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Uncertainty and Bias in Global to Regional Scale Assessments of Current and Future Coastal Flood Risk

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Key Points:

- We present the first comparison of uncertainties in global to world-regional scale assessments of current and future coastal flood risk
- The largest uncertainty relates to future coastal adaptation, which can influence future coastal flood risk by factors of 20–27
- Uncertainties in socioeconomic development, elevation data, defense levels, emissions and ice sheets can affect risks by factors of 2–6

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Abstract This study provides a literature-based comparative assessment of uncertainties and biases in global to world-regional scale assessments of current and future coastal flood risks, considering mean and extreme sea-level hazards, the propagation of these into the floodplain, people and coastal assets exposed, and their vulnerability. Globally, by far the largest bias is introduced by not considering human adaptation, which can lead to an overestimation of coastal flood risk in 2100 by up to factor 1300. But even when considering adaptation, uncertainties in how coastal societies will adapt to sea-level rise dominate with a factor of up to 27 all other uncertainties. Other large uncertainties that have been quantified globally are associated with socio-economic development (factors 2.3–5.8), digital elevation data (factors 1.2–3.8), ice sheet models (factor 1.6–3.8) and greenhouse gas emissions (factors 1.6–2.1). Local uncertainties that stand out but have not been quantified globally, relate to depth-damage functions, defense failure mechanisms, surge and wave heights in areas affected by tropical cyclones (in particular for large return periods), as well as nearshore interactions between mean sea-levels, storm surges, tides and waves. Advancing the state-of-the-art requires analyzing and reporting more comprehensively on underlying uncertainties, including those in data, methods and adaptation scenarios. Epistemic uncertainties in digital elevation, coastal protection levels and depth-damage functions would be best reduced through open community-based efforts, in which many scholars work together in collecting and validating these data.

Plain Language Summary One of the main impacts of climate change is sea-level rise leading to more frequent flooding of low lying coastal areas through higher tides, storm surges and waves. In this context, assessments of current and future coastal flood risk at global to world-regional scales are needed to inform policy decisions on greenhouse gas reduction targets and finance of adaptation and flood disaster risk reduction. A key requirement for such assessments is that they consider all major uncertainties in models, methods and data applied, because the failure to do so may lead to poor policy outcomes. So far, this key requirement has not been met. To address this limitation, this paper provides the first comparative assessment of uncertainties in global to world-regional scale studies of current and future coastal flood risks based on the published literature. We find that globally, by far the largest uncertainty concerns how coastal societies will adapt to sea-level rise, which can influence future flood risk by factors 20–27. Other large global uncertainties are associated with socio-economic development, digital elevation data, greenhouse gas emissions, and ice sheet evolution, influencing global exposure and flood risk by factors of up to 2 to 6.

1. Introduction

The increase of damages due to flooding caused by coastal extreme sea-level events, resulting from the interplay of tides, mean sea level rise, storm surges, and waves, may be one of the costliest aspects of climate change. Global to world-regional scale (called broad scale, hereafter) assessments of current and future coastal flood risks (CFR) are thus needed to inform a range of policy decisions including: (i) setting global mitigation targets in the context of the United Nations Framework Convention on Climate Change (UNFCCC) to avoid "dangerous interference with the climate system" (UNFCCC, 1992); (ii) informing Global Assessment Reports on Disaster Risk Reduction by the United Nations Office for Disaster Risk Reduction (UNDRR, 2019); (iii) designing global financial mechanisms for adaptation (UNEP, 2016), disaster relief and loss & damage (Jongman et al., 2014); and (iv) strategic long-term development and adaptation planning.

A key requirement for informing these policy decisions, as well as for informing decisions in general, is that underlying assessments need to consider all major uncertainties in models, methods and data applied, because the failure to do so may mislead policy decisions leading to poor policy outcomes (Jones et al., 2014; Kunreuther et al., 2013; Morgan et al., 1990; Simpson et al., 2016).

The state-of-the-art of climate impact assessments generally, and broad-scale CFR assessments specifically, does not yet meet this requirement. Most efforts, notably those under the Climate Model Intercomparison Project (Eyring et al., 2016) and the Intergovernmental Panel on Climate Change (IPCC, 2014a), have focused on the exploration of uncertainty in climate models under different emission scenarios. More recently, a range of impact model intercomparison projects united under the umbrella of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP; https://www.isimip.org/) have started to explore uncertainties in impact models across different sectors such as water (Zaherpour et al., 2018) or forests (Petter et al., 2020). However, there are also many uncertainties beyond climate and impact models, which have been hardly explored, even though many of these uncertainties are known to be substantial. For broad-scale CFR assessments, these include uncertainties in subnational population data (Merkens et al, 2016), flood depth damage functions (Huizinga et al., 2017), extreme value analysis (EVA) methods (Mentaschi et al., 2016; Wahl et al., 2017), defense failure mechanisms (Allsop et al., 2007), and adaptation scenarios. To the best of our knowledge, no study has attempted to assemble and compare all major dimensions of uncertainty underlying current and future CFR.

This study contributes to filling these gaps by providing a literature-based comparative assessment of the major sources of uncertainty and biases relevant in broad-scale CFR assessments. We focus on broad-scale assessments, because the methods applied differ from methods applied in local-scale assessments (de Moel et al., 2015), mainly due to the limited availability of global data and computational resources. Assessing and comparing uncertainties in these methods is particularly timely, because they have developed substantially in recent years (Abadie et al., 2016; Diaz, 2016; Hallegatte et al., 2013; Hinkel et al., 2014; Lincke & Hinkel, 2018; Tiggeloven et al., 2020; Voudoukas, Mentaschi, et al., 2020; Vousdoukas et al., 2018) with broad-scale extreme sea-level models and datasets becoming increasingly available (Calafat & Marcos, 2020; Mentaschi et al., 2017; Morim et al., 2019; Muis et al., 2020; Tadesse et al., 2020; Vitousek et al., 2017; Vousdoukas et al., 2017; Woodworth et al., 2016).

In our uncertainty assessment we consider uncertainty in drivers and future projections of the four components of CFR, following the risk definition of the Intergovernmental Panel on Climate Change (IPCC) (Oppenheimer et al., 2019; Wong et al., 2014):

1. *Mean and extreme sea-level hazards*, including sea-level rise, tides, surges, waves, river run-off and their interactions;
2. *Hazard propagation* onto the shore and the floodplain, including interaction with natural (e.g., dunes) and artificial (e.g., dikes) defences;
3. *Exposure* in terms of area, people and coastal assets potentially threatened by these hazards; and
4. *Vulnerability*, which refers to the propensity of the exposure to be adversely affected by the flood hazard (IPCC, 2014b).

For each component and driver we extract, to the extent available in the literature, quantitative estimates of how sensitive components and resulting flood risk are to variations in the drivers. Finally, we compare

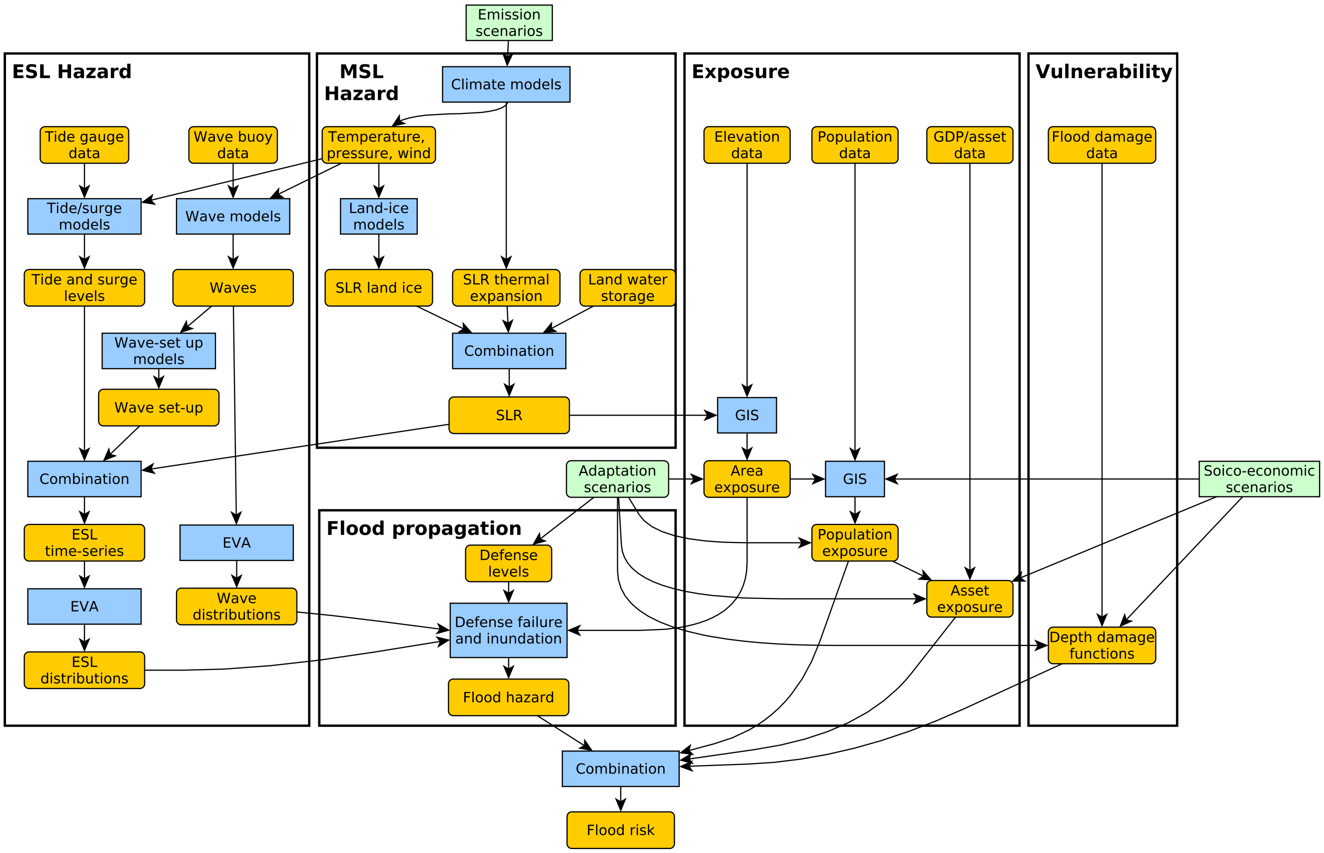

Figure 1. Methodological steps in broad-scale coastal flood risk assessments. Green boxes denote scenarios, blue boxes methods and yellow boxes data. Abbreviations: ESL=extreme sea-levels, MSL=mean sea-level, GIS = Geographic Information Systems, SLR=sea-level rise, EVA= extreme value analysis.

results across components and drivers, and provide directions for future research toward the goal of attaining broad-scale CFR estimates that consider all major dimensions of uncertainty and thus adequately inform relevant policy processes. This paper is a product of the Coastal Impact Model Intercomparison Project (COASTMIP; www.coastmip.org), a community-driven effort bringing together coastal system and impact modellers from around the world to better understand and project the long-term impacts of climate change on coastal systems.

2. Materials and Methods

Broad-scale assessment of CFR involves the application of many datasets and chains of numerical and statistical models, including climate models, land-ice models, tide, surge and waves models, defense failure models, inundation models, and damages models. Figure 1 provides an overview of how these data and models are generally combined in CFR assessments. Each step involved is discussed in more detail in the subsections that follow. A major methodological difference in those broad-scale CFR assessments is that they have either been conducted for collections of major European or global coastal cities (Abadie, 2018; Abadie et al., 2016; Hallegatte et al., 2013; Hunter et al., 2017; Prahl et al., 2018) or for entire coasts at continental or global scales (Brown et al., 2016, 2019; Diaz, 2016; Hinkel et al., 2014; Lincke & Hinkel, 2018; Nicholls et al., 2018; Tiggeloven et al., 2020; Vousdoukas et al., 2020). While the former studies generally take information on extreme sea-levels directly from observations (e.g., tide gauges located near the cities), the latter ones require the application of tide, surge and wave models to also have information for ungauged locations.

In an ideal situation, uncertainty assessment could proceed as a *global sensitivity analysis* using an integrated modeling system that covers all of the steps of Figure 1, and allowing all uncertain variables to vary

10.1029/2020EF001882

Table 1
Uncertainty in Global Mean Sea-Level Rise. A->B Denotes a Variation in a Variable From Value A to Value B and the Variation Factor is B/A

Variation in source variable				Effect on global mean sea-level rise	
Variable	Variation	Study	Assumptions	Variation (cm)	Factor
Emissions (mean SLR forcing)	RCP2.6 -> RCP8.5	(Oppenheimer et al., 2019)	17th percentile	29->61	2.1
			50th percentile	43->84	2.0
			83rd percentile	59->110	1.9
	Low (slightly warmer than RCP2.6) -> High (roughly RCP8.5)	(Bamber et al., 2019)	17th percentile	36->62	1.7
			50th percentile	69->111	1.6
			83rd percentile	126->238	1.9
Climate and land ice models	17th -> 83rd percentile	(Oppenheimer et al., 2019)	RCP2.6	29->59	2.0
	17th -> 83rd percentile		RCP8.5	61->110	1.8
	17th -> 83rd percentile	(Bamber et al., 2019)	RCP2.6[a]	49->98	2.0
	17th -> 83rd percentile		RCP8.5[a]	79->174	2.2
	5th -> 95th percentile		RCP8.5[a]	62->238	3.8
Ice sheet models	Process-model based -> expert judgment based ice sheet contributions	Oppenheimer et al. (2019) -> Bamber et al. (2019)	RCP2.6[a], 83rd percentile	59->98	1.7
			RCP8.5[a], 83rd percentile	110->174	1.6
Climate models	Lowest -> highest climate model (4 models)	Hinkel et al. (2014)	RCP2.6, 50th percentile	30->39	1.3
			RCP8.5, 50th percentile	73->86	1.2

[a]Bamber et al. (2019) do not use RCP8.5, but a comparable scenario that stabilizes global mean temperature at +5°C in 2100 relative to 1850–1900. The median global warming under RCP8.5 is +4.3°C in 2081–2100 relative to 1850–1900 (Collins et al., 2013). Likewise they do not use RCP2.6, but a comparable scenario that stabilizes global mean temperature at +2°C in 2100 relative to 1850–1900. The median global warming of RCP2.6 is +1.6°C in 2081–2100 relative to 1850–1900 (Collins et al., 2013).

simultaneously (Saltelli et al., 2008). Given the number of datasets, models (including their alternative formulations and parameterizations), and the large number of uncertain variables involved, as well as the high computational costs required for running these models, this is far from being possible today. As a consequence, the available literature on uncertainty in CFR specifically, and on climate impacts generally, has focused on exploring few selected dimensions of uncertainty, mostly by varying one or few uncertain variables at a time (Frieler et al., 2017). Furthermore, the literature is compartmentalized into sets of literature addressing uncertainty in individual components of CFR. For example, part of the literature focuses on mean-sea-level rise uncertainty, part focuses on extreme sea-level uncertainty, part focuses on wave uncertainty, and part focuses on uncertainty in flood exposure. As our paper assesses uncertainty based on the published literature, we structure the presentations of results according to these components.

For each of the four components of CFR we consider one or several *target variables*, which are the outcome variables that broad-scale studies generally report upon. These are mean-sea-level rise (Table 1), extreme sea-levels (Table 2), wave heights (Table 3), flood damages (Tables 4 and 6), and area, people and asset exposure (Table 5). For each of the target variables, we consider one or several *sources of uncertainty* pertaining to the following three dimensions:

1. *Scenario uncertainties*, which are due to unpredictable human choice and include here socio-economic development scenarios, greenhouse gas emission/concentration scenarios and adaptation scenarios.
2. *Epistemic uncertainties*, which are due to imperfect knowledge and hence can be reduced in principle. This includes data uncertainty (e.g., digital elevation data, population data, etc.), climate model uncertainty (including downscaling methods), impact model uncertainty (e.g., hydrodynamic model used to simulate tides, waves and surges and their interactions; defense failure models and inundation models applied) and methodological uncertainty (e.g., uncertainty in methods for extreme value analysis).
3. *Aleatory uncertainty*, which is internal to the system studied and cannot be reduced (e.g., natural climate variability).

Table 2
Uncertainty and Bias in Current and Future Extreme Sea-Levels. A->B Denotes a Variation in a Variable From Value A to Value B and the Variation Factor is B/A

Variation of source variable				Effect on extreme sea level (ESL)			
Variable	Study area	Variation	Assumptions (study)	Variable	Spatial metric[a]	Variation (cm)	Factor
Current extreme sea-levels (ESL)							
Tide-surge modeling	Global tide gauges	GTSR model -> tide gauge observations	(Wahl et al. 2017)	100-year ESL	Mean	+33	NR
			(Muis et al., 2017)	100-year ESL	Mean	+19	NR
	European tide gauges	Statistical model -> tide gauge observations	(Calafat & Marcos, 2020)	50-year ESL	Median	±10	NR
	Global tide gauges	Including statistical dependence between tides and surges -> not including this	(Arns et al., 2020)	100-year ESL	Mean	+28	NR
					Max	+70	1.3
Wave set up	Global coastline	No wave set up -> wave set-up (0.2*Hs)	(Kirezci et al., 2020)	100-year ESL	Max	+50	NR
		Wave set-up w/o -> wave setup with accounting for interdependence between surges and waves	(Marcos et al., 2019)	50-year ESL	Median	+91	NR
					Max	+300	NR
EVA methods	Global coastline	Generalized Pareto Distribution->Gumbel distribution	(Wahl et al. 2017)	100-year ESL	Mean	+22	NR
	Global tide-gauges	Decadal variability in global tide gauge records	(Marcos et al., 2015)	50-year ESL	Mean	±5-6	NR
ESL data record	Global coastline	20 years -> 70 years record length	(Wahl et al. 2017)	100-year ESL	Mean	+15	NR
	Northern Australia coast	61 years climate simulation -> 10,000 years of synthetic tropical cyclones	(Haigh et al., 2014)	1,000-year ESL	Max	300-> 600	2.0
Extreme sea-levels in 2100							
Emissions (atmospheric forcing)	E Africa	Constant storminess -> considering changes in storminess	RCP8.5 (Vousdoukas et al., 2018)	100-year ESL	Median	−21	0.8
	E China Sea/Sea of Japan				Median	+27	NR
	North Europe		RCP8.5 (Vousdoukas et al, 2017)	100-year ESL	Median	+6	1.1
	South Europe				Median	−20	NR
Wave set up	Global coastline	W/o wave set-up -> with wave set up	RCP8.5 (Kirezci et al., 2020)	100-year floodplain (10^3 km^2)	Mean	780 -> 820	1.1
Climate models	European coastline	Ensemble spread among six CMIP5 climate models	(Vousdoukas et al, 2017)	100-year ESL	Mean	NR	1.2
EVA methods	Global tide gauges	Stationary -> instationary EVA methods	(Vousdoukas et al., 2017; Mentaschi et al., 2016)	100-year ESL	Mean	+10	1.1

Note. NR Stands for Values Not Reported and AIS for Antarctic Ice Sheet.
[a]Spatial metric denotes the method applied to aggregate values from different locations (e.g., grid cells, tide gauges) of the study area. This includes "Mean", "Median", "Max" (i.e., maximum) and, in the case results are reported for a single location, "None".

We assess by how much the target variables vary within the uncertainty range of each individual source variable. The results are shown in Tables 1–6. If possible, we report on uncertainty ranges of target variables in absolute and relative terms. We thereby denote the absolute variation in a variable from value A to value B as "A->B". If a study does not report on A and B explicitly, we report on the absolute difference between A and B (i.e., B–A). The relative size of the variation in the target variable is given as the *variation factor* B/A. This factor is then used to compare uncertainties across target and source variables.

To the extent allowed by the published studies, we try to use consistent uncertainty ranges for the source variables. For greenhouse gas emission/concentration uncertainty, we use the range from the representative

Table 3
Uncertainty and Bias in Current and Future Wave Height. A->B Denotes a Variation in a Variable From Value A to Value B and the Variation Factor is B/A

Variation in source variable				Effect on wave height			
Source	Study area	Variation	Assumptions (study)	Variable	Spatial Metric[a]	Variation (cm)	Factor
Current waves							
Wave models	Global	Observation -> model	Ensemble of wave models (Morim et al., 2019)	CRMSD[b] of mean Hs[c]	Max	+50	NR
		Lowest-> highest calibration wave data set	WWIII, 12 wave datasets used (Stopa, 2018)	100-year Hs[c]	Max	900->1,700	1.7
	North Atlantic	WWIII -> WAM	Same wind forcing (Swain et al., 2017)	Mean wave height	Mean	NR	1.1
Wave model resolution	Global	40 km -> 150 km spatial resolution	(Mentaschi, 2018)	10-year Hmax[d]	Mean	NR	0.96
	Area with tropical cyclones	1° -> 0.25° spatial resolution	(Timmermans et al., 2017)	Hmax[d]	Max	+1,500	NR
	Areas w/o tropical cyclones				Max	+500	NR
EVA methods	Global	EVA on single model -> EVA on pooled data from model ensembles	(Meucci et al., 2018)	100-year Hs[d]	Max	1,400-> 1,600	1.1
Future waves (year 2100)							
Emissions (atmospheric forcing)	Global	Today -> 2100	Climate and wave mode ensembles, RCP4.5 and 8.5 (Morim et al., 2019)	Mean Hs[b]	Mean	NR	1.1–1.2
	Central North Atlantic	Today -> 2100	RCP4.5 (Aarnes et al., 2017)	Mean wave height	Mean	NR	0.94
		Today -> 2100	RCP8.5 (Aarnes et al., 2017)		Mean	NR	0.90
		RCP4.5 -> RCP8.5	(Aarnes et al., 2017)	Mean wave height	Mean	NR	0.96
Climate models (atmospheric forcing)	Global	Lowest -> highest climate and wave model combination	RCP8.5 (Morim et al., 2019)	Mean Hs[b]	Max	NR	1.2
				100-year Hs[b]	Max	NR	1.4
EVA methods	Global	EVA on single model -> EVA on pooled data from model ensembles	(Meucci et al., 2020)	100-year Hs[b]	Max	+500	1.5

Note. NR stands for values not reported.
[a]Spatial metric denotes the method applied to aggregate values from different locations (e.g., grid cells, tide gauges) of the study area. This includes "Mean", "Median", "Max" (i.e., maximum) and in the case results are reported for a single location, "None". [b]centered-root-mean-square-difference. [c]significant wave height. [d]maximum wave height.

concentration pathways (RCP) 2.6 to 8.5, as this is the range most commonly reported upon in the literature. For socioeconomic uncertainty we use the range over the Shared Socioeconomic Pathways (SSP), which is the standard set of socioeconomic scenarios used in climate change-related research and consists of five alternative futures describing different challenges to adaptation and mitigation (Kriegler et al, 2012; O'Neill et al., 2017). We acknowledge that these two ranges might not necessarily span the full range of uncertainties. For example, alternative socio-economic scenarios have come up with both higher and lower population numbers in 2100 than the SSPs (Vollset et al., 2020). Similarly, some authors argue that there is a 35% chance of exceeding RCP8.5 (Christensen et al., 2018) and others argue that RCP8.5 is an extreme and very unlikely case (Hausfather & Peters, 2020).

Generally, we aim to report on both uncertainty and bias. Bias is assessed either as the difference between observations and model or method results. When observations are not available, as is the case for many

Table 4
Uncertainty and Bias in Flood Propagation. A->B Denotes a Variation in a Variable From Value A to Value B and the Variation Factor is B/A

Variation in source variable				Effect on flood damage		
Variable	Study area	Variation	Assumptions (study)	Variable	Variation	Factor
Current flooding						
Inundation model	Europe	LISFLOOD-FP -> Bathtub	(Vousdoukas et al., 2016)	Flood area (10^3 km^2)	31->50	1.6
Future flooding (2100)						
SLR scenario	Global	RCP2.6 -> RCP8.5	Robust CBA adaptation, SPP2 (Lincke and Hinkel, 2018)	EAD[a] (billion US$/yr))	230-> 420	1.8
Socio-economic scenario	Global	SSP3 (lowest scenario) -> SSP5 (highest scenario)	Robust CBA adaptation, RCP8.5 (Lincke and Hinkel, 2018)	EAD[a] (billion US$/yr)	260-> 590	2.3
			Constant protection levels, RCP8.5 (Tiggeloven et al., 2020)	EAD[a] (billion US$/yr)	[b]380-> 2,200	[b]5.8
Adaptation scenario	Global	Demand for safety protection -> no adaptation	3 RCPs, 5 SSP (Hinkel et al., 2014)	Max. EAD[a] (billion US$/yr)	75-> 100,000	1300.0
		Cost-benefit protection -> constant protection levels	RCP2.6, SSP2 (Nicholls et al., 2019)	EAD[a] (billion US$/yr)	55-1,1000	20.0
			RCP8.5, SSP2 (Nicholls et al., 2019)	EAD[a] (billion US$/yr)	120->3,200	26.7

[a]EAD= expected annual damages. [b]These are 2080 values as the authors do not report on 2100.

components of CFR, we report on uncertainty ranges for target variables obtained through the use of alternative datasets, models or methods, as generally done in climate and impact model intercomparison projects. Uncertainties in future components of flood risk are reported for 2100, because this is the time horizon most frequently used in assessments.

3. Results

3.1. Hazard

3.1.1. Mean Sea-Levels

Methods applied. The mean sea-level metric relevant for CFR assessments is local relative sea-level change, which is generally obtained by combining information on the following components: (i) sterodynamic SLR obtained from multi-model ensembles of Atmosphere-Ocean General Circulation Models (AOGCM), (ii) contribution of land-ice models (Antarctica, Greenland) and glaciers forced by AOGCM output in terms of mainly temperature and precipitation, (iii) contribution of land water storage changes. From these components local relative sea-level rise is obtained with a sea-level equation model that calculates the gravitational and rotational patterns in sea-level rise (Slangen et al., 2014); (iv) contribution of glacial-isostatic adjustment; and v) contribution of uplift and subsidence processes, especially in geologically recent sedimentary deposits such as deltas and alluvial plains (Nicholls et al., 2014). Results are typically expressed by their mean values and a selected percentiles (e.g., 17%–83%, Oppenheimer et al., 2019), but full probability density distributions have also been produced (Kopp et al., 2014).

Major uncertainties. According to the process-model based assessment of the IPCC's Special Report on the Oceans and the Cryosphere in a Changing Climate (SROCC; Oppenheimer et al., 2019), uncertainties in 21st century global mean SLR due to uncertainty in emission scenarios and uncertainty in models (climate and land-ice) are roughly at equal footing (Table 1). The minor part of model uncertainty relates to climate model uncertainty, which has been found to influence global mean SLR in 2100 by factors 1.2–1.3 (i.e., 13 cm under RCP8.5) for an ensemble of 4 climate models (Table 1; Hinkel et al., 2014). Considering a larger ensemble of climate models, Little et al. (2015) find a variation of steric global mean SLR of about 20 cm under RCP8.5 in 2090, but the authors do not report on total global mean SLR. In any case, the major part of model uncertainty is associated with the land-ice contributions of Greenland and Antarctica to global

Table 5
Uncertainty in Current and Future Exposure. A->B Denotes a Variation in a Variable From Value A to Value B and the Variation Factor is B/A

Variation in source variable				Effect on exposure		
Variable	Study area	Variation	Assumptions (study)	Variable	Variation	Relative
Current exposure						
Elevation datasets	Global	SRTM -> GLOBE	(Lichter et al., 2011)	LECZ[a] area (10^3 km^2)	2,400-> 2,800	1.2
		SRTM90 -> CoastalDEM	Landscan-2010 (Kulp & Strauss, 2019)	LECZ[a] population (millions)	780->1040	1.3
		SRTM -> GLOBE	GRUMP (Hinkel et al., 2014)	100-year floodplain (10^3 km^2)	660-> 1,200	1.8
				100-year floodplain population (millions)	160 -> 310	1.9
		SRTM90 -> CoastalDEM	LandScan-2010 (Kulp & Strauss, 2018)	1-year floodplain population (millions)	65 -> 250	3.8
		SRTM90 -> GLL_DTM_v1	Vernimmen et al., (2020)	Land below 2 m between 60°N and 56°S (10^3 km^2)	317->934	2.9
Population datasets	Global	LandScan -> GRUMP population data	SRTM (Hinkel et al., 2014)	100-year floodplain population (million)	93->160	1.7
			GLOBE (Hinkel et al., 2014)		290 -> 310	1.1
Future exposure (2100)						
SLR scenarios	Global	RCP2.6 -> RCP8.5	SSP2; 50th percentile SLR (Merkens et al., 2018)	100-year floodplain population (millions)	149->170	1.1
		17th percentile -> 83rd percentile SLR	RCP8.5; SSP2 (Merkens et al., 2018)		155->187	1.2
		Without -> with wave set up	RCP8.5 (Kirezci et al., 2020)	100-year floodplain (10^3 km^2)	780 -> 820	1.1
Socio-economic scenarios	Global	Lowest -> highest SSP	(Merkens et al., 2016)	LECZ population (millions)	850 -> 1,200	1.4
			(Jones & O' Neill, 2016)		490 -> 1,100	1.5
		National -> regionalized population projections	SSP1 (Merkens et al., 2016)	LECZ population (millions)	620 -> 850	1.4
			SSP5; 50th percentile SLR; RCP6.0 (Merkens et al., 2018)	100-year floodplain population (millions)	129 -> 179	1.4

Note. NR stands for values not reported.
[a]low elevation coastal zone.

mean SLR (van de Wal et al., 2019). Uncertainties in the ice-sheet contributions are high because some of the processes that may lead to large contributions by the end of the century are only captured in a highly parameterized way in state-of-the-art ice-sheet models. This includes hydrofracturing of ice shelves, leading to enhanced mass loss from the ice sheet by marine ice sheet or marine ice cliff instability (DeConto & Pollard, 2016; Pattyn et al., 2018), or the development of dark ice surfaces due to inorganic matter or ice algae accumulating due to warmer and wetter conditions on the ice sheet of Greenland, which in turn accelerates surface melting (Tedstone et al., 2017). For this, and other reasons, expert elicitation studies (Bamber et al., 2019) on the contributions of the ice-sheets to SLR consistently produce higher SLR estimates than process-model based studies, particularly for higher RCPs and higher percentiles. In these studies, 21st century global mean SLR is about twice as sensitive to model uncertainties (including expert judgment for ice-sheets) as compared to emission uncertainties (Table 1) for the 95% percentile.

Related to this, epistemic uncertainties exist on the covariance between the contributions of different components (Lambert et al., 2021). Most studies use Monte-Carlo Analysis assuming complete independence, which certainly is not justified for some components as they are driven by the same climate forcing. Including this could significantly increase or decrease the uncertainty in the local relative SLR and thereby affect the higher and lower percentiles of the probability distribution function.

Table 6
Uncertainty in Current Local Vulnerability and Flood Damage. A->B Denotes a Variation in a Variable From Value A to Value B and the Variation Factor is B/A

Variation in source variable				Variation in flood damage		
Variable	Study area	Variation	Assumptions (study)	Variable	Variation	Factor
Depth-damage function (DDF)	The Netherlands	2.5th -> 97.5th percentile using alternative damage models	(de Moel et al., 2012)	Damage	NR	8.0
	Eilenberg (Germany)	Lowest -> highest damages of 7 different river flood damage models	(Jongman et al., 2012)	Damage (million €)	55-> 470	8.5
	Rotterdam	No freeboard -> 50 cm freeboard	(de Moel et al., 2013)	Damage	NR	0.5
	New York	local DDF (Aerts et al, 2014) -> continental DDF	(Huizinga et al., 2017)	Damage (billion €)	44->99	2.3
	São Tomé and Príncipe	Local DDF -> country/continental scale DDF	(Parodi et al., 2020)	Damage	NR	16.0

Note. NR stands for values not reported.

Another major dimension of local mean sea-level uncertainty is human-induced subsidence, which is mainly the enhancement of sediment compaction through the actions of humans, especially through groundwater withdrawal (Shirzaei et al., 2020; Syvitski et al., 2009). The effect of this is small in terms of global mean sea-levels, but it is large in terms of flood risk, because coastal populations are preferentially located in subsiding locations such as the large river deltas and their associated cities in Asia. While the global average rate of mean sea-level rise is 3.3 mm/yr (Oppenheimer et al., 2019), the average rate experienced in subsiding regions is currently up to three times faster at 8–10 mm/yr (Nicholls et al., 2021). Maximum current subsidence rates in some of the worst affected delta cities are as high as 120 mm/yr in Bangkok and 180 mm/yr in Jakarta (Erkens et al., 2015; Herrera-García et al., 2021). These rates are, however, difficult to extrapolate into the future, because even such high rates of subsidence can be reduced or stopped through appropriate water management measures, as has happened, for example, in Tokyo. The global effects of this uncertainty have therefore not been explored yet.

3.1.2. Extreme Sea-Levels

Methods applied. Global data on ESL hazard is generated based on high frequency tide gauge records where available, and on numerical tidal, storm surge, wave and river models for ungauged locations and future conditions. Numerical storm surge simulations generated with process-based models are now becoming available at broad scales (Muis et al., 2020; Vousdoukas et al., 2017). Computationally more efficient numerical models based on statistical relationships between surges and atmospheric pressure fields have demonstrated similar performance as process-based models, at least in some regions (Cid et al., 2018; Rashid & Wahl, 2020; Tadesse et al., 2020), but they require observations (or output from process-based models) for training and have not yet been applied for broad-scale CFR assessments. A new observation-based probabilistic assessment of ESL has recently been applied along the European coasts (Calafat & Marcos, 2020), providing improved accuracy at both gauged and ungauged sites. Despite its promising performance, these types of models are still at their initial stages and further developments are needed for CFR.

Tide-surge models generally underestimate observed ESL by a few decimeters for the 100 years events on average (Table 2), but the underestimation of the surge models of the strongest events is much higher than the global average value. Differences between modeled and observed ESL are significantly larger in areas hit by tropical cyclones, specifically for large return periods, because the temporal and spatial resolution of climate reanalysis/simulations are insufficient to fully include the strong winds of tropical cyclones and do not contain a sufficient number of tropical cyclones to obtain reliable statistics of extreme values (Hodges et al., 2017; Muis et al., 2020; Woodruff et al., 2013). For example, maximum observed ESL in New Orleans during hurricane Katrina have been found to be 2.7 to 4 times higher than simulated 1000-yr ESL (Muis et al., 2016). Ongoing work is addressing these limitations. For example, using high-resolution climate data (Bloemendaal et al., 2018) or parametric wind models combined with best track data (Lin & Emanuel, 2016) are able to resolve the maximum surge height within centimeters (Haigh et al., 2014).

Furthermore, synthetic resampling techniques can be applied to extend the observed records to thousands of years (Bloemendaal et al., 2020; Emanuel et al., 2006).

Wave set-up and run-up. Wind-waves contribute to ESL via three processes: infragravity waves, wave setup and wave runup (Dodet et al., 2019) with uncertainties associated with each, introduced via uncertainties in: (i) offshore wave characteristics, that is, how well observed or simulated they are, which will be described in the next subsection; and (ii) how waves propagate and interact with the nearshore morphology and coastal profile. Considering wave contributions to ESL via process-based modeling is challenging at broad scales, due to the computational cost of large-scale numerical models with the necessary high spatio-temporal resolution, and a lack of observational records as coastal tide-gauges are generally preferentially positioned in locations sheltered from any contribution from wind-waves. As a result, only a few broad-scale CFR assessments have considered the contribution of wave-set up to coastal flooding, and those that have, used simple parameterisations dependent on offshore wave information and coastal morphology (Kirezci et al., 2020; Vousdoukas et al., 2018). Alternative parameterizations for assessing wave set up for sandy coasts are available, for example, setup = 0.2*Hs by Holthuijsen (2010), or that of Stockdon et al. (2006), which have been applied globally for beach shorelines (Melet et al., 2020; Rueda et al., 2017; Vitousek et al., 2017) or modified for other environments such as coral reefs (Beck et al., 2018).

The simple parameterization of Holthuijsen (2010) can significantly overestimate wave-setup locally. For example, using a local coupled surge-wave model, Amores et al. (2020) find a wave set-up of 40 cm caused by waves with a significant height of about 800 cm during the storm Gloria in the north-western Mediterranean, as compared to 160 cm that would be obtained by applying the Holthuijsen (2010). One major uncertainty in applying other parametrizations that rely on input parameters such as beach slope is the lack of broad-scale data on morphology across the shoreface (nearshore, foreshore and backshore), due to the lack of an observing system capable of measuring this at an affordable cost and appropriate spatio-temporal scales. To circumvent the problem, global studies have assumed a constant beach slope, for example, 0.1, by Melet et al. (2018), which can locally over- or under-estimate wave set-up given that observed beach slope ranges between 0.001 and 0.6 (10th to 90th percentiles) globally (Athanasiou et al., 2019). On a global average, the contribution of wave-set up to ESL is relatively small (Kirezci et al., 2020), but wave-set up can locally reach 40–50 cm under strong storm conditions (Amores et al., 2020; Bertin et al., 2015).

Wave-run up contributions were considered in broad scale studies by Melet et al. (2018, 2020). While these contributions are short time scale (on order of wind-wave frequencies) and unlikely to lead to sustained flooding, they can play an important role in initializing failure of coastal defenses such as dikes or dunes. Runup estimates are very sensitive to beach slope assumptions (Stockdon et al., 2006).

Statistical dependencies between ESL components. Further bias in broad-scale assessments of ESL is introduced through the non-consideration of the statistical dependence between surge, tide, river discharge and wave contributions to ESL. While tides are the major contributor to ESL globally (Merrifield et al., 2013), nonlinear tide-surge interactions are generally not considered in broad-scale assessments of ESL, which can overestimate ESL by up to 70 cm at some locations (Arns et al., 2020). Similarly, broad-scale ESL assessments generally do not include the influence of river discharge on ESL in river deltas and estuaries. This effect has not been quantified for river months at global scale, but it has been found that including the coastal ESL into river flood models increases extreme water levels on average by about 10 cm for many global deltas and estuaries (Eilander et al., 2020; Ikeuchi et al., 2017). Finally, the occurrence of high storm surges and wind waves is correlated at about 55% of the global coastline, and neglecting this effect can underestimate the contribution of wave setup to ESL significantly (Marcos et al., 2019). This also holds true for many ESL records from tide gauge locations, as gauges are usually located in wave-sheltered harbors and hence underestimate the contribution of waves to ESL (Lambert et al., 2020).

Extreme value analysis (EVA) methods. Uncertainties in ESL also arise from the different extreme value analysis (EVA) methods regarding the selected frequency analysis approach, statistical model applied and the return period curve fitting (Buchanan et al., 2017; Hamdi et al., 2014; Wahl et al., 2017). The Gumbel distribution, for example, which has been extensively used in broad-scale ESL studies (Hunter, 2012; Hunter et al., 2013; Muis et al., 2016), tends to overestimate global return levels by 22 cm on average as compared to the Generalized Pareto Distribution (Wahl et al., 2017). In many studies, stationary EVA models are applied to quasi-stationary slices of data, typically with a length of 30 years (Vousdoukas et al., 2016). Nonstationary EVA methods enable studying time-varying return levels and thus increase the sample, generally leading to a decrease of the statistical uncertainty (Menendez et al., 2009; Mentaschi et al., 2016).

Furthermore, limitations in the observational data set, including short length of the time series, lack of representativeness and, associated to this, a lack of observed strong events, limits the accuracy of ESL estimates, in particular for long period return levels (Table 2). Globally, Wahl et al. (2017), for example, quantified that the 100-year ESL increases about 15 cm on global average, and up to more than half a meter at certain locations, when 70 years instead of 20 years of observations are used. This effect is specifically pronounced if exceptionally large extreme events have not been included in the extreme value analyses. Including such events, either by updating return levels after large events or by extending tide gauge records with information on ESL found in historical documents or through modeling efforts (see section on Tide-surge models) can reduce these uncertainties. For example, integrating historical records into the tide gauge record of Venice increases the 50-year ESL by factor 1.3 (Marcos et al., 2009). Decadal variability of 50-year ESL has been found to lie at around 10 cm (Marcos et al., 2015; Menendez & Woodworth, 2010; Rashid et al., 2019).

Future ESL. At broad-scales estimates of future ESL have been generally produced by considering the following two climate change effects separately: (i) effects of mean SLR on ESL (*mean SLR forcing*, hereafter) are captured by displacing ESL distributions upwards (or downwards) with changes in mean sea-levels, which means that the uncertainties involved are those related to mean sea-levels presented above; and ii) effects of changing atmospheric conditions on ESL (*atmospheric forcing* hereafter) are assessed by forcing surge models with wind and pressure data from climate models. The latter effect has been studied less at broad scales, but generally this effect is much smaller as compared to the former, estimated to influence ESL by less than 10% on global average under RCP4.5 and RCP8.5 (Vousdoukas et al., 2018). These estimates are median values based on multi-model ensembles and locally changes in storminess can have a larger effect on ESL, either positive or negative. Further uncertainties in estimating future ESL that have hardly been quantified at broad scales include ocean model errors related to the reduced spatial resolution of both the meteorological forcing and model grid (Calafat et al., 2014; Conte & Lionello, 2013).

Uncertainties related to *future tides*, which change due to a number of processes including mean sea-level change (Haigh et al., 2020) have generally not been considered in broad scale CFR analysis. SLR alters tides by reducing bottom friction, changing resonance properties and increasing reflection at the coast (Idier et al., 2017). The effect of SLR on tides has been estimated to be smaller than ±16 cm change in MHW under 1 m SLR at the 136 largest coastal cities, assuming a fixed coastline (Pickering et al., 2017).

A further source of uncertainty in future ESL relates to *local nearshore effects of rising mean-sea levels on waves, tides and surges* Arns et al., 2015; Du et al., 2018; ;Roland et al., 2012; Schmitt et al., 2018; Zijl et al., 2013). For example, sea-level rise increases shallow water depth, which can increase tidal ranges and surges by reducing damping friction. Furthermore, deeper nearshore waters reduce wave set up but increase wave amplitudes and hence wave runup in the case of rigid/fixed coastlines (Cheon & Suh, 2016). In the case of sandy beaches that are able to retreat landwards wave setup will remain constant, since the beach profile will not change. These effects are specifically pronounced in shallow continental shelf areas such as the German Bight, where it has been found that these effects have the same order of magnitude as the direct increase of ESL through mean sea-levels (Arns et al., 2017). While some of these effects are beginning to be captured globally, for example, the effects of SLR on tides (Haigh et al., 2020) and tide-surge dynamics (Muis et al., 2020), these effects have so far not been considered in broad-scale CFR analysis.

Combining MSL and ESL. Finally, for the interpretation of projections of future ESL, it is important to note that different approaches have been applied for combining MSL and ESL. One approach adds ESL distribution to deterministic scenarios of MSL (Hallegatte et al., 2013; Hinkel et al., 2014) and the other approach convolutes ESL distributions with probabilistic sea-level scenarios (Buchanan et al., 2017; Vousdoukas et al., 2018). Care needs to be taken, because the resulting future ESL distributions have different interpretations. In the former case, the ESL distribution attained represents a possible ESL that could occur in the future under the assumption that the chosen deterministic SLR scenario materializes. In the latter case, the future distribution of ESL attained will never materialize (i.e., probabilistic scenarios do not materialize by definition). The obtained distribution rather represents the likelihood of occurrence of a specific ESL at a given moment in the future.

3.1.3. Wind Waves

Methods applied. In-situ wave observations (wave buoys) provide measurements of the full wave spectrum in deep waters, thus resolving wave period and length. Wave buoys are, however, sparsely distributed globally, have limited record lengths and, in many instances, there are homogeneity issues due to changing buoy measuring platforms (Gemmrich et al., 2011). Globally wave observations have been available for the last 40 years from satellite altimetry, but this provides only information on wave heights at low temporal resolution (∼10 days) and not on wave periods or directions. Hence, understanding global-scale wave characteristics relies heavily on numerical models, typically third-generation spectral models such as Wavewatch III (Tolman, 2009), WAM (Komen et al., 1996) or SWAN (Booij et al., 1997) or statistical models that capture the relationships between wave heights and atmospheric fields (Camus et al., 2011; Wang et al., 2014).

Current wind waves. Averaged over broad-scales, models simulate wave heights remarkably well, but variations in calibration data (observed waves) and forcing products (surface winds of varying spatial or temporal resolution) can lead to significant uncertainties (Table 3), typically greatest for the extreme waves, which are also those most relevant for flood risk. Low space-time resolution increases the uncertainty related to numerics in dynamical wave models and model calibrations can be resolution dependent. Furthermore, subscale processes such as unresolved islands can have significant consequences on the model skill if not properly parameterized (Mentaschi et al., 2020; Tolman, 2003). Locally, the uncertainty in extreme waves is thereby stronger for events dominated by mesoscale dynamics (Mentaschi et al., 2015), notably for tropical cyclones, for which increasing model resolutions can increase maximum wave heights significantly (Table 3). Similar to the surge component of sea-level hazard discussed above, model calibration and validation during tropical-cyclones is hampered by the scarcity of observations. Uncertainties in wave period and direction, which are equally important for the wave-related coastal flooding, are greater compared to wave heights.

Low spatial resolution of wave models is also a particular limitation for the coastal and nearshore zone, as the nearshore wave dynamics, such as wave setup, are poorly resolved (Saulter et al., 2017). Model resolution (spatial and spectral) also limits representation of important processes in determining wave driven coastal sea-level, for example, infragravity waves. Generally, the comparison between climate change wave studies is hampered by the inconsistency of wave variables reported (Morim et al., 2018).

Future wind waves. Broad scale ESL studies and CFR assessments commonly assume wave climate stationarity (Kirezci et al., 2020; Melet et al., 2018; Vitousek et al., 2017). Of studies that consider climate driven changes in wave characteristics, uncertainties in projections of future offshore wave conditions are dominated by uncertainties in future forcing from climate models, followed by wave model uncertainty and RCP uncertainty has the smallest contribution. Climate model uncertainty is globally significant and an order of magnitude larger than climate scenario uncertainty (Wang et al., 2015). Using an ensemble of 148 wave climate projections using different global climate and wave models shows robust changes in at least one parameter of wave climate (significant wave height, wave period and wave direction) for about 50% of the ocean (Morim et al., 2019). Under RCP4.5, however, all robust changes in wave climate fall within the present-day natural variability, but under RCP8.5 changes exceed this over ∼50% of the world's ice-free ocean area. Other sources of uncertainty include unresolved forcing characteristics, for example, tropical cyclones (Appendini et al., 2017; Timmermans et al., 2017) and those associated with model resolution and uncertainties surrounding EVA methods.

Nearshore wave climate is generally more sensitive to climate change than offshore wave climate due to effects of SLR on coastal morphology (e.g., deeper waters) (Wandres et al., 2017). Uncertainties surrounding future coastal morphology including, for example, issues around sediment availability and shoreface slope changes (Cowell et al., 1995; Goodwin et al., 2006) and reef stability (Hongo et al., 2018) have, however, not been explored at broad-scale.

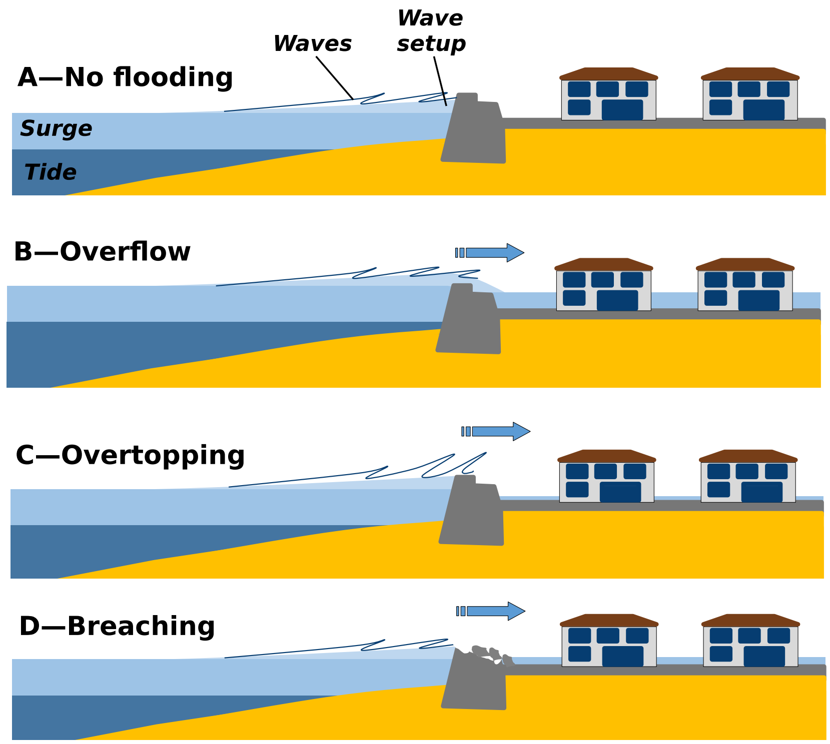

Figure 2. Defense failure mechanisms.

3.2. Hazard Propagation

Processes and methods applied. The propagation of mean and extreme sea-levels into the hinterland causing coastal flooding is shaped by how sea levels interact with the coastal profile including the natural (e.g., dunes) and artificial (e.g., dikes, seawalls) flood barriers in place. The presence or absence of coastal protection and its design standard have large effects on flood extent and depth. If no barriers exist, ESL propagate inland where they exceed land elevation. Where barriers are present, flooding is caused by the following three *failure mechanisms*: (i) *defense overtopping* by waves, if wave runup exceeds the height of the defenses; (ii) *defense overflowing* by ESL, if ESL exceed the height of the defenses; and (iii) *defense breaching,* where part of the defense is removed by ESL and waves, or geotechnical failure (Figure 2). Furthermore, different types of inundation models are applied to assess flood propagation, ranging from static, bathtub approaches to hydrodynamic models.

Defense failure mechanisms. The uncertainties of many of the above processes have only been quantified at local scales (Le Cozannet et al., 2015). Modeling defense failure mechanisms, in particular wave overtopping and breaching, requires high resolution hydro-morphodynamic modeling and data on coastal profiles and defense designs, which are not available at broad scales. Hence broad scale CFR assessments have either: (i) focused on flood exposure and ignored coastal protection (Hanson et al., 2011); (ii) only considered overflow but not breaching (Vousdoukas Bianchi, et al., 2018); or (iii) only considered breaching assuming that once an ESL exceeds defense heights, defenses breach and fail completely (Diaz, 2016; Hinkel et al., 2014; Lincke & Hinkel, 2018; Tamura et al., 2019), or a combination of the latter two (Hallegatte et al., 2013). Ignoring coastal protection is misleading because extensive defense systems exist in developed and well populated coastal locations around the world, with notable concentrations in East Asia and North-West Europe, and many populated deltas (Oppenheimer et al., 2019). Concentrating on defense overflow considers that flood defenses may still provide some protection even if ESL exceeds their height, as defenses still reduce the amount of water flowing into the floodplain. However, it has also been found that coastal defenses often breach once overflow occurs (Hall et al., 2003). These different approaches have not been compared, and the uncertainties have not been assessed at broad-scales, but have been shown to be large at local scale. For the

Solent in the UK, for example, it has been shown that switching from simulating overflow to overtopping and breaching increases the number of properties inundated by factor 3.7 (Wadey et al., 2012). Not considering wave overtopping in broad-scale analysis leads to an underestimation of CFR in areas in which flooding is wave-dominated as found in mid to low latitudes such as western Australia, eastern Madagascar, the Maldives and small islands in the Pacific (Beetham & Kench, 2018; Rueda et al., 2017; Wadey et al., 2017).

Current protection levels. Independent of how defense failure mechanisms are modeled, there is a large uncertainty on current protection levels, because data on the presence of coastal defences, their nominal protection standard, probability of failure, and maintenance level are not systematically available at broad scales. While efforts are underway to collect some of this data (e.g., the FLOPROS database by Scussolini et al., 2016), expert judgment and modeling is presently required to fill the large gaps. For example, Yohe and Tol (2002) and Hinkel et al. (2014) model protection standards as a function of societal wealth and land use/population density. For the 136 largest coastal cities in the world using data supplemented by expert judgment it was estimated that 60% of city defences are below 1 in 100 years, 30% are 1-in-100 years, and 10 per cent were above 1-in-100 years up to 1 in 10,000 years for Amsterdam and Rotterdam in the Netherlands, where the highest defense standards in the world are presently found (Hallegatte et al., 2013). Using the FLOPROS modeling approach, Tiggeloven et al. (2020) have also estimated coastal flood protection for all regions of the world. Uncertainty in resulting protection levels differs substantially between regions but this has hardly been explored.

Inundation modeling. Local scale process-based inundation models are computationally too expensive for broad-scale analysis and require high resolution topographic data that are not readily available. Therefore, broad-scale studies have applied either computationally more efficient reduced-complexity models like LISFLOOD-FP (Bates et al., 2010), for example, at European scales (Vousdoukas et al., 2016), or a static inundation model (i.e., a bathtub approach) in which the coastal water levels are projected inland across the floodplain where defences are overtopped (Diaz, 2016; Hallegatte et al., 2013; Hinkel et al., 2014; Lincke & Hinkel, 2018; Tamura et al., 2019). Locally, the static approach has been found to overestimate flood extents in flatter terrains as compared to dynamic approaches by factor 0.5–2, when the main flooding process involved is overflow (Breilh et al., 2013; Gallien, 2016; Ramirez et al., 2016; Seenath et al., 2016). At broad scales, this has hardly been assessed. Only one study has compared the bathtub approach with LISFLOOD at the European scale, finding that flood extents using the former are about 1.6 times larger than using the latter (Vousdoukas et al., 2016). In this context it should be noted that hydrodynamic models are not necessarily providing better results either, but need to be calibrated to regional circumstances, which is difficult at broad scales. In terms of flood damages, both approaches have been found to produce similar results for Europe (Vousdoukas et al., 2020), which could be explained by an overestimation of the protective effect of defenses being overflown in the dynamic approach, as discussed above.

Irrespective of the type of inundation model applied, other key uncertainties relate to the accuracy of digital elevation model (discussed in the next Subsection), its resolution and, in the case of hydrodynamic approaches, data on surface roughness. As a pixel represents the average elevation height, lower resolutions lead to simplifications and smoothing of the terrain, having indications on the modeling of the flood propagation. For example, increasing the resolution of Lidar data from 100 to 10 m and using a hydrodynamic inundation model has been found to double the 100-year coastal floodplain in Faro, Portugal (Vousdoukas et al., 2018). In contrast, in North Carolina it was found that increasing the DEM resolution from 15 to 6 m using a bathtub 8-side connectivity model reduces the area below 1.1 m by factor 0.8 (Poulter & Halpin, 2008).

Future adaptation. Many CFR assessments do not consider human adaptation when assessing future flood risk, which leads to an overestimation (called no adaptation bias hereafter) of CFR by 2–3 orders of magnitude under SLR in 2100 (Oppenheimer et al., 2019; Hinkel et al., 2014, Table 4). There is wide consensus, both in the flood risk literature generally (Aerts et al., 2018; Di Baldassarre et al., 2015; Haer et al., 2019), and the coastal flood risks literature specifically (Hinkel et al., 2014; Oppenheimer et al., 2019; Wong et al., 2014), that assuming no adaptation is not a plausible scenario for several reasons. Coastal adaptation, specifically the form of building and enhancing coastal defenses, is widespread today, very effective in reducing CFR and societies have a long history of reducing CFR through adaptation (Charlier et al., 2005). This specifically includes these places where potentially the highest coastal flood damages could occur, such as urban areas in river deltas, where local sea-levels have risen by up to several meters due to human-induced subsidence during the last 100 years (See Section 3.1.1). Furthermore, coastal urban areas are also those places where protection is economically very favorable, with benefits of protection being much higher than its costs during the 21st century, even under high SLR scenarios, which suggest that this approach will be widespread in the future (Aerts et al., 2014; Hallegatte et al., 2013; Hinkel et al., 2018; Lincke & Hinkel, 2018; Oppenheimer et al., 2019; Scussolini et al., 2017). As a result, the bias introduced by not considering adaptation in assessing CFR is very large.

But even when considering adaptation, uncertainties in future CFR are large, because a wide range of alternative coastal adaptation scenarios are plausible for several reasons. First, current adaptation practise is diverse, ranging from high flood hazard standards over cost-benefit analysis to large adaptation deficits (Bisaro et al., 2020; McEvoy et al., 2021; Nicholls et al., 2019). Second, adaptation has been mostly reactive depending on the experience of an extreme sea-level event (Rasmussen et al., 2021). Third, social conflicts often impede adaptation efforts and it is impossible to predict how this will evolve in the future (Hinkel et al., 2018).

Despite adaptation scenarios uncertainty being large, this has hardly been explored at broad scales. Adaptation modeling has almost exclusively focused on coastal protection and most studies have thereby focused on normative adaptation models such as maintaining protection levels (i.e., the annual probability of being flooded) constant (Hallegatte et al., 2013; Hoozemans et al., 1993; Nicholls et al., 2019; Tiggeloven et al., 2020), static cost-benefit analysis (Diaz, 2016; Nicholls et al., 2019; Tiggeloven et al., 2020; Vousdoukas et al., 2020), and robust adaptation using the criterion of benefit-cost ratios (Lincke & Hinkel, 2018). Based on these kinds of models it was found that alternative adaptation scenarios influence CFR in 2100 by factors of 20–27 (Nicholls et al., 2019, Table 4). Future work is needed to also explore other adaptation options such as accommodation, retreat and advance and it is expected that this will increase the adaptation scenarios uncertainty range. Furthermore, descriptive models, which are models aiming at mimicking actual human adaptation behavior, have not much been developed, with the exception of Hinkel et al. (2014), who applied an econometric model that explains observed protection levels through socio-economic indicators.

Future shoreline change. Another set of uncertainties is related to future shoreline change and the feed-back that coastal adaptation has on this in terms of preventing shoreline change. Generally, broad-scale assessments of CFR assume that the shorelines (and beach morphology) will not change, which is obviously not generally the case. Currently about 24% of the global sandy beaches are eroding at rates exceeding 0.5 m/yr and 28% are accreting (Luijendijk et al., 2018). SLR could lead to a complete loss of 50% of the world's sandy beaches (Vousdoukas et al., 2020) and local studies show that these effects alter flood extent (Passeri et al., 2015). Furthermore, it has been shown that allowing the shoreline to retreat with SLR (rather than fixing the coastline through protection) influences tidal characteristics and extreme water levels and hence flooding (Idier et al., 2017).

3.3. Exposure

Methods. The broad-scale assessment of exposure of land, population and assets is based on combining elevation data with spatially explicit datasets of population and land-use, and, in the case of exposure to ESL, applying inundation models for assessing the exposure to a flood with a given return period (e.g., 100-year flood). Hence, the main uncertainties in assessing current exposure are associated with the accuracy of the underlying elevation, population and asset datasets. If exposure relative to a given ESL is assessed, then uncertainties in hazard and hazard propagation as discussed in Sections 3.1 and 3.2 also play a key role. Generally, there is little information and systematic exploration of the error introduced in exposure estimates through data (in-)accuracy. However, a range of studies has explored the uncertainty in exposure through applying alternative datasets.

Elevation data. Large uncertainties in exposure are associated with the accuracy of near-global digital elevation models (DEM). Most of these are digital surface models (DSM) and not digital terrain models (DTM), which means they represent the elevation value of the first reflectance surface and not necessarily the terrain itself (McClean et al., 2020). The DEM widely used in earlier broad-scale coastal flood exposure and risk studies include GTOPO30, GLOBE and SRTM30, which all have a spatial resolution of 30 arc-seconds

(~1 km at the equator) (Lichter et al., 2011; McGranahan et al., 2007). More recent studies have employed the newer versions of SRTM90, which have a spatial resolution of 3 arc-seconds (approximately 90 m at the equator) or derivatives that improved SRTM such as MERIT (Yamazaki et al., 2017) and CoastalDEM (Kulp & Strauss, 2018). According to the product specification, the root mean square error (RMSE) of SRTM30 is 9.7 m (Rodriguez et al., 2005), but this has a considerable spatial variation and numerous studies have reported considerably higher accuracies, with errors of 7, 5, 2 m or even 0.5 m, particularly in coastal areas (Gorokhovich & Voustianiouk, 2006; Kellndorfer et al., 2004; Luana et al., 2015). For the Low Elevation Coastal Zone (LECZ), which is the area below 10 m that is hydrologically connected to the ocean, for example, the RMSE of SRTM90 has been estimated at 5.6 m, and those of its derivatives MERIT and CoastalDEM to 3.1 m (Gesch, 2018).

As there is a lack of global high accuracy data against which to validate global DEM, claims about the performance of global DEM in assessing flood exposure need to be taken with caution. Generally, one would expect DSM such as SRTM to underestimate flood extent. For example, the CoastalDEM correction of SRTM increases global population in the LECZ by factor 1.3 and the population in the 1-year floodplain by factor 3.7, but the neural network applied for this correction has only be trained in the US and Australia where local LIDAR (Light Detection and Ranging) data was available (Kulp & Strauss, 2018), and its performance in other regions of the world is largely unknown. Conversely, local scale analysis have found SRTM and other global DEM to overestimate both coastal (Wolff et al., 2016) and river flood extents (McClean et al., 2020). The recently released open Global Lowland DTM (GLL_DTM_v1), based on satellite LIDAR, has a RMSE of 0.5 m in the LECZ (Vernimmen et al., 2020), but only a horizontal resolution of 5.6 km, which makes it currently unsuitable for CFR assessment. Higher resolution versions are announced to be produced, which could then significantly improve broad-scale CFR assessments.

Further uncertainties that have not been explored at broad scales relate to the horizontal resolution of DEM (see subsection on inundation modeling above) and overlaying elevation data with the coastline and population data as these datasets don't match (Lichter et al., 2011; McGranahan et al., 2007; Neumann et al., 2015).

Current population exposure. The main uncertainties in population exposure relate to: (i) the temporal and spatial quality/accuracy of the census input population data; (ii) the implications of the methodological population redistribution approach applied; and (iii) the quality and spatial/temporal accuracies of the ancillary/covariate data used and offsets between DEMs and population data, for instance, due to different coastlines. A number of studies have explored uncertainties in global population exposure by using different global population and elevation datasets (Hinkel et al., 2014; Kulp & Strauss, 2019; Lichter et al., 2011; Mondal & Tatem, 2012; Neumann et al., 2015). Switching between the two most widely used spatial global population datasets, Global Rural-Urban Mapping Project (GRUMP) (CIESIN et al., 2011) and LandScan (Dobson et al., 2003) increases current global exposure estimates by a factor of up to 1.7, depending on the elevation data used (Table 5). This difference is due to different approaches applied and in particular the extent to which population data distribution is modeled. GRUMP is a lightly modeled population data set that assumes that people live where they are registered and that within administrative units the population is allocated to urban or rural areas, which are determined based on settlement points and night-time lights (Balk et al., 2006). Conversely LandScan is a highly modeled population data set that represents the ambient (average over 24 h) population by using roads, land cover and slope to redistribute population within administrative areas (Dobson et al., 2003). There are two more recent higher resolution global population datasets, but these have not been compared to GRUMP and LandScan. The Gridded Population of the World (GPWv4) (Center For International Earth Science Information Network-CIESIN-Columbia University, 2016) gives the non-modeled population per administrative unit and has a spatial resolution of 30 arc seconds. Worldpop (Tatem, 2017) provides a modeled population at the spatially finest resolution of 100 m. Worldpop, GPW and GRUMP have in common that they are adjusted to UN-estimates, whereas LandScan gives the ambient 24 h population and is therefore not adjusted to UN-estimates.

Current assets exposure. For broad-scale assessments, information about individual assets is usually not available and hence this is derived based on other datasets. One approach (Hallegatte et al., 2013; Hinkel et al., 2014) uses data on population exposure and population-to-assets multipliers that are empirically derived from global economic data such as the Penn World Table (Feenstra et al., 2015). Other approaches

(Huizinga et al., 2017) use land-use maps and national information on building construction or replacement cost density. Various datasets exist at relatively high resolution, such as the 30 m GLC30 data set (Chen et al., 2015), and products denoting the percentage of urban surface are also becoming increasingly available, such as the Global Human Settlement Layer (Pesaresi et al., 2013). These global maps represent generic urban areas not subdivided into different types of uses (e.g., commercial, industrial, etc.), which represents an important uncertainty in broad-scale assessments compared to local scale assessment, for which generally a more detailed categorization of uses is available (de Moel et al., 2015). To the best of our knowledge, no study has so far explored the uncertainty in data and methods applied for generating assets exposure at broad scales.

Future exposure. For the assessment of future exposure, sea-level rise, socio-economic and adaptation scenario uncertainties become relevant. Most broad-scale CFR assessments have focused on future population exposure applying national population growth to current exposure under different SSPs (Merkens et al., 2016, 2018; Neumann et al., 2015), which ignores the spatial dynamics of exposure due to processes such as urbanization, land use change and coastward migration. To address this, Jones and O' Neill (2016) and Merkens et al. (2016) created spatial explicit global population grids for each SSP based on the population projections of KC and Lutz (2017). The main difference between the approaches is that Jones and O' Neill (2016) used a gravity-based downscaling model to account for changes in urban extents, whereas Merkens et al. (2016) explicitly accounted for differences in coastal to inland population changes. These subnational projections increase exposure by up to a factor of 1.4 as compared to applying national average population growth. The effect of regionalized population projections on global population exposure has the same magnitude as the effect of switching between SSP scenarios, but a larger magnitude than switching between SLR scenarios.

3.4. Vulnerability

Methods. Broad scale CFR assessments have focused on asset vulnerability, generally represented as depth-damage functions (DDF) that map the water depth to a relative or absolute damage. There is a wide variety of DDF, generally developed for a specific country, such as HAZUS for the USA (Scawthorn et al., 2006) or the multi-colored manual for the United Kingdom (Penning-Rowsell et al., 2014), though also a global database has been developed (Huizinga et al, 2017). Local studies apply DDF to different building types, but as such detailed data are not available at broad scales, broad scale studies apply DDF to either land-use types (Tiggeloven et al., 2020; Vousdoukas et al., 2018), or assets (Hallegatte et al., 2013; Hinkel et al., 2014). Contrary to global river flood assessments, human vulnerability, for example, in terms of flood mortality rates (Dottori et al., 2018; Jongman et al., 2015), has not been studied much in broad-scale CFR assessments.

Depth-damage functions. While uncertainties in DDF at broad scales have hardly been studied, a wide range of local studies has investigated the uncertainty in flood damage modeling, often focusing on river flooding, but sometimes also addressing coastal flooding. Such studies have shown that uncertainties in the damage estimation are usually the same order of magnitude or larger as uncertainties in the flood hazard assessment (de Moel & Aerts, 2011; de Moel et al., 2014; Jongman et al., 2012; Winter et al., 2018). For example, in a sensitivity analysis, de Moel et al. (2012) find that when varying flood damage model parameters, flood damages vary by up to factor 8 in breach locations on the coast of the Netherlands, with DDF being the biggest contributor to total damage uncertainty (about 30%–45%). Similar ranges have been found for coastal flooding on Small Islands (Parodi et al., 2020) and river floods in case studies in the UK and Germany (Jongman et al., 2012). On top of this, the elevation of exposed assets with respect to the ground surface can influence damage estimates considerably (Koivumäki et al., 2010). For example, flood risk reduces by 50% when assuming that the ground floor of all buildings is 50 cm above the ground surface, or 61% when assuming that all buildings would be dry flood proofed (de Moel et al., 2013).

When drawing conclusions for broad scale CFR analysis from these local findings, assumptions on heterogeneity are critically important, because when modeling a large number of individual objects, uncertainties cancel out if they are considered completely independent in terms of vulnerability and asset value (Saint-Geours et al., 2015; Wagenaar et al., 2016). Given the nature of building types in coastal cities, complete independence per object does not seem reasonable, though some heterogeneity is obviously present. Any

Table 7
Overview of Uncertainties and Biases That Have Been Quantified at Global Scales

Source of uncertainty or bias	Target variable	Variation factor	Source Tables
No-adaptation bias	Flood damage	up to 1,300.0	4
Adaptation scenario uncertainty	Flood damage	20.0–26.7	4
Socio-economic scenarios uncertainty	Flood exposure, flood damage	2.3–5.8	4
Ice sheet model uncertainty	Mean sea-level	1.6–3.8	1
Digital elevation model uncertainty	Flood extent, area exposure, people exposure	1.2–3.8	5
Emission scenario uncertainty (mean SLR forcing)	Mean sea-level, extreme sea-levels, flood damage	1.6–2.1	1,4
Population data uncertainty	Population exposure	1.1–1.7	5
Wave calibration datasets uncertainty	Significant wave height	1.7	3
Inundation model bias/uncertainty*	Flood damages	1.6	4
EVA method uncertainty (waves and surges)	Extreme sea-levels, significant wave height	1.1–1.5	2,3
Regionalization of population projections uncertainty	Flood exposure	1.4	5
Emission scenario uncertainty (atmospheric forcing)	Extreme sea-levels	0.8–1.1	2
No-wave-set-up bias	Extreme sea-levels	1.1	5

*The study from which the number is taken covers only Europe.

bias in the functional form of the DDF chosen, however, will not be canceled out. Overall, studies show that between sets of damage functions there are large differences, but uncertainty estimates within a set of functions, generally associated with the value at risk, is substantially lower, as is illustrated by the different estimates of the Multi-Colored Manual (Penning-Rowsell, 2013) and the global database developed by the JRC (Huizinga et al., 2017). Further uncertainties, which have however not been explored at broad scales, relate to water depth being the only variable taken into account in the calculation of damage with DDF, which means that other factors also mediating the damage caused, such as hydraulic pressure, wave forces and salinity, are not considered.

Future vulnerability. Projecting future CFR requires understanding the vulnerability of future societies. While globally, both human and economic vulnerability has decreased significantly in recent decades (Bouwer & Jonkman, 2018; Formetta & Feyen, 2019; Kreibich et al., 2017), the future dynamics in vulnerability (e.g., due to improved early warning and emergency response, flood proofing of infrastructures, better health care, more resistant building practices etc.), have not been addressed in broad-scale CFR assessments studies.

4. Discussion

4.1. What are the Major Uncertainties and Biases and How Could They be Reduced?

When comparing uncertainties and biases across dimensions of broad-scale CFR assessments, by far the largest ones are associated with future human adaptation behavior, which potentially has a multiple order of magnitude effect on future flood risk (Table 7). The largest part of this effect is due to the no-adaptation bias, resulting from ignoring coastal adaptation, which is still a default assumption in many broad-scale CFR assessments (and which dominates associated media coverage). This assumption is, however, misleading and should not be included in the sets of adaptation scenarios that inform policy. In today's world we see extensive adaptation (mainly protection) in coastal areas, high economic benefits thereof and widespread discussion and plans for further adaptation. Hence, it can be asserted that no adaptation scenarios describe a future that will never be seen. The other part of this effect is adaptation scenario uncertainty (factors 20–27), which cannot, by definition, be reduced in principle, because it is not possible to predict how societies will adapt in the future (Oppenheimer et al., 2019). A diversity of adaptation behaviors is plausible, ranging from hard engineered to nature-based solutions and coastal retreat, which need to be explored in broad scale CFR assessments. This can be supported by developing sets of plausible adaptation scenarios that can be used consistently across modeling efforts, similarly to the SSPs.

Next down the ladder of highest global uncertainties are those associated with socio-economic development, ice sheet models and digital elevation data influencing CFR by factors of 2.3–5.8, 1.6–3.8 and 1.2–3.8, respectively (Table 7). Regarding the digital elevation data, it has been argued that a collaborative and open effort toward a freely available high accuracy DEM is needed to address this limitation (Gesch, 2018; McClean et al., 2020; Schumann & Bates, 2018). A higher resolution version of the newly released and freely available satellite LIDAR-based Global Lowland digital terrain model by Vernimmen et al. (2020) may constitute a big step in this direction.

This is followed by GHG emission uncertainty (mean SLR forcing), which contributes with factors of up 1.6 to 2.1 to global mean sea-level uncertainty. Uncertainties in population data, wave model calibration datasets and inundation models have not been studied much at broad scales, but in the few available broad-scale studies these are globally relevant with factors of around 1.5. Emission uncertainty due to atmospheric forcing driving changes in surges and waves is comparably small. The same holds true for the bias introduced by not considering the wave set up contribution globally. While being small in terms of global mean SLR uncertainty, the contribution of human-induced subsidence to local relative sea-level rise in river deltas, especially the rapid subsidence observed in many urban areas in such settings, is globally substantial at least until 2050. Given that this is influenced directly by human agency, however, future human-induced subsidence is highly uncertain.

There are also uncertainties that have been observed to be significant locally, but that have not been quantified at broad scales. Concerning the sea-level hazard, by far the largest uncertainty is related to maximum surge and wave heights under tropical cyclones (Tables 2 and 3). For example, locally surge models have underestimated ESL of large return periods during tropical cyclones by up to a factor of 4 (Muis et al., 2016). What this means for flood risk, which integrates over all return periods, is yet unknown, but as a large fraction of the global coastal zone is exposed to tropical cyclones, these uncertainties are expected to also be significant at global scale. Other uncertainties in sea-level hazard are locally significant for some regions, but probably not so relevant globally. This includes uncertainties due to local shallow water interactions between SLR, tides, waves and surges. In locations with shallow water slopes or extensive tidal flats, such as the German Bight, these processes can double ESL in 2100 (Arns et al., 2017). Ongoing efforts to implement numerical models fed with all forcings is expected to reduce these uncertainties.

Concerning the other components of CFR, uncertainties that have been observed to be significant locally, but that have not been quantified at broad scales, include, foremost, uncertainties in depth-damage functions, for which local studies have shown an effect on flood damages by up to factor 16 (Table 6). Related to this, uncertainties in asset exposure are also expected to be significant globally, given the prevalent large uncertainties in estimates of local GDP and fixed capital stock (Huizinga et al., 2017). With regards to hazard propagation, large uncertainties lie in levels, quality and associated failure modes of coastal defenses. The latter, for example, has been shown to affect flood damages by a factor of up to 4 (Wadey et al., 2012), which is much larger than the local biases reported in association to the bathtub approach (factors 0.5 to 2). Addressing these uncertainties requires the collection of large amounts of local data on observed depth-damage relationships and defense failures, and this would, similarly to what was described above for digital elevation data, also benefit from open community efforts.

4.2. What do These Uncertainties Mean for the Interpretation of CFR Assessment?

When interpreting our results, it is important to recognize that the information on global uncertainties available in the literature is limited, and as a result, we may have overestimated or underestimated some uncertainties. For some dimensions of uncertainties such as defense levels, defense failure and depth damage models, for example, only local estimates were available. Local estimates are generally higher than broad-scale estimates, because in aggregation some of the local uncertainties are canceled out. Furthermore, local studies are generally conducted where uncertainties are expected to be particularly large, which can distort the broad-scale picture. But uncertainties may also be overestimated in broad-scale studies themselves, because many studies have only explored uncertainty ranges, ignoring that the likelihood of the "true" value is generally not uniformly distributed across these ranges.

Another limitation inherent in our literature-based approach to CFR uncertainty as compared to a full *global sensitivity analysis* (see Section 2) is that we were not able to vary all uncertain variables simultaneously and hence may not have captured all interactions between uncertain variables. It turns out, however, that the most important interactions, specifically between different components of CFR, have been covered by the available studies. Hence, it is highly unlikely that conducting a global sensitivity analysis would change the results of this paper significantly. Arguably the major source of nonlinearity in CFR assessments comes from the non-linear distribution of exposure across elevation levels. This could lead to the situation that under low SLR (and hence lower ESL) variations in exposure (or vulnerability, adaptation, etc.) may only have a small effect on CFR, while under high SLR the effect would be large. Hence, it is important to assess interactions specifically between SLR and other uncertain variables, which is generally done by CFR studies because SLR is the main motivation of these studies in the first place. For example, the high sensitivity of damages to adaptation is found for the full range of plausible 21st century sea-level rise scenarios (Table 4).

Nevertheless, uncertainties in broad-scale CFR assessments remain substantial and their results must be understood as indicative of the broad magnitude of flood risks. For the purpose of addressing some of the broad-scale economic questions listed in the Introduction (e.g., global cost of adaptation, risk transfer mechanisms, disaster relief funds, etc.), this is generally not problematic because outputs of CFR, such as expected annual flood damages, must be seen in relation to other economic variables such GDP, population or asset density, which all differ by several orders of magnitude between regions and countries. Furthermore, annual GDP growth rates and discount rates, which typically lie in the order of several percent, inflate or deflate economic variables faster on decadal time scales than sea-levels rise. Both of these points are, for example, illustrated in broad scale cost-benefit analysis of coastal protection measures (Diaz, 2016; Hinkel et al., 2018; Tiggeloven et al., 2020; Vousdoukas et al., 2020), which show order of magnitude differences between benefit-cost ratios around the world's coasts. The same holds true for expected annual coastal flood damages relative to national GDP (Hinkel et al., 2012; Lincke & Hinkel, 2018; Tol, 2007).

Against this background, a number of simplifications made in broad-scale CFR assessments can be justified or are even necessary in order to enable the large number of simulations necessary for some economic analysis. One example is the use of the bathtub model in economic optimization approaches, because the large number of simulations required for this can generally not be conducted with hydrodynamic flood models (Lincke & Hinkel, 2018; Tiggeloven et al., 2020). At the same time, there is a need to better explore the biases in both bathtub and reduced-complexity hydrodynamic models in conjunction with defense failure modes, which has hardly been investigated at broader scales. Another example of a feasible simplification is to ignore changes in ESL distribution due to changing wind and pressure fields under different emission scenarios (atmospheric forcing) and climate models (also called changes in storminess). Given that the contribution of these processes to changes in future ESL is about one order of magnitude smaller than the contribution of changes in mean sea-levels to future ESL (Table 7), substantial computation time can be saved by displacing extreme water levels upwards with mean sea-levels only, instead of also running tide-surge models forced with wind and pressure fields from climate models.

For other purposes such as flood hazard mapping, or when zooming into a particular location, epistemic uncertainties in mean and extreme sea-level hazards, though smaller than socio-economic ones, become very relevant. Determining how safe coastal populations are in a given place requires a much higher accuracy in the water levels and elevation than the broad scale, more economically oriented studies.

Finally, we note that we only considered CFR in terms of direct damages, ignoring the propagation of these through the economic and financial systems to cause indirect economic damages, which extend beyond the flooded area. For example, floods interrupt the production and flow of goods, decrease labor productivity of those affected, and land permanently submerged leads to a loss of land input into agricultural production. This, together with rising adaptation costs, increases the demand for construction services and capital, and hence public debt (Parrado et al., 2020), which in turn propagates through global economic (Bosello et al., 2012; Parrado et al., 2020; Schinko et al., 2020) and financial (Mandel et al., 2020) networks. Locally, and in the direct aftermath of disasters, indirect effects increase overall damages. For example, this has been estimated to account for 40% of the total damages in the case of Hurricane Katrina (Hallegatte, 2008). Longer term macroeconomic effects of disasters can be both positive and negative (Lazzaroni & van Bergeijk, 2014), and one major uncertainty thereby is the economic dynamics of recovery after the event (Koks et al., 2019). We do not consider these effects here, because their assessment relies on wider assumptions on the whole economy, which cannot be covered in this study.

5. Conclusions

This study provided a literature-based comparative assessment of the major sources of uncertainty and bias in broad-scale CFR assessment, considering the four components of: (i) mean and extreme sea-level hazards (including sea-level rise, tides, surges, waves, river run-off and their interactions); (ii) propagation of these hazards into the floodplain, including their interaction with natural and artificial flood barriers; (iii) exposure in terms of area, people and coastal assets threatened by these hazards; and (iv) vulnerability, mainly in terms of depth-damage functions of coastal assets.

We find that there are substantial uncertainties in all dimensions, which highlights the interdisciplinary nature of CFR assessments and the need for dedicated disciplinary efforts to improve the assessment of each dimension. At the same time, there is the need to collectively work across disciplines and toward the needs of the global policy community, as the importance of some issues/uncertainties only become apparent when looking beyond disciplinary bounds. For example, while from a disciplinary perspective there are many uncertainties worth exploring in sea level, from a transdisciplinary perspective of supporting global policy, uncertainties in the order of 10 or 20 cm higher or lower sea-levels may be secondary to many of the other uncertainties raised in this paper.

Globally, by far the largest bias in assessing future CFR is introduced by not considering human adaptation, which can lead to an overestimation of CFR in 2100 by up to factor 1300. But even when considering adaptation, uncertainties in how coastal societies will adapt to sea-level rise dominate, with a factor of up to 27, all other uncertainties. Other large uncertainties that have been quantified globally are associated with socio-economic development (factors 2.3–5.8), digital elevation data (factors 1.2–3.8), ice sheet models (factor 1.6–3.8) and greenhouse gas emissions (factors 1.6–2.1). Local uncertainties that stand out but have not been quantified globally, relate to depth-damage functions, defense failure mechanisms, surge and wave heights in areas affected by tropical cyclones (in particular for large return periods), as well as nearshore interactions between mean sea-levels, storm surges, tides and waves.

We conclude that the advancement of broad-scale CFR assessment requires more comprehensive analysis of uncertainties, including considering uncertainties in methods and data, which have received little attention so far. In particular, adaptation should be considered more explicitly and community efforts to develop consistent adaptation scenarios to be tested in CFR models would be beneficial. The reduction of epistemic uncertainties in hazards requires continued incorporation of new developments in numerical and statistical modeling, specifically taking into account the non-linear interactions between mean sea-level rise, surges, tides and waves. Finally, reducing epistemic uncertainties in digital elevation, coastal protection levels and depth-damage functions requires open community-based efforts, in which many scholars work together in quantifying and validating data from multiple sources.

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Data were not used, nor created for this research.

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