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Uncertainty representations of mean sea-level change: a telephone game?

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Abstract

For the long-term management of coastal flood risks, investment and policy strategies need to be developed in light of the full range of uncertainties associated with mean sea-level rise (SLR). This, however, remains a challenge due to deep uncertainties involved in SLR assessments, many ways of representing uncertainties and a lack of common terminology for referring to these. To contribute to addressing these limitations, this paper first develops a typology of representations of SLR uncertainty by categorising these at three levels: (i) SLR scenarios versus SLR predictions, (ii) the type of variable that is used to represent SLR uncertainty, and (iii) partial versus complete uncertainty representations. Next, it is analysed how mean SLR uncertainty is represented and how representations are converted within the following three strands of literature: SLR assessments, impact assessments and decision analyses. We find that SLR assessments mostly produce partial or complete precise probabilistic scenarios. The likely ranges in the report of the Intergovernmental Panel on Climate Change are a noteworthy example of partial imprecise probabilistic scenarios. SLR impact assessments and decision analyses mostly use deterministic scenarios. In conversions of uncertainty representations, a range of arbitrary assumptions are made, for example on functional forms of probability distributions and relevant confidence levels. The loss of quality and the loss of information can be reduced by disregarding deterministic and complete precise probabilistic predictions for decisions with time horizons of several decades or centuries and by constructing imprecise probabilistic predictions and using these in approaches for robust decision-making.

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1 Introduction

For the long-term management of local coastal flood risks, investment and policy strategies need to be developed in light of the full range of uncertainties associated with future mean sea-level rise (SLR). This is not an easy task due to deep uncertainties (Kwakkel et al. 2010) involved in the assessment of future local sea-level changes. For example, it is ambiguous how to define or produce SLR upper bounds for decision-making (Pfeffer et al. 2008; Lowe et al. 2009; Hinkel et al. 2015), mean SLR ranges diverge between process-based and semi-empirical SLR assessment methods (Church et al. 2013a) and different assumptions on ice-sheet processes can be made that have a major impact on projected ice-sheet contributions and total SLR in the second half of this century and beyond (Kopp et al. 2014; DeConto and Pollard 2016; Kopp et al. 2017). In the presence of such deep uncertainties, choices have to be made on which uncertainties to represent and how (Bakker et al. 2017a). SLR uncertainty can for example be summarised by likely ranges (Church et al. 2013a) or by probabilistic scenarios that also provide information on plausible but less likely SLR futures (Kopp et al. 2014; Jackson and Jevrejeva 2016; Nauels et al. 2017; Le Bars et al. 2017).

In the face of deep uncertainties and multiple ways of representing uncertainty, the challenge for impact assessment and decision analysis lies in retaining decision-relevant information about the full range of potential SLR, while converting this information to fit decisions and context in which these are taken. This involves two challenges. First, SLR information needs to be converted between different uncertainty representations on its way from production to its use in impact assessments and decision analyses. In every conversion, additional assumptions are made that are possibly not grounded in SLR physics, or information is lost. This could alter decisions.

Second, terminology on uncertainty representations and assumptions behind these are ambiguous in the literature, which has been a source of confusion and misinterpretation of SLR information. For example, the upper bound of the global mean SLR that *likely* ranges under the highest greenhouse gas concentration scenario in the Intergovernmental Panel on Climate Change (IPCC) report (Church et al. 2013a) has been misinterpreted as a worst-case upper bound (Church et al. 2013b). Another example is found in Bakker et al. (2017a), who discussed that the likely ranges of IPCC AR5 have been interpreted in different ways, for example as likely = 66% or likely = 90%, across SLR assessments without an explicit reference to these interpretations.

The array of uncertainty representations applied and the associated interpretation problems has triggered a renewed debate about which method or methods to use for representing mean SLR uncertainty. For example, Cooke (2015) argues that subjective probabilities are the only relevant way to represent and quantify climate change uncertainty. In contrast, Bakker et al. (2017b) and Le Cozannet et al. (2017) argue that probabilistic SLR scenarios need to reflect deep uncertainties or imprecision in SLR assessments, and Hinkel et al. (2015) argue that tailored high-end SLR information at different time scales is needed for different decisions and contexts. This debate is also complicated by the absence of a shared terminology to refer to uncertainty representations, which we consider to be a prerequisite to ensure a shared understanding of SLR information, co-produce useful SLR information and select appropriate impact assessment and decision analysis methods. Whereas the many methods for representing uncertainty have generally been extensively studied in theoretical research (Dubois et al. 2000; Walley 2000) and in related research fields, such as hydrology and structural engineering (Krzysztofowicz 2001; Gao et al. 2010), their applications have not been systematically studied in the SLR literature. To our knowledge, a concise categorisation of uncertainty representations is currently unavailable in this literature.

This paper aims to contribute to addressing these limitations by developing a typology of uncertainty representations (Section 2) and by analysing the use of uncertainty representations of mean SLR across SLR assessments, impact assessments and decision analyses (Section 3). Section 4 illustrates sequences of uncertainty representation conversions and assumptions made. Directions for a more consistent treatment of SLR uncertainty across studies are discussed.

2 Typology of uncertainty representations

This section introduces a typology of uncertainty representations of mean SLR (Section 2.1) and illustrates the resulting categories of uncertainty representations (Section 2.2).

2.1 Typology development

Uncertainty representations of mean SLR were categorised by answering the following three questions:

Level 1. Do pathways of future mean sea levels depend on a plausible storyline of, for example, greenhouse gas emissions or concentrations?
YES: SLR scenario, NO: SLR prediction

Level 2. What kind of variable is used to represent mean SLR uncertainty?
(i) DETERMINISTIC VARIABLE: deterministic representation, (ii) INTERVAL VARIABLE: interval representation, (iii) FUZZY or FUZZY RANDOM VARIABLE: imprecise probabilistic representation, (iv) RANDOM VARIABLE: precise probabilistic representation

Level 3. Is SLR uncertainty fully quantified within the scenario or prediction?
YES: complete representation, NO: partial representation

The top level of the typology distinguishes between SLR scenarios and SLR predictions. In this research, an SLR scenario is defined as a quantitative description of pathways of future mean sea levels that depend on a plausible storyline. A SLR prediction, in contrast, is defined as a quantitative description of unconditional pathways of future mean sea levels in this research. A plausible storyline is a narrative of, for example, greenhouse gas emissions (Nicholls and Tol 2006) or greenhouse gas concentrations (Riahi et al. 2011). These rely on assumptions about future socioeconomic, political, technological or other developments that are "deeply" uncertain. Deep uncertainty implies that multiple scenarios can be enumerated, but without specification of their likelihood and without the ability to rank or order the scenarios on their likelihood or plausibility (Kwakkel et al. 2010).

The second level of the typology distinguishes between variable types that are commonly used to represent uncertainty: deterministic variables, interval variables, fuzzy or fuzzy random variables and random variables (Krzysztofowicz 2001; Gao et al. 2010). Any variable type can be used in both scenarios and predictions. For example, a prediction using a deterministic variable will be called a "deterministic prediction" or a prediction using a random variable a "precise probabilistic prediction".

The third level of the typology distinguishes between complete and partial SLR uncertainty representations. The former provides a full quantification of the uncertainty within a scenario or prediction, whereas the latter does not. In this research, an uncertainty representation that does not quantify uncertainty below some lower percentile strictly greater than 0% or beyond some higher percentile smaller than 100% is categorised as partial. This distinction was only applied to precise probabilistic and imprecise probabilistic scenarios or predictions, because deterministic and interval scenarios and predictions are complete by definition. Interval predictions can be imprecise: for example, info-gap theory represents uncertainty by nested uncertainty sets (Ben-Haim 2006). This case was excluded from the analysis: we are aware of only one SLR application (Hall and Harvey 2009).

2.2 Illustration of the typology

The typology results in 12 categories of uncertainty representations. In what follows, each of these categories is introduced by an example shown in Fig. 1. All examples use the likely SLR ranges of the latest IPCC report under RCP 2.6 and RCP 8.5 (Church et al. 2013a). The likely ranges were converted into other uncertainty representations by making arbitrary assumptions, which are further investigated in Section 4.

Deterministic SLR scenarios specify one SLR value at a moment in time for two or more greenhouse gas or other scenarios. Figure 1a displays a numerical example. In this example, SLR will be 0.44 m by 2100 under RCP 2.6, and 0.74 m by 2100 under RCP 8.5. No uncertainty is considered within the scenarios. A deterministic prediction suppresses uncertainty and specifies a single SLR value at a moment in time. For example, Fig. 1b displays the deterministic prediction "SLR will be 0.57 m by 2100".

Interval SLR scenarios represent SLR uncertainty within a greenhouse gas scenario by an interval variable: an interval of SLR with a given lower and a given upper bound. The SLR values of an interval are not associated with any probability.[1] Figure 1c displays two interval scenarios: "global mean SLR will lie between 0.28 m and 0.61 m by 2100 under RCP 2.6" and "global mean SLR will lie between 0.52 m and 0.98 m under RCP 8.5". An interval prediction specifies a single SLR interval. Figure 1d displays the interval prediction "global mean SLR will lie between 0.28 m and 0.98 m by 2100".

Complete precise probabilistic SLR scenarios represent uncertainty within a greenhouse gas scenario by a single and fully specified probability distribution. Figure 1e provides an example of two complete precise probabilistic scenarios: conditional global mean SLR probability distributions under RCP 2.6 and RCP 8.5. A complete precise probabilistic prediction provides a full specification of an unconditional probability distribution. Figure 1f displays a complete precise probabilistic prediction that assumes that global mean SLR is normally distributed.

Partial precise probabilistic SLR scenarios represent uncertainty within a greenhouse gas scenario by a probability range or point estimates of interest. A probability range includes probabilistic information on the likelihood that SLR does not fall within this range. Figure 1g displays an example of two partial precise probabilistic scenarios that together provide two 5–95% probability ranges. Figure 1h displays a partial precise probabilistic prediction by an unconditional median estimate and a 5–95% probability range.

[1] An interval projection becomes a complete precise probabilistic projection if a uniform or other probability distribution function is defined. Non-probabilistic decision analyses, for example minimax analysis, do not use probabilistic information.

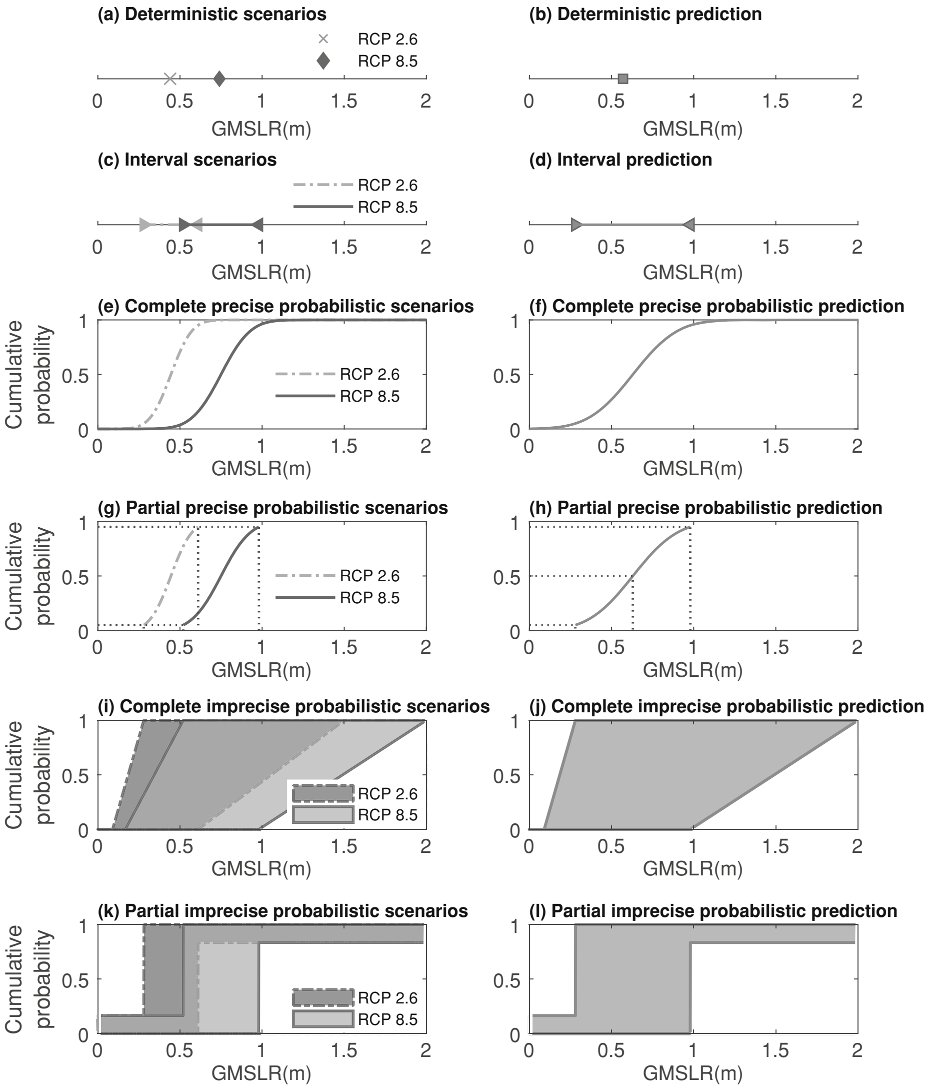

Fig. 1 **a**–**l** Uncertainty representations of global mean sea-level rise (GMSLR) by 2100. The left panels display GMSLR scenarios, and the right panels display GMSLR predictions

Complete imprecise probabilistic SLR scenarios represent uncertainty within a greenhouse gas scenario by imprecise probabilities, i.e. a set of fully specified probability distributions (Dubois et al. 2000). Figure 1i displays an example of two complete imprecise probabilistic scenarios. The interpretation is as follows: an ill-known cumulative distribution function (CDF) is contained in a conditional probability box (P-box). Under RCP 2.6, this is the dashed trapezoid. Figure 1j displays a complete imprecise probabilistic prediction: an unconditional P-box. It was obtained by taking the uppermost CDF under RCP 2.6, and the lowest CDF under RCP 8.5.

Partial imprecise probabilistic scenarios are a mixture of imprecise probabilistic and partial probabilistic scenarios. Within a greenhouse gas scenario, SLR uncertainty is represented by partial probabilistic information on a set of probability distributions. Figure 1k shows two examples of partial imprecise probabilistic scenarios: partially specified P-boxes for RCPs 2.6 and 8.5. Figure 1l displays a corresponding partial imprecise probabilistic prediction if it is assumed that RCP 2.6 is the best-case scenario, and RCP 8.5 is the worst-case scenario.

3 Uncertainty representations of sea-level rise in the literature

Uncertainty representations of mean SLR of 147 papers were categorised across the following three types of studies: SLR assessments (N1 = 29), impact assessments of SLR (N2 = 77) and SLR decision analyses (N3 = 41). Details on the sample selection procedures are provided in Supplementary Information 1, and the sample coding of these papers is provided in Supplementary Information 2.

We distinguish between SLR impact assessments and SLR decision analyses based on their respective aims (Hinkel and Bisaro 2015). The former aims to assess impacts of SLR, such as the increase in the number of people at risk of flooding or the change in monetary damage potential. Potential and residual impact assessments are distinguished. The latter include additional coastal adaptation alternatives as compared to a benchmark, e.g. no adaptation or continuation of an existing flood risk policy.

A decision analysis, in contrast, aims to quantify decision trade-offs to provide insights in the preferred choice between adaptation alternatives. For example, a decision analysis can be performed to identify one optimal alternative from a set of alternatives with one or more decision criterions. Please note that there are many decision analysis methods, and the sample of decision analysis papers in Supplementary Information 2 contains a limited number of examples of some of these methods. Moreover, the distinction between a local residual impact assessment and a decision analysis is arbitrary if the primary goals of study are to both assess local impacts descriptively and to identify a preferred adaptation alternative.

3.1 Scientific sea-level rise assessments

Table 1 shows examples of SLR uncertainty representations that are used in SLR assessments. Partial precise probabilistic scenarios are the most common uncertainty representation in the SLR assessment literature. For example, Schaeffer et al. (2012) use a semi-empirical modelling (SEM) approach to investigate mean SLR under temperature target scenarios. Uncertainty is represented by median SLR estimates and 90% probability ranges. Horton et al. (2014) use an expert elicitation (EE) method and report medians, first and third quartiles and "likely" (17–83%) and "very likely" (5–95%) SLR ranges for two RCPs. DeConto and Pollard (2016) use a process-based modelling (PBM) approach and summarise the simulation results by ensemble means and probability ranges of one standard deviation for RCP scenarios.

Complete precise probabilistic scenarios have been increasingly used for representing mean SLR uncertainty in recent years. These sets of scenarios largely diverge across studies and strongly depend on ice-sheet assumptions. For example, Kopp et al. (2014) use a PBM approach that is combined with the EE study on ice-sheet contributions of Bamber and Aspinall (2013). Local probability distributions of SLR are estimated by sampling from the probability distributions of the contributions of the sea-level components for the RCP 2.6, 4.5 and 8.5 scenarios. Grinsted et al. (2015) estimate regional SLR probability distributions for Northern Europe under RCP 8.5. Le Bars et al. (2017) investigate the effect of temperature-dependent Antarctic ice-sheet

Table 1 Examples of uncertainty representations of SLR information in scientific SLR assessments

Uncertainty representation	Literature example	Time horizon	Assessment approach	SLR information/numerical example year 2100 (y: base year)
Deterministic scenarios	Miller et al. (2013)	2100	Paleo rec., PBM	SLR mid-Atlantic US/1.50 m under high scenario (y2000)
Interval prediction	Rahmstorf (2007)	2100	SEM	GMSLR/[0.5,1.4] m (y1990)
Complete precise probabilistic scenarios	Kopp et al. (2014)	2200	PBM, EE	Local PDFs world RCP scenarios/ 0.5–99.5% range GMSLR 0.39–1.76 m under RCP 8.5 (y2000)
	Grinsted et al. (2015)	2100	PBM, EE	Local PDFs Northern Europe RCP 8.5/5–95% range GMSLR 0.45–1.83 m (y2000)
	Le Bars et al. (2017)	2100	PBM	GMSLR PDFs RCP scenarios/5–95% range 0.81–2.92 m under RCP 8.5 (y1986–2005)
Complete precise probabilistic prediction	Bamber and Aspinall (2013)	2100	EE	PDF GMSLR rate due to ice sheets/5–95% range 1.34–17.61 mm per year by 2100
Partial precise probabilistic scenarios	Schaeffer et al. (2012)	2300	SEM	GMSLR median values and probability ranges temperature target and other scenarios/5–95% range 0.56–1.05 m under Stab 2 °C scenario (y2000)
	Horton et al. (2014)	2300	EE	GMSLR probability ranges RCP scenarios/5–95% range 0.5–1.5 m under RCP 8.5 (y2000)
	DeConto and Pollard (2016)	2500	PBM	GMSLR ensemble means and probability ranges RCP scenarios/ 1.05 ± 0.30 m 1sd under RCP 8.5 (y2000)
Complete imprecise probabilistic scenarios	Le Cozannet et al. (2017)	2100	Study combination	GMSLR possibility distributions RCP 8.5/SLR upper bounds of 1.5 m, 2.0 m or 5.0 m (y1986–2005)
Complete imprecise probabilistic prediction	Abdallah et al. (2014)	2100	Study combination	GMSLR plausibility and belief functions/ belief F(SLR) = 0 for SLR < 0.79 m, F(SLR) = 1 for SLR > 2 m (y2000)
Partial imprecise probabilistic scenarios	Church et al. (2013a)	2100	PBM	GMSLR median values and likely ranges RCP scenarios/0.45–0.82 m 2081–2100 under RCP8.5 (y1986–2005)

contributions, and estimate a probabilistic SLR scenario under RCP 8.5 that is compared to the SLR scenarios of IPCC (Church et al. 2013a) and DeConto and Pollard (2016).

A small minority of SLR assessments uses interval predictions, deterministic scenarios or complete precise probabilistic predictions for representing mean SLR uncertainty for time horizons up to 2100 or beyond. For example, Rahmstorf (2007) converts temperature scenarios from IPCC AR3 ranges into a single interval. This interval is then used as an input to a SLR equation. The output is an SLR interval prediction, i.e. one SLR interval for 2100. Miller et al. (2013) construct four deterministic relative SLR scenarios for 2030, 2050 and 2100 for the mid-Atlantic US region. These include deterministic scenarios of regional oceanographic effects and deterministic scenarios of local subsidence. An example of a complete precise probabilistic prediction of a sea-level component for 2100 is the unconditional PDF of the Greenland and Antarctic ice-sheet contributions in Bamber and Aspinall (2013). Note that it has been derived from partial probabilistic expert judgements obtained from Cooke's expert elicitation method.

Not surprisingly, no deterministic SLR predictions were identified, and to the best of our knowledge, these do not exist. Only few studies use complete or partial imprecise probabilistic scenarios or predictions for representing mean SLR uncertainty. Le Cozannet et al. (2017) construct complete possibilistic[2] or imprecise probabilistic scenarios, and Abdallah et al. (2014) a complete imprecise probabilistic prediction. The likely ranges of global mean SLR in the IPCC AR5 report (Church et al. 2013a) provide a noteworthy example of partial imprecise probabilistic scenarios. AR5 estimates that global mean sea level is *likely* to rise by 0.26–0.55 m from 1986–2005 to 2081–2100 under RCP2.6 and 0.45–0.82 m under RCP8.5. Likely is defined as 66–100% probability in the calibrated uncertainty language of IPCC. Church et al. (2013b), however, state that this interpretation implies a "roughly a one-third probability that mean SLR by 2100 may lie outside the "likely" range", which arguably is a different set of partial imprecise probabilistic scenarios.

3.2 Sea-level rise impact assessments

In contrast to SLR assessments, most assessments of SLR impacts represent mean SLR uncertainty by a set of deterministic scenarios. SLR impacts are typically assessed with deterministic scenarios for time horizons beyond 2050. This observation appears to be largely independent of the type of assessment: local or global assessments, potential or residual impact and monetised or non-monetised impacts. Table 2 illustrates this.

Local impact assessments apply various local SLR scenarios. For example, Hall et al. (2005) apply national scenarios to analyse potential flood risk increases in England and Wales. Local impact assessments also apply deterministic scenarios of global SLR scenarios. For example, Cooper et al. (2013) apply "best" (0.75 m) and "worst case" (1.90 m) SLR scenarios of Vermeer and Rahmstorf (2009) to analyse potential area and monetary losses for the case of Maui, Hawaii. Ward et al. (2011) represent SLR uncertainty by taking the minimum and maximum values of the likely global SLR ranges of the IPCC AR4 scenarios, 0.18 and 0.59 m, to analyse the potential damage exposure increase for Jakarta. Impact studies at supranational spatial scales usually apply

[2] Imprecise probability theories include possibility and necessity measures, plausibility and belief functions and various other mathematical models (Walley 2000). Le Cozannet et al. (2017) convert partial probabilistic projections for RCP 8.5 into possibilistic projections ("probability-possibility transformation"). These are then converted into imprecise probabilities ("possibility-probability transformation").

Table 2 Examples of uncertainty representations of SLR information in SLR impact assessments

Uncertainty representation	Literature example	Time horizon	Spatial scale	Assessment approach	SLR information applied (y: base year)
Deterministic scenarios	Hall et al. (2005)	2080	England and Wales	PIA: monetary	0.26 m and 0.86 m local SLR in south-east England by 2080 (y2002)
	Cooper et al. (2008)	2100	New Jersey, USA	PIA: non-monetary	0.61 m and 1.22 m local SLR by 2100 (y1988)
	Ward et al. (2011)	2100, N/A	Jakarta, Indonesia	PIA: monetary	0.18 m and 0.59 m by 2100 (y1980–1999), and 0.0 to 6.0 m in steps of 0.5 m
	Yoo et al. (2011)	N/A	Busan, South Korea	PIA: non-monetary	0.5 m, 1.0 m, 2.0 m, and 3.0 m local SLR
	Bosello et al. (2012)	2080	25 EU countries	RIA: monetary	GMSLR HADCM3 B2 Low 0.194 m, (..), ECHAM4 A2 High 0.585 m by 2100 (y1990)
	Cooper et al. (2013)	2100	Maui, Hawaii	PIA: monetary	GMSLR 0.75 m and 1.90 m by 2100 (y1983–2001)
	Hinkel et al. (2014)	2100	Global	RIA: monetary	GMSLR IPSL-CM5A-LR RCP 2.6 0.30 m, (..), MIROC-ESM-CHEM RCP 8.5 0.86 m by 2100 (y1986–2005)
Deterministic prediction	Najjar et al. (2000)	2095	Mid-Atlantic coastal region	PIA: non-monetary	0.61 m local SLR by 2095
	Kont et al. (2003)	2100	Estonia	PIA: non-monetary	1.0 m local SLR by 2100
	Hanson et al. (2011)	2070	136 port cities	RIA: monetary	0.5 m GMSLR by 2070 (y2005)
	Neumann et al. (2015)	2060	Global	PIA: non-monetary	0.21 m by 2060 (y1990)
Complete precise probabilistic scenarios	Diaz (2016)	2100	Global	RIA: monetary	Local probabilistic SLR scenarios Kopp et al. (2014)
	Lin and Shullman (2017)	2100	New York City	PIA: monetary	Local probabilistic SLR scenarios Kopp et al. (2014)
Complete precise probabilistic prediction	Purvis et al. (2008)	2100	Somerset, England	PIA: monetary	Triangular distribution on interval [0.09,0.88] m GMSLR by 2100 (y1990)

PIA, potential impact assessment; *RIA*, residual impact assessment a set of deterministic SLR scenarios from a set of climate models, for example to estimate residual SLR impacts in Europe (Bosello et al. 2012) or global adaptation costs (Hinkel et al. 2014).

In some cases, deterministic scenarios are pragmatically specified for modelling or other reasons. For example, Cooper et al. (2008) pragmatically specify 0.61 m (2 ft) and 1.22 m (4 ft) SLR (2100) to analyse the potential SLR impacts on the coastal region of New Jersey, USA. Yoo et al. (2011) pragmatically specify 0.5 m, 1 m, 2 m and 3 m SLR to analyse potential impacts of SLR on the city of Busan, South Korea.

Deterministic predictions are also frequently applied in SLR impact assessments. For example, Hanson et al. (2011) apply 0.5 m global mean SLR by 2070 to analyse population and asset values exposed to coastal flooding in coastal cities around the world. Najjar et al. (2000) apply 0.61 m (2 ft) SLR by 2095 for a potential impact assessment for the mid-Atlantic coastal region. Neumann et al. (2015) apply 0.21 m SLR by 2060 to assess the increase in global exposure due to SLR. Kont et al. (2003) apply 1 m of SLR by 2100 to assess potential SLR impacts for Estonia.

Some impact assessments use probabilistic uncertainty representations, such as complete precise probabilistic predictions or complete precise probabilistic scenarios. The latter are applied in Diaz (2016) and Lin and Shullman (2017). An example of an application of a complete precise probabilistic prediction of global mean SLR is found in Purvis et al. (2008). An unconditional SLR probability distribution is obtained by fitting a triangular probability distribution to the lower and upper bounds of earlier IPCC scenarios.

3.3 Sea-level rise decision analyses

Table 3 shows examples of SLR uncertainty representations that are used in decision analyses. SLR decision analyses appraise coastal risk management and adaptation investments or policies in the face of relative sea-level change. The mean SLR uncertainty representations that are frequently applied in these decision analyses are similar to the ones applied in SLR impact assessments and are again different from the ones that are frequently applied in SLR assessments. Time horizons of decision analyses diverge and depend on the characteristics of the adaptation alternatives. However, decision analyses are in many cases either about or include structural flood protection alternatives, and these alternatives typically require time horizons of several decades or longer.

A majority of SLR decision analyses represent mean SLR uncertainty by deterministic scenarios. The SLR scenarios applied thereby diverge across studies. For example, Kirshen et al. (2008) apply 0.6 and 1.0 m (2100) to study damage and costs of adaptation alternatives in Metro Boston, whereas King et al. (2016) apply 1.0 m, 1.4 m and 2.0 m local mean SLR (2100) in a cost-effectiveness approach (CEA) to support flood risk management in California. One explanation for such differences is provided by the variation in high-end scenarios that are specified to represent a SLR worst-case upper bound for flood risk management purposes. For example, Koks et al. (2014) consider next to a moderate scenario, a worst-case scenario of 2.0 m of local SLR by 2100 for the analysis of coastal flood risk and adaptation alternatives in Belgium. Lonsdale et al. (2008) apply deterministic SLR scenarios up to 5 m to analyse adaptation responses in the Thames Estuary under a surprise scenario of a rapid collapse of the West Antarctic ice sheet.

Deterministic SLR predictions are also frequently applied in decision analyses, and some decision analysis methods tend to use these if the aim is to find an alternative that performs

Table 3 Examples of uncertainty representations of SLR information in SLR decision analyses

Uncertainty representation	Literature example	Time horizon	Spatial scale	Decision approach	SLR information applied (y: base year)
Deterministic scenarios	Kirshen et al. (2008)	2100	Metro Boston	CEA/CBA	Local SLR 0.6 m and 1.0 m by 2100 (y2000)
	Lonsdale et al. (2008)	2150	Thames Estuary	Adaptive management	Up to 5.0 m GMSLR by 2130 (y2000)
	Brekelmans et al. (2012)	2310	Dike rings Netherlands	Regret analysis	Low, average and high local SLR rates
	Koks et al. (2014)	2100	Belgium	Benefit analysis	0.60 m and 2.00 m by 2100 (y2005)
	King et al. (2016)	2100	California	CEA	1.0 m, 1.4 m and 2.0 m SLR by 2100 (y2000)
	Eijgenraam et al. (2017)	Infinity	Dike rings Netherlands	CBA	Local SLR rates based on KNMI scenarios
Deterministic prediction	Raaijmakers et al. (2008)	2051	Ebro Delta, Spain	MCA	Local SLR 3 mm/year
Interval prediction	Klijn et al. (2012)	2050	Dike rings Netherlands	Exploratory policy analysis	[0.15,0.35] m local SLR by 2050 (y2005)
Complete precise probabilistic scenarios	Abadie et al. (2017)	2100	120 coastal cities	Expected shortfall, value-at-risk	Geometric Brownian motion calibrated with local SLR scenarios Kopp et al. (2014)
	Wong et al. (2017)	2100	New Orleans, Louisiana	CBA	PDFs RCP scenarios, 5–95% ranges: 0.43–0.74 m under RCP2.6, 0.56–1.30 m under RCP4.5, and 1.09–2.07 m under RCP8.5 (y1986–2005)
Complete precise probabilistic prediction	Woodward et al. (2014)	2100	Thames Estuary	ROA	Normal distribution fitted to UKCP09 SLR scenarios for emission scenarios, to which equal probabilities are assigned
Partial imprecise probabilistic prediction	Buchanan et al. (2016)	2100	71 US tide gauge locations	Constant hazard allowance	Limited degree of confidence criterion calibrated with partial probabilistic information of local SLR scenarios Kopp et al. (2014)
	Dawson et al. (2018)	2060	Dawlish, Devon	ROA	Probability weights applied to percentile values UKCP02 and UKCP09 SLR scenarios

"best" across states of the world. An example is found in Raaijmakers et al. (2008), in which a spatial multi-criteria analysis (MCA) approach is developed. MCAs generally need single-valued effect scores for each decision criterion to determine a single ordering of alternatives. The case study application uses a deterministic SLR prediction for 2051 to achieve this.

Some decision analysis methods may need some modifications to allow for other uncertainty representations. For example, Eijgenraam et al. (2017) apply deterministic SLR scenarios in a cost-benefit analysis (CBA) of dike investments and flood protection standards. In related work, a Monte Carlo simulation was performed of uncertain variables to investigate the robustness of the results of the CBA (Kind 2014). The latter uses a correlation between damages and optimal protection for computational reasons. Robust decision-support methods do not necessarily use different uncertainty representations as CBA, but may help to select a preferred alternative across SLR scenarios. For example, Brekelmans et al. (2012) apply deterministic SLR scenarios in regret analyses.

SLR interval scenarios and interval predictions are rarely applied in decision analyses. An example is found in Klijn et al. (2012), which uses a 0.15–0.35 m SLR interval prediction for the year 2050. Various robust decision-support methods can apply SLR interval predictions, but this is not commonplace. The same holds for partial and complete imprecise probabilistic SLR scenarios and predictions, although this might change in the future due to recent development of methods that can use these. We mention Buchanan et al. (2016) and Dawson et al. (2018) as examples.

SLR decision analyses that apply complete precise probabilistic scenarios or predictions can be divided in applications without and with investment flexibility. An example of the first is found in Wong et al. (2017): probabilistic SLR scenarios are applied in a CBA. The latter are typically found in classical real options approaches (ROAs). For example, Abadie et al. (2017) apply complete precise probabilistic scenarios for RCPs, and Woodward et al. (2014) apply a complete precise probabilistic prediction. Two types of these representations can be distinguished. The first type considers a probability distribution of SLR for a year in the future and assumes a gradual change of mean sea levels between two decision moments. The second type considers mean sea level to randomly change over time by assuming a stochastic process. Woodward et al. (2014) provides an example of the first, whereas Abadie et al. (2017) provides an example of the latter.

4 Conversions between uncertainty representations

The literature reviewed shows that diverse conversions between uncertainty representations are applied in the chain from producing SLR information to using this information for coastal decision-making. These conversions deserve attention as they may introduce additional assumptions or lead to a loss of information, both of which may misguide the use of SLR information in decision-making. We illustrate this by investigating chains of uncertainty representations and assumptions made for five cases.

The first case is the one of IPCC AR5, which represents uncertainty in the form of partial imprecise probabilistic scenarios (i.e. the likely ranges). To convert a set of SLR simulations from different climate models into these ranges, two conversions between uncertainty representations and a number of assumptions were made. First, a functional form was assumed and a confidence level was selected to generate partial probabilistic scenarios from SLR simulations. Specifically, the CMIP5 model spread was treated as a normal distribution, and a 90%

probability range was generated for each RCP scenario (Church et al. 2013c). Next, these ranges were converted into partial imprecise probabilistic scenarios by interpreting them as likely (66–100%) ranges. These, in turn, were interpreted again as partial precise probabilistic scenarios by other assessment studies (Bakker et al. 2017a).

The second case is the construction of a complete precise probabilistic prediction from IPCC AR4 likely ranges illustrated by Hunter et al. (2013). The chain of uncertainty representations starts from the 5–95% model-based ranges of IPCC AR4. These ranges are converted into complete precise probabilistic scenarios by assuming a SLR probability distribution function: a normal and a raised cosine distribution are applied. Next, the probabilistic SLR scenario under the A1FI emission scenario is selected to determine the vertical distance that an asset needs to be raised to keep the flood probability the same as today. Hunter et al. (2013) use this scenario "because this is the one that the world is broadly following at present". Following our definition, this corresponds to an uncertainty representation by a complete precise probabilistic prediction.

The third case is the construction of an interval prediction from IPCC AR5 likely ranges as illustrated by Bierkandt et al. (2015). The authors take the upper bound of the IPCC AR5 likely range for RCP 8.5, 1-m global mean SLR by 2100, and apply it to assess potential impacts of SLR on US power plants. This involves two key assumptions. The first assumption made is that the SLR upper bound under RCP 8.5 is an expected upper bound. This interpretation corresponds to the conversion of a partial imprecise probabilistic scenario of IPCC into an interval scenario. Note that it is obtained if it is assumed that likely = 100%. The second assumption made is that the RCP 8.5 scenario is the greenhouse gas concentration scenario "expected to occur without effective mitigation policies" (Bierkandt et al. 2015). This assumption converts the interval scenarios into an interval prediction.

The fourth case consists in combining SLR information from multiple studies into deterministic scenarios. Antonioli et al. (2017) construct and apply deterministic SLR scenarios by combining two SLR scenarios with different uncertainty representations: the likely ranges of IPCC AR5 (Church et al. 2013a) and the interval prediction of Rahmstorf (2007). The latter representation was investigated in Section 3.1. First, the SLR scenario under RCP 8.5 is converted into an interval scenario, and the SLR range of Rahmstorf (2007) is added as a second interval scenario. Next, these two interval scenarios are converted into four deterministic scenarios by selecting the minimum and the maximum values of the interval scenarios. Note, however, that the conversion between interval and deterministic representations does not have to make such an ad hoc selection. Instead, it may also provide a discrete approximation of an interval. Hallegatte et al. (2011), for example, approximate an SLR interval prediction of zero to 1.25 m by steps of 0.25 m.

The fifth case consists in combining SLR information from multiple studies into a complete imprecise probabilistic prediction. To achieve this, a fuzzy interval of SLR has to be constructed first, which can then be converted into an imprecise probabilistic prediction. A fuzzy interval specifies an interval with fuzzy bounds rather than crisp, i.e. single-number, upper and lower bounds. A fuzzy interval consists of a kernel or core, which is the crisp set that contains elements that have membership one, and the bounded support, which contains elements that have nonzero membership (Dubois et al. 2000). An illustration of fuzzy intervals and their conversion into a complete imprecise probabilistic prediction is provided in Supplementary Information 1.

Abdallah et al. (2014) obtain the core of a fuzzy interval of SLR by converting the SLR scenarios of AR4 into an interval prediction, which is combined with the SEM study of

Rahmstorf (2007). Specifically, the authors construct an SLR interval with a lower bound of the AR4 model-based range under the SRES B1 scenario and define an upper bound that exceeds the likely range under the SRES A1FI scenario by 0.2 m. The intersection of this interval and the one of Rahmstorf (2007) is used as the core of the fuzzy interval. To derive the support of the fuzzy interval, a lower bound of zero is assumed and the study of Pfeffer et al. (2008) is used to define an upper bound. Lastly, three different functional forms of the membership function are considered, and each of these fuzzy intervals is converted into a complete imprecise probabilistic prediction.

5 Ways forward

SLR uncertainty representations in the decision-making literature are driven by the choice and information requirements of decision-support methods. From this perspective, the reviewed literature shows a tendency to use deterministic scenarios, deterministic predictions and complete precise probabilistic predictions. This is probably due to the fact that this kind of SLR information can be directly used in "predict-then-act" approaches to decision-making (Weaver et al. 2013), such as CBA or ROA (Watkiss et al. 2015). Deterministic predictions do not communicate how sensitive SLR impacts or decision outcomes are to SLR uncertainty, and this information may be essential to inform coastal adaptation decision-making. Therefore, one has to be cautious with the use of deterministic SLR predictions and decision-support methods that may use these to inform decisions across states of the world, such as multi-criteria analysis. Section 3 also pointed out that some other decision-support methods, such as classical ROA methods,[3] use complete precise probabilistic predictions by design. ROA methods analyse future decisions, and this increases the length of the time horizon as compared to one-shot decisions that are taken now. Complete precise probabilistic scenarios across RCPs may not differ much up to 2030 or 2040 or further at some locations (Kopp et al. 2014; Le Cozannet et al. 2015). However, long-term decision analyses that apply complete precise probabilistic SLR predictions well beyond such time horizons ignore the theoretical difficulties to assign probabilities to greenhouse gas emissions (Wong et al. 2014).

In recent years, some global and local impact assessments (Diaz 2016; Lin and Shullman 2017) have applied complete precise probabilistic scenarios of Kopp et al. (2014). However, long-term potential flood impacts can be dramatically higher under other ice-sheet assumptions, for example Kopp et al. (2017). The usefulness of one set of complete precise probabilistic scenarios for long-term adaptation decision-making needs to be critically questioned given their consequences for estimated impacts, and if used, the choice of scenarios has to be made with the local decisions and context, such as economic and technical lifetimes, fixed and variable costs, societal intolerance to uncertainty and policy objectives, in mind.

A promising way forward is offered by complete or partial imprecise probabilistic SLR scenarios and complete or partial imprecise probabilistic predictions, and their use in approaches for robust decision-making (see example 5 in Section 4). Both of these uncertainty representations can be derived in a straightforward manner from the complete and partial precise probabilistic scenarios offered by the SLR assessment literature. Imprecise

[3] Classical ROA methods analyse the value of investment flexibility in stochastic settings (Dixit and Pindyck 1994). Recent methods have started to explore imprecise probabilistic concepts, such as probability thresholds (Lempert et al. 2012) or multiple SLR priors (Dawson et al. 2018).

probabilistic scenarios can combine the scenarios from multiple studies without losing information, which is one core requirement for decision-making given the ambiguity between expert opinions and studies. For example, one could combine the AR5 scenarios with recent probabilistic SLR scenarios. These have fatter tails than earlier ones, because new but uncertain physical processes in ice-sheet dynamics are considered (Kopp et al. 2014; DeConto and Pollard 2016; Kopp et al. 2017; Le Bars et al. 2017). Imprecise probabilistic scenarios can be further converted into an imprecise probabilistic prediction by combining these across greenhouse gas scenarios. This requires to assume a worst-case and a best-case scenario. While this is a difficult assumption to make, it is made implicitly by using RCP2.6 as the best case and RCP8.5 as the worst case.

Imprecise probabilistic predictions can be used for robust decision-making in at least two ways. First, robust decision-support methods can be considered that apply either complete or partial imprecise probabilistic predictions. To date, few SLR decision analyses have done so (Section 3.3). Second, a complete or partial imprecise probabilistic prediction can be used to formulate an interval prediction that is in line with the decisions and context at hand. For example, an imprecise probabilistic prediction leaves the choice of the decision-relevant percentiles and the worst case considered to decision-makers. A risk-averse decision-maker could e.g. choose a 95th or 99th percentile of a worst-case probability distribution from a complete imprecise probabilistic prediction. Such interval predictions can then be used in robust decision-support methods that can apply these, for example "robust optimisation" (Ben-Tal et al. 2009) or minimax or regret analyses (Giuliani and Castelletti 2016). Many other approaches have been advocated to support robust decision-making on climate change adaptation alternatives (Hall et al. 2012; Kwakkel et al. 2016). Yet, SLR applications of various approaches for robust decision-making have remained relatively scarce.

This paper has not systematically investigated the interplay between the choice of SLR uncertainty representations and the choice of impact assessment or decision analysis methods in a given decision context (e.g. Heal and Millner 2014). This constitutes an important area of future research, specifically because recent literature has emphasised that efforts to produce SLR information should start from the perspective of the users and decisions they are facing (Kunreuther et al. 2013; Hinkel et al. 2015; Weaver et al. 2017; Helgeson 2018). This includes the choice of uncertainty characterisations appropriate for a given decision context and decision-support methods relevant for that context, as well as for the production and presentation of SLR information in scientific assessments. The presented typology could be applied for such in-depth analyses.

This paper has restricted attention to representing mean SLR uncertainty due to climate change. However, these methods are also applicable to other sea-level uncertainties, for example to land subsidence or changes in extreme sea levels.

6 Conclusions

Uncertainty representations are essential to be able to represent uncertain information in geophysical studies about future mean sea-level rise (SLR), in assessments of impacts of SLR and in analyses of long-term adaptation decisions. However, coastal decision-making may be misguided if an uncertainty representation of SLR is selected that does not match with the full range of SLR information that is available or that does not match with the decisions and context in which these are taken. Specifically, two issues arise.

First, while SLR assessments tend to use partial or complete precise probabilistic scenarios, the majority of SLR impact assessments and decision analyses represent mean SLR uncertainty by deterministic scenarios. In converting from the former to the latter, information that may be essential for decision-making is lost and arbitrary additional assumptions that may misguide decision-making are made.

Second, there is ambiguity about uncertainty representations within the SLR assessment literature. On the one hand, complete precise probabilistic SLR scenarios are produced that can be directly applied or easily converted into formats suitable for decision-making. On the other hand, it is questioned whether precise probabilities can be quantified both within and beyond likely ranges, amongst others due to deep uncertainty in ice-sheet responses. The partial probabilistic scenarios attained when not quantifying the tails, however, cannot be applied in a decision analysis without additional assumptions on for example lower and upper SLR bounds.

Both of these issues can be addressed by using common uncertainty representations across the SLR assessment, impact assessment and decision analysis literature. This would avoid losing information or making arbitrary assumptions in converting between types of studies. Specifically, our analysis suggests to (i) disregard deterministic and complete precise probabilistic predictions for long-term adaptation decisions and (ii) construct imprecise probabilistic predictions and use these in approaches for robust decision-making. Furthermore, the application of our framework for referring to uncertainty representations can contribute to resolving confusion or misinterpretation about SLR information, for example about the meaning of likely ranges.

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