US\$13.15 bn). Although the flood extents applied are different, the fact that the EAD (probability × damage) of this study is higher than the EAD by Aerts and Botzen[13] can be largely explained by the larger numbers of events that we included in our EAD calculation (the full integral underneath the EPL curve) compared with only assessing the damage that belongs to either a 1/100 or a 1/500 event. In that respect, the EAD estimates in our study are more comprehensive than those in earlier research.

Flood damage methods used in the various studies for NYC differ in the following three main methodological approaches: (1) they use different selections of inundation scenarios, such as differences in flood extents; (2) they apply distinct catastrophe models, which implies that damage curves and data on exposed assets differ; and (3) studies estimate different damage categories, for example, economic (or "indirect") flood damage is not—or partly—included.[9,13,34] In the next section our results are discussed within the context of these methodological issues, and some additional considerations will be provided.

5.1. Uncertainty About Flood Extent Mapping

5.1.1. Differences with Existing Flood-Extent Mapping

When comparing our results and methods with Nicholls *et al.*,[5] it appears that the latter study addresses exposure to floods and covers the 1/100 flood zones for the whole NYC-Newark region and, hence, results in a much larger potential flood zone area compared with our study. That the whole NYC-Newark region will be flooded at the same time is an unrealistic scenario, which explains the larger numbers estimated by Nicholls *et al.*[5] Furthermore,

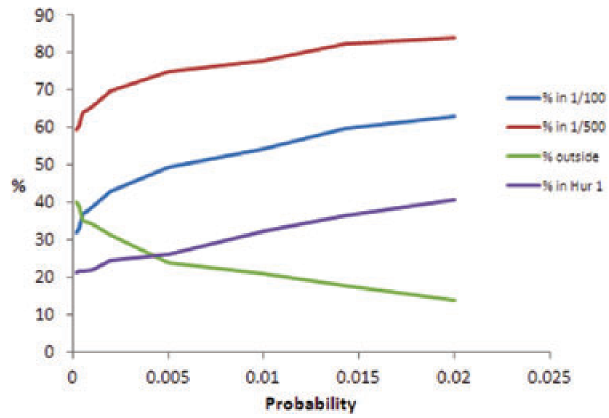

Fig. 8. Percentage of damage in flood zones.
Notes: The curve "% outside" shows the percentage of flood damage simulated in this study that is suffered outside the combined 1/100 and 1/500 FEMA flood zones. The curves "% in 1/100," "% in 1/500," and "% in Hur 1" show the percentages of simulated flood damage of our study that are suffered within, respectively, the FEMA 1/100 flood zone, 1/500 flood zone, and Hurricane Evacuation Zone 1.

differences in flood damage estimates between this study and the study by Aerts and Botzen[13] can also be partially explained by differences in flood extent mapping. For example, the extent of our interpolated 1/100 and 1/500 inundation maps differ from the standard FEMA 1/100, 1/500 flood zones that were used by Aerts and Botzen.[13] As Fig. 8 illustrates, the percentage of flood damage in our study is simulated outside ("% outside," Fig. 8) and inside ("% in," Fig. 8) the FEMA flood zones. For relatively high probability events (1/50, $p = 0.02$), approximately 14% of the flood damage is located outside the combined FEMA 1/100- and 1/500-flood zones. For lower probability events ($<$1/200, $p < 0.005$), this percentage is considerably higher at 23–40%.

The existing FEMA 1/100 flood zone is an estimate of a 1/100 flood either based on a historical storm event or an average calculated on the basis of several hypothetical storm events that may be unrealistic and cannot cover the spectra of the characteristics of possible storms. This is the reason why our results show that much potential damage is caused outside the FEMA 1/100 flood zones. Although our model estimates are associated with uncertainties, the results indicate that properties that currently lie outside of the FEMA 1/100 flood zone can still be at risk from a 1/100 storm surge event.

Also, Hurricane Sandy (2012) included a surge of about 2.75 m (above the mean high water) at the Battery, approximately the 500-year surge level

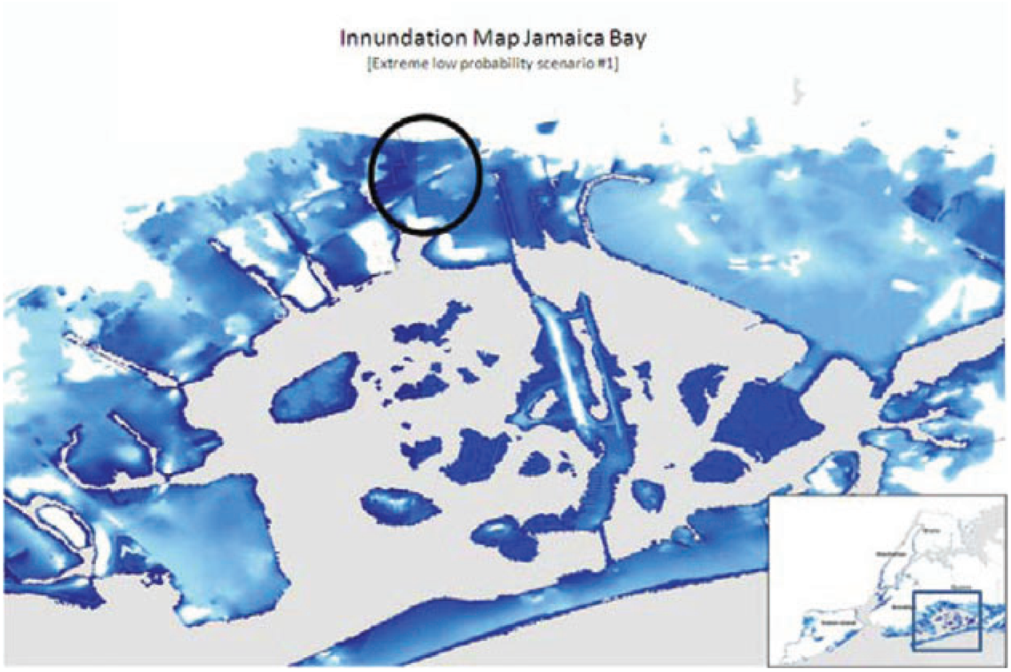

Fig. 9. Inundation map for an extreme low probability scenario (<1/1,000, $p < 0.001$) for the Jamaica Bay area in Queens.
Notes: In the circle, an abrupt transition can be observed between high (the left part of the circle) and lower inundation levels (the right part of the circle), which is caused by a lack of nearby surge-height points used for interpolation.

estimated by Lin *et al.*[11] However, the surge heights and their related probabilities in Lin *et al.*[11] result from simulations of hurricane-driven windfields. Hurricane Sandy was undergoing significant extratropical transition before and during landfall and is an example of a so-called hybrid storm, a combination of a hurricane and a winter storm. Hurricanes and winter storms are driven by different energy sources. Where a hurricane is powered by the evaporation of ocean water, winter storms are powered by horizontal temperature contrasts in the atmosphere. Hence, a hybrid storm like Sandy is able to tap into both energy sources, which is why the storm was so powerful. Research on extratropical transition and hybrid storms is currently limited[36] and some new theory and analysis methods are being developed.[37] Future surge risk assessment that account for the surges induced by hybrid storms may result in larger flood zones and higher surge return levels (or shorter surge return periods); the Hurricane Sandy induced surge may have a shorter (than 500 years) return period.

5.1.2. Interpolation Techniques

In general, flood extent mapping is associated with uncertainties. Uncertainty in flood extent mapping, described in Section 3.2, can be further illustrated by means of a visual inspection of the inundation maps. For example, Fig. 9 shows that, for some areas in the Jamaica Bay area in Queens, the interpolation method for creating inundation depths has resulted in abrupt transitions in flood depth. This can be explained by the lack of coastline surge-height points in the Jamaica Bay area that are used for the interpolation process. Surge heights for the inner Jamaica Bay area were taken from the coastline of the Rockaways (the coastal zone in the lower part of Fig. 9), which lies at some distance from Jamaica Bay. This may lead to an overestimation of surge heights in the Jamaica Bay area. However, Sanders,[38] who compares national elevation data (NED) for the United States with more detailed elevation data, such as LiDAR, argues that NED may cause a systematic underestimation of flood risks, which may compensate for the overestimation of surge heights in some areas, such as Jamaica Bay.

5.1.3. Flood Extent and Storm Characteristics

The variation in flood damage simulations is further illustrated in Fig. 10. This figure shows the total flood damage for all 214 simulated coastal floods

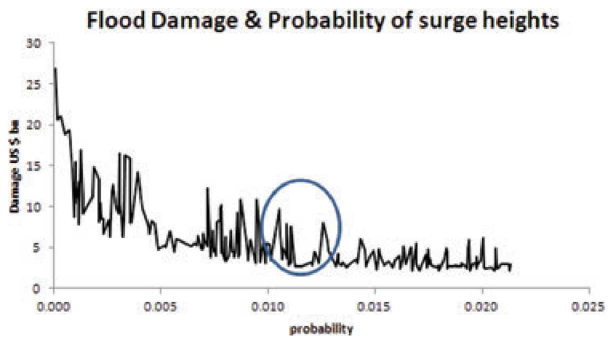

Fig. 10. Total simulated flood damage for NYC (in US$ bn) for all 214 simulated coastal floods and their probabilities using the medium damage curves of Table III, and the exceedance probabilities of the 214 storm surges.
Note: The circle shows the range of possible damages of storms with a probability of about 1/80.

(using the medium damage curves of Table II), versus the probabilities of the storm-surge heights (instead of the exceedance probabilities of the flood damage as in Fig. 5). Fig. 10 shows that the flood damage estimate for the area (NYC) is not a monotonic function of the surge height probability at a specific location (the Battery). Variations in the flood damage estimates are particularly large between the 1/80 ($p = 0.012$) and the 1/1,000 ($p = 0.001$) return period storms. The figure shows that a relatively high-probability storm of 1/80 may cause considerable damage comparable to a 1/1,000 storm, and that all the damage of storms around 1/80 range are between US$2 bn and 9 bn (see the circle in Fig. 10). Apparently, it is not only the probability of a storm and its related surge height at one location that determine flood damage over an area, but the flood extent related to all storm characteristics (i.e., intensity, size, track, and forward velocity) that affect the entire area. In this context, Lin *et al.*[11] state: "the storm that generates the highest surge level (4.75m) at the Battery (lower Manhattan) moves northeastward, and close to the city center." However, a relatively weaker storm that is located at greater distance from lower Manhattan produces a comparable surge (4.57 m) at the Battery, because a larger wind-field size, in combination with a northwestward translation, pushes water more directly into the NYC harbor.[11]

Also, although the surge is highly correlated throughout the area of study, the events may be in different order in terms of the surge height at different places in the area. For example, storms with an identical return period at a location can have different flood extent and flood damage associated with these flood scenarios. Fig. 11 exemplifies the variation in flood damage calculations by showing a sample of two storm-surge scenarios (1/90 and 1/80), numbered #154 and #169, respectively. Although simulations #154 and #169 have almost the same probability (at the Battery), they have a completely different spatial flood extent: namely, the flood extent of #169 is much larger despite the somewhat higher probability. The flood damage for simulation #169 of US$4.2bn is also much higher than the simulated flood extent of #154, with US$ 1.6 bn of damage. Therefore, our method of applying the entire storm set of the tail of the surge distribution (and conduct direct statistical analysis on the damage estimates) prevents potential errors included by selecting small number of storms only at several return periods.

Reliable flood extent and damage calculations are important; about 33,122 buildings are located in the official FEMA 1/100 flood zone, and 66,249 buildings are located in the FEMA 1/500 flood zone,[13] including 252 critical facilities, such as hospitals, fire departments, and police stations. A more detailed analysis of differences in flood zoning extent is provided in Fig. 12. This figure shows the current FEMA 1/100 flood zone for a part of the Upper East Side in Manhattan. It also shows (in blue) the extent of simulation run #169, which has a higher probability of 1/80. It can be clearly seen that some buildings are within the flood extent map of run #169, but not within the FEMA 1/100 flood zone, and hence, zoning policies and building codes do not apply for these buildings.[13] Of course, these maps must be evaluated with care, owing to uncertainties in different parts of our method and data, such as the applied interpolation method, the vertical and horizontal accuracy of the NED, and uncertainty in the storm-surge simulations. Nevertheless, this example stresses the need for a probabilistic approach of storm-surge analyses as the basis for defining FEMA flood zoning mapping.

5.2. Catastrophe Modeling

The studies by Linkin and Leblanc[19] and NYS[20] assess flood damage for a broader range of vulnerable assets than in our study, such as rail infrastructure and other vital infrastructure. This may explain the relatively high flood damage estimates found by these studies. An important asset that is not considered in our study is the potential damage to the NYC subway system. Currently, the Metropolitan

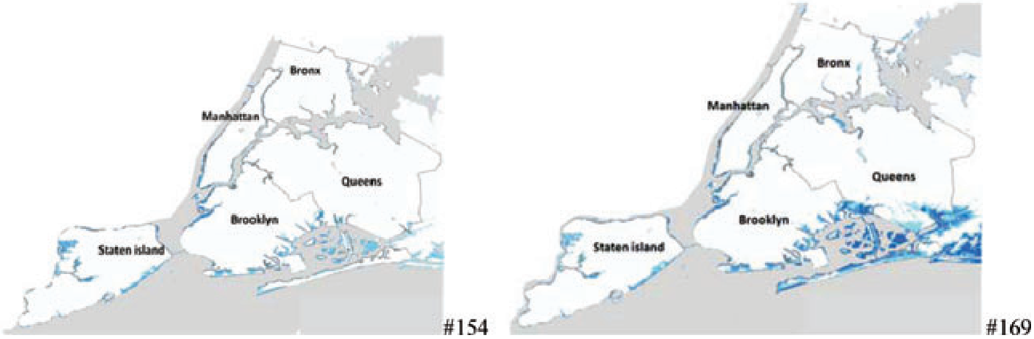

Fig. 11. Two flood extent and inundation maps with almost identical probabilities (#154: $p \sim 1/90$ and #169: $p \sim 1/80$). *Note*: The flood extent of #169 is much larger, despite the higher probability.

Fig. 12. The current FEMA 1/100 flood zone for a part of Manhattan and, shown in blue, the extent of simulation run #169 with a probability of 1/80.

Transportation Authority (MTA) has about 44,000 ft (>13 km) of underwater subway tunnels that need to be protected from flooding.(39) Several studies stress the high potential flood damage to the NYC subway rail and subway systems in the case of an extreme flood event.(20) Historic flood events showed that NYC rail systems are indeed very vulnerable. For example, the PATH rail system between NYC and New Jersey was flooded during a coastal flood in the winter of 1992,(40) which caused considerable damage of US$ 0.72 bn.(19)

The differences in damage curves used by Aerts and Botzen(13) may explain their higher estimation of flood damage compared with this study. Aerts and Botzen(13) use the total replacement value of the ground floor, even if potential water levels during a flood are low. This study uses SDFs, which calculate flood damage based on a fraction of the maximum damage for lower water levels. For example, only ~37–47% of the maximum damage is inflicted on low-density residential buildings for water levels of 0.25 m (see land-use categories #1 and # 2 in Table II, low SDF). Another important difference is that the replacement value of the ground floor used by Aerts and Botzen(13) is on average higher than the maximum damage that has been estimated with the three SDFs from the MCM that have been used in our study.(33)

The use of other SDFs can influence the results. For example, if we examine the Economic Guidance Memorandum (EGM) provided by the U.S. Army Corps of Engineers (USACE, 2003), we see the maximum inundation depth considered is about 16–17 ft (~4.9–5.2 m), which is higher than the maximum 3 m in the MCM curves. This means, that if the EGM would be used, additional damage occurs above 3 m inundation depth. Jongman *et al.*(41) compare seven different models using SDFs, including the MCM-based SDFs(33) and the US-FEMA based HAZUS SDFs.(42,43) It appears that the MCM and HAZUS use similar shapes for the curves and produce potential damages of the same magnitude. In addition, the SDFs used in this study are based on potential damage from fresh water, while salt water may cause larger damage as compared to river floods. This difference is the largest for agriculture and vehicles,(44) but also damage to building fabric may increase slightly if buildings are flooded by salt water.(33) Other issues that may influence the flood damage calculation, but that are not addressed in this method, are flood velocity and wave impacts.

5.3. Economic Damage

It is important to note that our study focuses on damages to assets that can be relatively easily evaluated in monetary terms (e.g., damage to buildings and parts of infrastructure). Intangible damage, such as the social and environmental impacts of floods,[45] also has important impacts,[46] as well as loss of human lives.[47] In general, this omission of intangible damage causes an underestimation of our flood damage estimates for NYC. Thus, another explanation for the difference between flood damage simulated in our study and that in existing studies is the inclusion of economic damage in other studies.[19,20] This study focuses on simulating direct flood damage, such as damage to buildings and economic assets.[45,49] Examples of indirect damage include disruption of traffic, trade, and public services.[50] Since these consequences are not considered in this study, the flood damage estimates presented here are most likely an underestimation of the total flood damage in NYC. As an illustration, Aerts and Botzen[13] estimate that the sum of direct and indirect economic losses to the subway and rail system operators caused by a 1/100 year flood varies between US$0.23 bn and US$1.49 bn. Note that these numbers only address ticket sale losses. However, the total of indirect flood damage is damage caused by disruption of the whole NYC economy, and the additional costs of emergency and other actions taken to prevent flood damage and other losses.[50] Hallegatte[51] estimates the damage caused by Hurricane Katrina to New Orleans and shows that the direct losses of Hurricane Katrina are estimated at US$107 bn, whereas indirect damage is estimated at an additional US$42 bn, hence, 28% of the total damage. These results indicate that indirect flood losses are an important category of damage.

6. CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

The main objective of this article was to develop a new methodology for assessing the full distribution of flood risk for NYC, including low-probability events. This distribution can be represented by EPL curves and the flood-risk indicator of the EAD, which is obtained by the integral of these curves. More than 200 low-probability storm-surge events for NYC were selected from the synthetic data set by Lin *et al.*,[11] which was developed using a coupled statistical-deterministic hurricane model and surge hydrodynamic models. For those events, we applied the coastal surge heights to create flood inundation maps, which have been combined with information on the exposed assets to generate flood damage maps and the EPL curves. Our 1/100 (~US$ 2–5 bn), 1/500 (~US$ 5–11 bn) and, extreme low-probability damage (~US$14–26 bn) estimates of flood damage are all close to the most recent estimates by Aerts and Botzen.[13] Our maximum EAD estimate of US$126 million/year can significantly increase when we include economic damage or other assets at stake (e.g., transport infrastructure) in our analyses. The approach followed in our study results in a more accurate estimation of direct flood risk in NYC than earlier studies because it considers many realistic flood events, and our flood damage estimates are based on more detailed spatial information on flood inundations and exposure of assets. Moreover, this study examined several uncertainties in the various steps of the risk analysis, which resulted in variations in flood damage simulations. These uncertainties include the interpolation of flood depths and the use of different flood damage curves. Our method, however, is relatively simple with several assumptions, and future flood risk analysis studies could further address these sources of uncertainty in other contexts.

Apart from applying more accurate techniques and data to reduce uncertainties, there are additional issues that deserve attention in future research. First, future trends, such as climate change and population growth, may further change EAD estimations in future 1/100 zones. Lin *et al.*[11] show that future climate effects may cause the present NYC 100-year surge flooding to occur every 3–20 years, and the present 500-year flooding to occur every 25–240 years, by the end of the century. In addition to climate change, socioeconomic developments, such as population and economic growth in hazard-prone areas, are likely to have a major impact on future flood risks. An upward trend in worldwide natural disaster losses can be observed. This has been mainly caused by socioeconomic developments, such as increased urbanization in coastal zones, which are likely to continue in the future.[52] NYC has been no exception to this global trend and has experienced considerable increases in concentrations of population and economic activities over time, which has heightened flood risk.[53] According to the NYC Department of City Planning, New York City's population is projected to continue to grow from over 8 million in 2000 to 9.1 million in 2030, which is an increase of 1.1 million or 13.9%. Finally, future research may examine land-use change[54,55] or optimal spatial patterns[56] of insured losses across the different boroughs and compare, as means of validation, how those spatial patterns match the simulated patterns of our damage simulations.

Second, our flood damage estimates provide a rationale for updating flood insurance and zoning policies[57] based on a probabilistic risk assessment approach. The U.S. National Flood Insurance Program (NFIP) currently insures a value of about US$8 bn in NYC and is an important program for achieving risk reduction.[58] The NFIP requires that new structures should be elevated to the expected water level of the 100-year flood. Based on Lin *et al.*,[11] at least parts of the 500-year zone may change into the 100-year flood zone in the future. However, the NFIP does not address climate change, and its regulations are restricted to the current 100-year flood zone.[59] For buildings in the 500-year zone, minimum elevation requirements do not apply. Insurance and the city's building code regulations could be applied to what is expected to be the future 1/100 flood-zone, and a building code policy could be designed that requires "freeboard" (elevating the ground floor above the 1/100 flood level) of up to ~0.6 or ~0.9 m (2 or 3 ft) for new structures in the 1/100 flood zone.[57,59] It has been demonstrated that investing in (additional) freeboard can be cost effective in terms of the reduced risk it delivers.[60] Moreover, zoning controls could be applied to limit potential flood damage, such as building restrictions or increasing the required "open space ratio," which implies a lower building footprint and, hence, lower potential flood damage.[61,62] Finally, hybrid storm Sandy showed more research is needed to assess the physical processes related to those storms and whether the frequency and magnitude of those storms will increase. Future surge risk analysis and loss estimation need to account for the effect of extratropical transition and hybrid storms.

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