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Damage functions for climate-related hazards: unification and uncertainty analysis

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Abstract

Most climate change impacts manifest in the form of natural hazards. For example, sea-level rise and changes in storm climatology are expected to increase the frequency and magnitude of flooding events. In practice there is a need for comprehensive damage assessment at an intermediate level of complexity. Answering this need, we reveal the common grounds of macroscale damage functions employed in storm damage, coastal-flood damage, and heat mortality assessment. The universal approach offers both bottom-up and top-down damage evaluation, employing either an explicit or an implicit portfolio description. Putting emphasis on the treatment of data uncertainties, we perform a sensitivity analysis across different scales. We find that the behaviour of intrinsic uncertainties on the microscale level (i.e. single item) does still persist on the macroscale level (i.e. portfolio). Furthermore, the analysis of uncertainties can reveal their specific relevance, allowing for simplification of the modelling chain. Our results shed light on the role of uncertainties and provide useful insight for the application of a unified damage function.

1 Introduction

It is apparent that most climate change impacts manifest in the form of natural hazards. For instance, sea-level rise does not bring about a slow perpetual flooding of low-lying areas. Instead, it contributes to (and potentially amplifies) the wide variability of sea levels dominated by tides, wind surges, and waves (Seneviratne et al., 2012; Boettle et al., 2013). Accordingly, in many cases sea-level rise and climate change are expected to be reflected by an increasing frequency and magnitude of storm surges and extreme events, respectively (IPCC, 2012).

Based on recent research on the costs of natural hazards (Meyer et al., 2013) and climate change (IPCC, 2014), we identify the two main challenges for an integrated multi-risk assessment of damages arising from climate-driven natural hazards:

1. Developing damage models on an intermediate level of complexity, bridging the gap between global and case-study impact assessment and providing transparent and transferable methodology.

2. Fostering the quantification and understanding of uncertainties arising along the causal chain, laying emphasis on their relevance and significance for well-informed decision making.

With this agenda in mind, we will reveal how damage functions of various impacts can be built upon the same foundations. This common ground represents a *unified damage function for climate-related hazards* and provides a platform to discuss the origin and relevance of potential uncertainties from a generic point of view, as we will show in the following.

A *damage function* provides the typical quantitative damage for an event of given magnitude. Often, a monetary assessment is the goal and corresponding damage functions relate the magnitude of the natural hazard and the monetary loss. However, the availability of damage functions is very limited. On the one hand, for many sites or impacts there are no recorded losses so that empirical damage functions cannot be characterised. When the hazard is rare or losses are not recorded, statistics is insufficient to derive or calibrate damage functions. In that case, one tries to explore so-called synthetic damage functions which are based on assumptions. On the other hand, the correlations between loss and explanatory variable might be weak, so that the expected loss and its uncertainty have a similar order of magnitude.

It follows that in practice there is a need for comprehensive approaches for risk analyses and management, enabling the quantification and comparison of the impacts from different natural hazards and their interactions (Kreibich et al., 2014). Hence, addressing our first main challenge, we elaborate an approach common in the assessment of coastal flood damages (e.g. Boettle et al., 2011; Hinkel et al., 2014) and identify links to the assessment of winterstorm damages (Heneka and Ruck, 2008). Moving towards a multi-risk assessment, we show how this unified damage function can be extended to the quantification of heat-wave mortality. Heat-wave mortality is of particular concern, as already today heat-related fatalities comprise over 90 % of total natural-hazard fatalities in Europe and are also a major concern for developing countries (Munich Re, 2013; Golnaraghi et al., 2014).

In coastal flooding, damage function have been employed, for example, for the assessment of the prospective flood risk for coastal mega-cities (Hallegatte et al., 2013) and global coastlines (Hinkel et al., 2014). However, little focus has been given to the uncertainties engrained within the damage function and their interactions. While on case study level a series of publications aim to quantify uncertainties with respect to coastal flooding (e.g. Apel et al., 2004; Merz and Thieken, 2009; de Moel and Aerts, 2011; de Moel et al., 2012; Aerts et al., 2014), a comprehensive yet universal discussion of uncertainties is still wanted.

A similar picture arises from studies focussing on European winterstorm loss (Schwierz et al., 2010; Donat et al., 2011), where mostly deterministic damage functions are employed. Employing probabilistic approaches, Heneka and Ruck (2008) and Prahl et al. (2012) offer some indication of uncertainty related to the hazard magnitude. Still, a comprehensive attribution and discussion of various uncertainty sources is lacking.

In the current scientific debate, as reflected by the recent IPPC report on climate change, strong emphasis is being put on the quantification and communication of risks emanating from climate change (IPCC, 2014; Mastrandrea et al., 2011; Adler and Hirsch Hadorn, 2014). Hence, addressing our second main challenge, we perform a variance-based sensitivity analysis of data uncertainties within the model chain, putting emphasis on the crossover between micro- and macroscale level. Finally, the work in hand sheds light on the role of individual sources of uncertainty and provides guardrails for the consideration of relevant uncertainties.

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2 Unified damage functions

2.1 Schematic outline

In the context of this work, a *damage function* is defined as the mathematical relation between the magnitude of a (natural) hazard and the typical damage caused on a specific item (building, person, etc.) or portfolio of items. We put emphasis on direct monetary damage (loss), but the basic findings can in principle be generalised to any quantifiable damage.

The damage function provides a means to estimate the loss caused by hazard events of a specific magnitude. It requires the definition of an indicator, or proxy, for the *hazard magnitude*, which should provide the highest explanatory power in regard to the damage type under scrutiny.

In the context of damage functions, we define the *microscale* level as relating to a single item. In contrast, the *macroscale* level refers to the examination of a granular portfolio of approximately homogeneous and independent items. With this definition, we go beyond similar definitions that define the macro domain solely via the spatial extent (e.g. Merz et al., 2010). For simplicity, we assume that all items within a portfolio are exposed to the same hazard magnitude. In the regional context a macroscale damage function may refer to a city or otherwise spatially delineated portfolio.

While being approximately homogeneous in type and value, individual items may differ in their susceptibility to the hazard. The fact that damages do not occur randomly, but rather in response to a certain hazard magnitude, implies an item-specific *hazard threshold*. Upon exceedance of this threshold the increase of damage is governed by a microscale damage function.

2.2 Model derivation for coastal flooding

We begin by considering damages from coastal flooding of an idealised city. As illustrated in Fig. 1a, the city is comprised by a spatially delineated ensemble of similar items, e.g. residential buildings. From first principles, the overall monetary damage in the city must be equal to the sum over the damage costs for each individual building. Without loss of generality we assume equal monetary value for each item, which simply facilitates aggregation of relative (i.e. fractional) damages. This assumption will be relaxed in the subsequent discussion on uncertainties (see Sect. 3).

Neglecting ancillary damaging effects, such as floating debris, the damage to an individual building is dominated by the hazard magnitude at the site. In case of floods, the hazard magnitude may be represented by a more or less complex indicator. Here, we choose the most basic indicator, maximum flood height, for a straightforward proof of concept.

Considering topography, it becomes evident that individual buildings will be diversely affected according to their geographic location. Damage is caused only if the local flood level exceeds the surrounding ground level (orographic elevation) of the building. Taking into account natural and man-made barriers, the hazard threshold (i.e. the flood level at which a particular building is affected) will be correlated with the orographic elevation of the building ground floor as illustrated in Fig. 3a. Thus, the city's building portfolio can be described by a distribution of hazard thresholds that are derived from the elevation levels of each building and its surroundings.

If *explicit* information on the elevation of each building is available, the entire portfolio can be described by a frequency distribution of hazard thresholds. This is typically the case for bottom-up approaches.

Where explicit information is not available, or a top-down approach is chosen, the hazard thresholds can often be described *implicitly* via a probability density distribution. Suitable distributions may be inferred from empirical data or via expert judgement.

A microscale damage function is used to estimate (relative) damage to those buildings, where the local hazard magnitude exceeds the hazard threshold. In the flooding example, we identify this exceedance as the inundation level of the building.

The average relative damage to all individual buildings determines the flood damage to the idealised city and, hence, constitutes the (unified) macroscale damage function.

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Mathematically, Eqs. (1a) and (1b) express the expected value of macroscale flood damage d at flood height x for the explicit and implicit portfolio description, respectively.

$$d_{\mathrm{expl}}(x) = \sum_k f(\lambda_k) g(x - \lambda_k) \tag{1a}$$

$$d_{\mathrm{impl}}(x) = \int_0^x f(\lambda) g(x - \lambda) \mathrm{d}\lambda \tag{1b}$$

Here, $f(\lambda_k)$ denotes a frequency distribution of discrete values λ_k. For the continuous representation of λ, $f(\lambda)$ denotes a probability density function. A detailed derivation of Eqs. (1a) and (1b) is provided in Appendix A.

Schematically, Fig. 2a–c shows the relationship between macroscale damage, portfolio composition, and microscale damage function for a given hazard of magnitude x_0. For the colour-coded portfolio segments, the macroscale damage results as the frequency weighted sum over the microscale damages indicated by the respective coloured arrows. Moreover, Figure 2d–f shows the actual damage function estimated for the case study of Lisbon, which is explained in more detail in Sect. 3.2.

2.3 Extension to further hazards: storm and heat

Formally, the mathematical relationships derived in the previous section also hold for other natural hazards such as storm damages and heat-related mortality. Figure 1 shows three different examples of previously published damage functions. Coastal flood damages to the case study Kalundborg have been estimated based on detailed microscale information (Fig. 1b). Storm damage for a German district (Fig. 1c) and heat mortality in Bologna (Fig. 1d) are based on statistical studies, additionally providing estimated confidence bounds. All three examples exhibit the characteristic monotonous increase and are a composite of microscale damages – differing essentially only in the microscale damage function and the distribution of hazard threshold.

For the case of storm hazard, the decisive factors for a building's resistance to wind speed are typically not known and the implicit description of the hazard threshold is particularly useful. Given sufficient damage information, e.g. from insurance loss records, it may be feasible to infer the actual shape of the probability density distribution. For example, Heneka and Ruck (2008) demonstrate the calibration of a Gaussian distribution for insurance storm-loss records. This calibration was used to produce Figs. 2g–i, which show the macroscale damage function, portfolio distribution, and microscale damage function, respectively. Prahl et al. (2015) have found that this damage function does perform well compared to other statistical damage models.

Similarly, the model can be set up to describe heat-related mortality. In general terms, the mortality rate is a measure of fatalities in a given population over a certain period of time. While it is not always possible to attribute distinct causes for these deaths, the effect of excess mortality due to the impact of heat waves has been widely studied (e.g. Leone et al., 2013; Gasparrini et al., 2015). Typically, excess mortality describes the increase of daily mortality in relation to a temperature indicator. In absolute terms, the increase in mortality can be defined as the daily number of heat-related fatalities divided by the total population.

Although it is a delicate issue to discuss human mortality in a technical language, we believe that it allows for an intuitive and meaningful application of the unified damage function. First, we model decease via a Heaviside step function, where 0 and 1 denote life and death, respectively. The step function takes the part of the microscale damage function in our unified model. Second, the hazard threshold directly defines the maximum heat-wave intensity (e.g. apparent temperature) tolerated by an individual. While this threshold is generally not known and may also fluctuate over time, a statistical description of the distribution of heat-wave thresholds within the population would be feasible. Figure 3b shows a stylised relationship between age and the heat hazard threshold based on the works of Hajat et al. (2007) and Basagaña et al. (2011).

Extending the regional focus, Leone et al. (2013) and others have shown an influence of local climatic conditions as well as socio-demographic and economic characteristics on the shape of the damage function. However, a comprehensive functional attribution of impacts on the hazard threshold is yet to be found.

Caution must be taken when considering the uncertainty of the hazard threshold (illustrated in Fig. 3). In contrast to the cases of coastal-flood and storm damages, where building portfolios change only gradually, human heat tolerance is subject to continuous biophysical, behavioural, and environmental changes. Hence, constant variation of the threshold exceedance must be taken into account for ongoing heat waves. Rather than modelling this uncertainty explicitly (as in Sect. 3.1), the microscale damage function could be redefined to describe a probability of decease via a suitable sigmoid curve.

3 Uncertainty

3.1 Brief taxonomy of uncertainty sources

Among the different scientific disciplines, and even within the field of natural hazards research, there are a multitude of different classifications of uncertainty (e.g. Merz and Thieken, 2009; de Moel and Aerts, 2011). For the work at hand, we define a minimal taxonomy of uncertainty sources relevant to our context.

Leaning on the simple definition by the IPCC (2005) and the uncertainty framework by Kreye et al. (2011), we broadly classify uncertainties relevant for the unified damage function into data (parametric) uncertainty and model (structural) uncertainty. Uncertainty of the former kind may arise from data incompleteness, where data cannot be estimated directly, or from measurement error. Model uncertainty may result from conceptual, from mathematical, and/or from computational uncertainty. While computational error should be negligible, uncertainty due to mathematical approximation and overall conceptualisation (e.g. functional form and parameter choice) plays a significant role. Schröter et al. (2014) show that models of increasing complexity not only reduce modelling uncertainty but also foster transferability.

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In the work at hand, we focus our discussion on data uncertainty with the intention of characterising the impact of various input parameters on the damage function. Precise understanding of the data uncertainty not only is key for the application of the damage function but is also a necessary prerequisite both for calibration and validation.

Data uncertainties arise at each step along the causal chain, from the modelling of the hazard through the estimation of specific microscale damage to the validation against reported losses. On the most general level, data uncertainties can be separated into intrinsic and extrinsic uncertainties. *Intrinsic uncertainties* arise from local variation or random fluctuation within the considered portfolio and affect the damage assessment of each individual portfolio item. In contrast, *extrinsic uncertainties* arise from external modelling or measurement and globally affect the entire portfolio. As such, they must be considered for the application or validation of the macroscale damage function.

An overview of uncertainties is given in Fig. 4. The figure shows the specific uncertainties considered and indicates their context for damage modelling. In the following, we describe each of the uncertainties (a)–(e) in detail.

a. At the lack of spatially resolved information, the distribution of asset values within a portfolio can cause uncertainty for macroscale loss estimation. Although a precise attribution of economic values is possible on a detailed case study level, large-scale assessment typically rely on by-proxy estimation of average asset value (e.g. Hallegatte et al., 2013; Hinkel et al., 2014), thus accepting a certain level of uncertainty.

b. In general, damaging processes are not well understood and are dependent on construction types and employed materials. While it is not feasible to model all physical processes in depth, engineering-based modelling or empirical research may at least allow for a stratification of microscale damage functions for a few predefined asset classes (Hammond et al., 2015). However, since a complete consideration of all physical characteristic remains elusive – and certainly goes beyond our envisaged intermediate level of complexity – the microscale damage level constitutes a significant source of uncertainty.

c. In our framework, we employ the idealised concept of a certain hazard threshold and consider the exceedance of the local hazard magnitude beyond the threshold. In practice, damages are dependent on a – often poorly understood – complex interplay of various physical attributes of the hazard. This aspect manifests in an imperfect correlation between the indicator-based hazard threshold and the actual damage occurrence, hence causing statistical uncertainty. In addition, there may also be variation in the hazard threshold due to incomplete information.

d. Data describing the hazard magnitude are required for the application of the damage function. Invariably, these data incorporate uncertainty which may for example originate from measurement error, a model ensemble, or statistical confidence bounds. Prahl et al. (2012) highlight the relevance of this uncertainty, showing evidence that variability of reported storm losses could be largely due to uncertainty in wind measurements.

e. For purposes of calibration and validation, model estimates are often put into comparison with reported figures of damage or economic loss. Like any other input to the damage function, these figures are subject to uncertainty. Reported figures may for example be affected by gradual damage accumulation masking the effect of individual hazard occurrences, by incentives for insurance holders (e.g. deductibles), and by wealth levels that affect both building quality and likelihood of purchasing insurance.

Evidently, there cannot be a general yet exhaustive discussion of uncertainties involved in damage estimation. Having covered the major uncertainties in a basic set-up of the unified damage function, we acknowledge that in a more case-specific set-up further uncertainties may arise. Such would be the case if e.g. large-scale protective measures (such as flood barriers) were in place, introducing a possibility of protection failure (de Moel et al., 2012).

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3.2 Exemplary case studies

Based on our taxonomy of uncertainties, we provide an exemplary parametrisation of the unified damage function for two separate climate- related hazards: (i) coastal flooding in Lisbon, Portugal, and (ii) winter-storm damage for a German building portfolio comprised of five thousand individual buildings. The Lisbon case exemplifies a bottom-up approach, where we derive a geo-referenced building portfolio from topographic and census data. As such, the individual hazard thresholds are known explicitly. A complementary top-down approach is pursued for the German portfolio, with an implicit description of the hazard threshold by mean of a probability density distribution. Table 1 summarises the parametrisation of the portfolio and the microscale damage function for both cases. For a discussion of the chosen parametrisation we refer the reader to Appendix C.

Figure 2d–f and g–i show the derived macroscale damage function, the portfolio definition, and the assumed microscale damage function for both cases, respectively.

Unlike the general features of the damage function, the nature of the uncertainties involved is typically not well understood and their quantification heavily relies on assumptions. Nonetheless, we attempt a parametrisation of the uncertainties defined in Sect. 3.1 for both exemplary cases. A comprehensive summary of the involved uncertainties, the employed parametrisation, and used references is provided in Table 2. A discussion of the parametrisation is given in Appendix C.

In the following, we conduct a detailed sensitivity analysis of the uncertainties, based on the parametrisation for the case of coastal flooding in Lisbon.

3.3 Sensitivity analysis

The relative influence of the various sources of uncertainty can be assessed by a global sensitivity analysis. Following the approach by Saltelli et al. (2008) we perform a variance-based sensitivity analysis. As the overall damage is effectively an aggregation of microscale damages, the analysis should take the different scales into account.

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We consider sensitivity on two distinct scales: (i) individual building, i.e. micro scale, and (ii) the city, i.e. macro scale. As an intermediate step, we consider the sole effect of intrinsic uncertainties on the macroscale damage. On each scale, we use a Monte Carlo sampling size of 10 000 and obtain boot-strapped confidence intervals from re-sampling 1000 times. We apply the Jansen estimator (Jansen, 1999; Saltelli et al., 2010) to estimate the total-effect index. A detailed account of the standard methodology used is included in the Supplement.

The total-effect index denotes the fraction of output variance (variance in macroscale loss) that has been caused by the variance of the respective input variable including all variance caused by its potential interactions (correlation) with other input variables. For the employed damage function, first-order effects dominate, and secondary interaction play a minor role only for small inundation/flood levels. At these levels, the uncertainty in threshold exceedance/hazard magnitude implies a non-zero probability for not causing any damage and, hence, acts as a switching element for the damage function and its remaining uncertainties. Detailed results for first-order effects as well as second- and third-order interactions are provided in the Supplement.

Figure 5 show the total-effects index for the Lisbon case study. Panel a shows the effect of the intrinsic uncertainties on the microscale damage function (i.e. concerning a single building). Clearly, uncertainty in the building's asset value dominates for inundation levels beyond 1 m, diminishing the impact of uncertainty in the hazard threshold exceedance, caused either by local hazard fluctuations or error in the hazard threshold, which dominates only for low levels of inundation. While the variance of the damage level is certainly significant (cf. Fig. 2f), it is generally outweighed by the variance in asset value.

The overall behaviour seen for the microscale case also holds true for the accumulated building portfolio of Lisbon. Excluding extrinsic uncertainty, Fig. 5b shows the sensitivity of the portfolio damage to microscale uncertainties. Again, the results have been obtained from a Monte Carlo simulation, this time sampling 10 000 random realisations for the entire building portfolio. In contrast to the microscale case, the plot

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indicates a stronger impact of the uncertainty in the threshold exceedance. This behaviour arises from the fact that there are additional buildings affected as the flood level increases. Hence, the marked bump of the curve above 4 m flood height is explained by the strong increase of affected buildings at that elevation (cf. Fig. 2e).

On the macro level, Fig. 5c shows the shares of total variance due to either the accumulated intrinsic uncertainties or an extrinsic uncertainty in the global hazard magnitude. The uncertainty in hazard magnitude, i.e. due to measurement or modelling error, is of particular importance, as it represents the only extrinsic uncertainty and hence does not scale with the inverse root of portfolio size. The complex behaviour seen, can be decomposed into two main aspects. Firstly, the relative importance of intrinsic uncertainties decrease with rising flood levels. Secondly, the strong impact of intrinsic uncertainties around a flood level of 2 m results from the very low increase of affected buildings, as is seen in Fig. 2e. Higher numbers of newly affected buildings at around 3 m, and in particular beyond 4 m, lead to an increased relevance of the uncertainty in hazard magnitude seen in Fig. 5c.

The variance caused by uncertain input variables is dominated by first order effects, i.e. input variance directly impacting output variance without interaction terms. In fact, our analysis shows that apart from very small flood levels, higher order effects play an insignificant role and may generally be neglected (see Supplement for detailed sensitivity analysis on first and higher order indices). Without interaction, the relevance of the uncertainties is determined by their relative magnitude. In this regard, Fig. 5d shows the isolated effect of selected input variables on the standard deviation of damage estimates. Comparison with panels b and c shows that the dominating source of uncertainty also exhibits the largest standard deviation.

4 Conclusions

A unified damage function was developed on common grounds in the assessment of flood and storm hazards. The approach comprises a synthesis of synthetic bottom-up

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and empirical top-down damage evaluation. It is hence identified as a valuable building block towards a *theory of damage functions*. Providing a general framework for the assessment of climate-related hazards, we proposed a widened scope of application to include, but not limited to, heat-wave mortality. Its broad scope admits a multi-hazard perspective on climate-related impacts at an intermediate level of complexity. Furthermore, cross-hazard comparison of uncertainties within the common framework has the potential to provide valuable insight, fostering our understanding of the nature and relevance of uncertainties along the causal chain.

From a practitioner's point of view, determining the relevant sources of uncertainty is arguably more important than identifying and quantifying all possible uncertainty sources. Answering this purpose, valuable insight could be gained from a variance-based sensitivity analysis of the unified damage function. Investigating the case of coastal flooding for the city of Lisbon, a set of general conclusions could be drawn.

On the most general level, we have distinguished between extrinsic and intrinsic sources of uncertainty. Extrinsic sources are defined as acting simultaneously on the entire portfolio (e.g. hazard magnitude), while intrinsic uncertainties arise locally and affect individual portfolio items (w.r.t. asset value, damage level, and threshold exceedance). As shown by the Lisbon case study, extrinsic uncertainty can play a crucial role as the dominant source of uncertainty. In contrast to the intrinsic uncertainties, whose standard deviation increases approximately with the root of the portfolio size, the magnitude of extrinsic uncertainty is strictly proportional to portfolio size. Hence, given a sufficiently large portfolio and wide uncertainty intervals of the hazard magnitude, inspection may show negligibility of intrinsic uncertainty sources. This is of particular importance in climate science, where practitioners often deal with ensemble simulations exhibiting large model spreads. It is also highly relevant for the field of natural hazards research, where extreme value theory often implies broad confidence intervals.

Considering the relevance of intrinsic uncertainty sources, our results demonstrate that intrinsic uncertainty on portfolio level is governed by the composition of uncertainties within the microscale damage function. Uncertainty due to local hazard fluctuations or variations in hazard threshold (modelled as exceedance uncertainty) show significance only for low hazard magnitudes. The relevance of this magnitude range depends on the modeller's objective. In certain cases (e.g. focussing at high-end scenarios or including protective measures such as flood barriers) hazard levels below a certain bound may not be relevant.

The Lisbon case study also shows the extent to which variability in asset values can dominate intrinsic uncertainty. While it could be significantly reduced by using of spatially-resolved data, this is not generally the case for data-scarce regions within developing countries, also being more severely affected by natural disasters (IPCC, 2012).

The universality of the conclusions on uncertainty also extends to other hazards that naturally require different microscale damage functions. Since the shape of the microscale damage functions is solely dependent on the hazard magnitude, different shapes could be obtained via simple axis transformations. For the sensitivity results this implies, for example, that a more shallow microscale damage function would result in a stretch along the hazard axis, while preserving overall behaviour.

Answering the need for comprehensive approaches for risk analyses and management, we pinpoint how the principles of unified damage functions could be extended from the quantification of coastal flood and storm damages to the estimation of heatwave fatalities. With its wide applicability to the assessment of both loss and fatalities, the unified damage function has the potential to narrow the gap towards a comprehensive multi-risk appraisal of climate-related hazards. Moving towards this goal, the interdependence and cascading effects of climate-related hazards become of wider concern. For further research, we hence envisage the extension of the universal damage function framework to include path-dependent non-stationary hazard thresholds.

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Appendix A: Mathematical derivations for the damage function

A1 Explicit threshold representation

We define a microscale damage function $g(x-\lambda_i)$ which expresses the damage fraction of a single item i, dependent on the exceedance of the hazard magnitude x over the individual hazard threshold λ_i.

This definition implies that a single item will suffer damage only if its hazard threshold is exceeded. Accordingly, the microscale damage function must evaluate to 0 for $x < \lambda_i$ and increase monotonically from 0 to an upper bound $g_{max} \leq 1$ for $x \geq \lambda_i$, where g_{max} represents maximum possible damage as a fraction of the item's value. In general, g can exhibit jumps and thus is not necessarily differentiable.

It is reasonable to assume that all items in the portfolio are exposed to the same hazard, i.e. with the same characteristics. This assumption is being relaxed only in the subsequent treatment of uncertainties (see Appendix B), where local hazard fluctuations are considered. The fraction of affected items c, i.e. the number of damaged items relative to the total number of portfolio items n, can hence be inferred via the number of items for which x reaches or exceeds λ_i. Explicitly,

$$c_{expl}(x) = \frac{1}{n}\sum_{i=1}^{n} u(x-\lambda_i), \tag{A1}$$

where u denotes the Heaviside step function, defined as

$$u(z) = \begin{cases} 0 & \text{, for } z < 0 \\ 1 & \text{, for } z \geq 0 \end{cases}. \tag{A2}$$

The damage ratio, i.e. the fractional damage to the entire portfolio, can be expressed as the average damage suffered by the individual items,

$$d_{expl}(x) = \frac{1}{n}\sum_{i=1}^{n} g(x-\lambda_i). \tag{A3}$$

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Alternatively we can aggregate portfolio items with identical hazard threshold λ_k and employ a discrete frequency distribution $f(\lambda_k)$, where k denotes distinct observations of λ. Thus, we obtain Eq. (1a), namely

$$d_{\mathrm{expl}}(x) = \sum_k f(\lambda_k)g(x-\lambda_k).$$

A2 Implicit threshold representation

From a probabilistic point of view, we consider the individual hazard thresholds, λ_i, of the portfolio items as (independent) realisations of a random variable Λ, for which a cumulative distribution function can be defined as

$$P(\Lambda \leq x) = \int_0^x f_\Lambda(\lambda)\mathrm{d}\lambda, \tag{A4}$$

where f_Λ denotes the probability density function (PDF) of Λ.

For a given portfolio, $P(\Lambda \leq x)$ can be interpreted as the expected value of the share of portfolio items whose hazard threshold has been attained or exceeded at a given x. Hence the fraction of affected items can be expressed as

$$c_{\mathrm{impl}}(x) = P(\Lambda \leq x). \tag{A5}$$

The portfolio loss ratio is given by the convolution of the probability density of the hazard threshold and the microscale damage curve, formally

$$\begin{aligned} d_{\mathrm{impl}}(x) &= \int_0^x f_\Lambda(\lambda)g(x-\lambda)\mathrm{d}\lambda \\ &= (f_\Lambda * g)(x). \end{aligned} \tag{A6}$$

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Appendix B: Mathematical description of the data uncertainties

We begin by defining random variables for each of the local and global (i.e. portfolio-wide) model variables. Local variables are the local hazard magnitude $\hat{X}$, the hazard resistance threshold Λ, the inflicted damage D, and the asset value V. Each of these variables is described by its respective probability density distribution (PDF), denoted as $f(\cdot)$. The loss for a single object is described by L.

Similarly, we define the global random variables X and $\widetilde{X}$ for the hazard magnitude and its measurement, respectively. Total portfolio loss is described by L_P.

The exceedance $e = x - \lambda$ closely links the uncertainty in the local hazard magnitude with the uncertainty of the hazard threshold. The PDF of the random variable E for the exceedance is hence given by the convolution of the PDFs of X and Λ as follows:

$$f_{E|X}(e;x) = f_{\hat{X}|X}(\hat{x};x) * f_{\Lambda}(-\lambda). \tag{B1}$$

The distribution of the damage caused is dependent on the level of exceedance, $f_{D|E}(d;e)$. Together with Eq. (B1) this yields

$$f_{D|X}(d;x) = \int_0^\infty f_{D|E}(d;e)\, f_{E|X}(e;x)\mathrm{d}e, \tag{B2}$$

In the case that asset values are not known, their PDF is assumed as $f_\mathrm{V}(v)$. In order to maintain relative loss figures, the nominal asset values may be rescaled such that the mean of the PDF equals one.

Combining the PDF of asset value with Eq. (B2) yields the PDF of relative loss,

$$f_{L|X}(l;x) = \int_0^\infty f_{D|X}(l/v;x)\, f_V(v)\mathrm{d}v. \tag{B3}$$

where we define the loss as the product of damage and asset value, $l = dv$.

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The PDF of portfolio loss l_P is given by the convolution of the loss PDF of each of the n portfolio items,

$$L_\mathrm{P} = \sum_{i=1}^{n} L_i$$

$$f_{L_\mathrm{P}|X}(l_\mathrm{P};x) = f_{L_1|X} * f_{L_2|X} * \ldots * f_{L_n|X}. \tag{B4}$$

Finally, uncertainty in the true hazard magnitude x (e.g. resulting from measurement or model output $\widetilde{x}$) is modelled via PDF $f_{X|\widetilde{X}}(x;\widetilde{x})$. Using Eq. (B4) it follows that

$$f_{L_\mathrm{P}|\widetilde{X}}(l_\mathrm{P};\widetilde{x}) = \int_0^\infty f_{L_\mathrm{P}|X}(l_\mathrm{P};x)\ f_{X|\widetilde{X}}(x;\widetilde{x})\mathrm{d}x. \tag{B5}$$

Appendix C: Case study parametrisation

In order to discuss the uncertainties involved in the estimation of the macroscale damage via its portfolio constituents, a relevant portfolio must be defined. Depending on the problem at hand, portfolio items can be described explicitly or implicitly (see Sect. A). Exploring both methods, we derive an explicit building portfolio from census data for the flood-risk case study of Lisbon and we employ an implicit description of a building distribution related to storm damages in Germany.

C1 Lisbon case study for coastal flooding

C1.1 Portfolio composition

Since coastal flooding is not bound by artificial administrative boundaries, we rather consider a *cluster* of continuous urban agglomeration comprising the city of Lisbon as well as connected suburbs. The cluster perimeter had been generated from 2006

CORINE landcover data (EEA, 2007) and was kindly supplied by Zhou et al. (2013), who also provide a description of the employed cluster algorithm. A map of the cluster is found in the Supplement.

The portfolio of flood-prone buildings within the cluster of Lisbon is based on statistical data provided by the Instituto Nacional de Estatística[1], the national Portuguese statistics institute. 2007 census data on the number of buildings at the highest resolution available (*Freguesia*, i.e. urban quarters) is downscaled via 2006 CORINE landcover data using the landcover classes for continuous and discontinuous urban fabric. Employing the EU-DEM[2], a hybrid digital elevation model based mainly on SRTM and ASTER GDEM data, the number of buildings within each CORINE cell were assigned to elevation levels, proportional to the spatial overlap between CORINE and EU-DEM cells. Following Poulter and Halpin (2008), a flood-fill algorithm with 8-side connectivity was employed to determine which DEM cells are affected at varying flood levels, also taking into account potential barriers or basins. As a result, Figure 2e shows the incremental building count for flood levels being increased by discrete steps of 0.5 m up to a maximum of 10 m. All employed data have been publicly available.

C1.2 Microscale damage function

The characteristic shape of the mean damage function for microscale damage is highly dependent on the type of hazard. Flooded buildings suffer considerable damage already at low inundations levels and damage increases slower at high inundation levels, suggesting function that is concave overall. We follow Hinkel et al. (2014), who employ a saturating power-law $z/(z+1\,\mathrm{m})$, implying that relative damage increases proportional to the inundation level for $z \ll 1\,\mathrm{m}$ and saturates at 1 for large z.

[1] http://www.ine.pt

[2] http://www.eea.europa.eu/data-and-maps/data/eu-dem

C1.3 Hazard magnitude uncertainty

On the macroscopic scale, the hazard magnitude is typically described by a single indicator, e.g. the maximum flood level or in case of storm the maximum wind speed. For all practical purposes, this indicator is subject to uncertainty, stemming either from imprecise measurement, uncertain model output, or estimated confidence levels drawn from extreme value statistics (Coles and Tawn, 2005). Considering flood level estimates, protection levels are commonly designed with a 30 cm safety margin (de Moel et al., 2012; Ministerie van V&W and ENW, 2007). If ensemble predictions of surge levels are available, the ensemble spread (standard deviation) can serve as a indicator for the forecast error (Flowerdew et al., 2009, 2010). For our case study region, the Portuguese coast and in particular Cascais, Fortunato et al. (2014) estimate a tidal uncertainty of 5 cm and an uncertainty of approximately 10 cm for extreme water levels calculated by a dedicated circulation model. Based on this result and due to the lack of information on the distribution of uncertainty, we make the assumption of a normally distributed error in overall flood level with a standard deviation of 10 cm.

C1.4 Threshold exceedance uncertainty

On the microscopic scale, local fluctuations of the hazard magnitude are interconnected with uncertainty in the individual hazard threshold. We hence directly parametrise the conjoint uncertainty in the threshold exceedance. Modelling flood damages, exceedance uncertainty is mostly driven by errors related to the elevation model used. For Portugal, statistical validation of the EU-DEM against ICESat measurements (EEA, 2014) indicates a mean error > 0.5 m and an average standard deviation of approximately 2 m. However, in flood-prone lowlands errors are expected to exhibit a comparatively stronger long-wavelength component (i.e. regional bias) and reduced short wavelength fluctuations (Hallegatte et al., 2013). In the lack of a detailed DEM validation for Lisbon, we assume a modest normally distributed pixel error with a standard deviation of 0.2 m.

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C1.5 Damage level uncertainty

Another significant source of uncertainty is related to the relative damage that an individual item sustains at a certain hazard intensity. Uncertainty of this kind is typically estimated from empirical records or ad-hoc assumptions. However, actuarial practice suggests that the log-normal distribution may serve as a first approximation to the broadly skewed damage claim distributions (Lawrence, 1988). By applying a constant scale factor, the log-normal distribution represents a multiplicative error term that is hence proportional to the average damage caused. Defining the microscale damage curve as the mean of the log-normal distribution, we set the scale factor such that the standard deviation $\sigma = 0.1$ at a relative damage $d = 0.5$, implying a standard deviation of approximately 20 % for $d \ll 1$. The upper tail of the log-normal damage distribution is truncated at $d = 1$, which represents complete destruction and loss.

C1.6 Asset value variation

When assessing damages on a portfolio level, individual asset values must be taken into account. Regarding storm or flood damages to individual buildings, the built-up values can be approximated by the distribution in house prices. For the case of Tokyo, Ohnishi et al. (2011) show that house-prices generally follow a log-normal distribution, with price-bubbles affecting mainly the tails of the distribution. In the absence of comparable studies for European buildings, we derive a distribution of relative house prices by approximating the shown results by a log-normal distribution normalized to an average value $\mu = 1$ and with a standard deviation $\sigma = 0.5$.

C2 Storm damages to a German building portfolio

C2.1 Portfolio composition

In the case of storm hazard, the determinants of the hazard threshold are less clear-cut than for flood damages. While they depend strongly on construction type and building

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age, a strong residual uncertainty remains. Heneka and Ruck (2008) argue for a simple statistical description via a normal distribution with mean $55\,\mathrm{m\,s^{-1}}$ and standard deviation $7.8\,\mathrm{m\,s^{-1}}$. In the lack of similar works, we adopt their parametrisation to generate a generic portfolio of 5000 residential buildings.

C2.2 Microscale damage function

The mean microscale damage caused by severe winds is often described as a power-law with an upper bound representing complete destruction (Prahl et al., 2015). Again following Heneka and Ruck (2008), we apply a simple square power-law as given in Table 1.

C2.3 Hazard magnitude uncertainty

For maximum wind gusts, required for the assessment of storm damages, Prahl et al. (2012) report a strong variation between measurements at nearby sites and estimate that 75 % of measurements fall within the range of $\pm 1.5\,\mathrm{m\,s^{-1}}$. Reports show an even stronger modelling uncertainty comparing gust estimates from a mesoscale atmospheric model with measured gusts (e.g. Hofherr and Kunz, 2010; Ágústsson and Ólafsson, 2009). In our calculations, we hence assume wind gust uncertainty to follow normal distribution with a standard deviation $\sigma = 1.5\,\mathrm{m\,s^{-1}}$.

C2.4 Threshold exceedance uncertainty

Wind gusts exhibit a strong spatial variability at short ranges. This aspect is demonstrated, inter alia, by the fact that the 3 s gust factor (relating extreme wind gust to mean wind speed) drops by more than 20 % if spatial averaging is applied for short distances less than 1 km (Mitsuta and Tsukamoto, 1989). While there is no indication in the scientific literature on the uncertainty in storm hazard threshold, the macroscale uncertainty in storm gust speed poses an upper bound for the local gust variability. In line with macroscale gust speed uncertainty, we assume a normally distributed local variability, albeit with a reduced standard deviation of $1\,\mathrm{m\,s^{-1}}$.

C2.5 Damage level uncertainty and variation in asset values

In the lack of local empirical studies for the uncertainty in damage levels or the variation in asset values, we employ an identical parametrisation for both the coastal flooding and the storm hazard case studies. The parametrisation for the damage level uncertainty and the variation in asset values is described in Sect. C1.

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Table 1. Assumptions on the portfolio and the microscale damage function for the estimation of damage from coastal flooding in Lisbon and the storm-damage simulation for a German building portfolio. The variables μ and σ denote the mean and standard deviation, respectively.

Component of damage function	Hazard	
	Coastal flooding	Windstorm
Portfolio composition: the distribution of hazard thresholds within the portfolio	Frequency distribution for Lisbon, see Sect. C1.1 and Fig. 2e	$\mathcal{N}(\mu = 50.5\,\mathrm{m\,s^{-1}}, \sigma = 7.8\,\mathrm{m\,s^{-1}})$, from Heneka and Ruck (2008)
Microscale damage function: the typical damage of a single building at hazard level z	$g(z) = \frac{z}{z+1\,\mathrm{m}}$, from Hinkel et al. (2014)	$g(z) = \left(\frac{z}{70\,\mathrm{m\,s^{-1}}}\right)^2$, from Heneka and Ruck (2008)

Table 2. Assumptions regarding the uncertainties involved in the estimation of flood damage due to coastal flooding in Lisbon and the storm damage simulation for a fictitious German town. Throughout, the variables μ and σ denote the mean and standard deviation, respectively.

Source of uncertainty	Hazard	
	Coastal flooding	Windstorm
Asset value: variations in the economic value of buildings within the portfolio	for both hazards: Log$\mathcal{N}(\mu = 1, \sigma = 0.5)$, adapted from Ohnishi et al. (2011) in Sect. C1.6	
Damage level: incomplete knowledge of the damaging processes and building state	for both hazards: Log$\mathcal{N}(\mu = g, \sigma_{g=0.5} = 0.1)$, derived in Sect. C1.5 in accord with Lawrence (1988)	
Threshold exceedance: conjoint effect of micro-scale fluctuations in the hazard magnitude and uncertainty in the estimation of hazard thresholds	$\mathcal{N}(\mu = x - \lambda, \sigma = 0.2\,\mathrm{m})$, based on Hallegatte et al. (2013) and EEA (2014)	$\mathcal{N}(\mu = x - \lambda, \sigma = 1\,\mathrm{m\,s^{-1}})$, see Sect. C2.4 and Mitsuta and Tsukamoto (1989)
Hazard magnitude: global uncertainty due to measurement error or (external) modelling error	$\mathcal{N}(\mu = x, \sigma = 0.1\,\mathrm{m})$, based on Fortunato et al. (2014)	$\mathcal{N}(\mu = x, \sigma = 1.5\,\mathrm{m\,s^{-1}})$, based on Prahl et al. (2012) and Hofherr and Kunz (2010)

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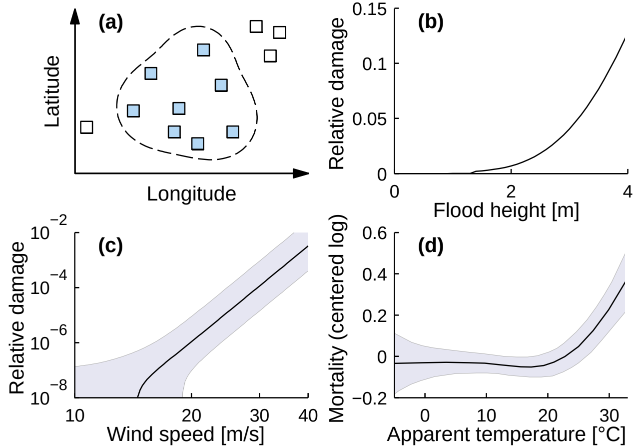

Figure 1. (a) Illustrative example for a spatially delineated building portfolio. **(b)** Relative flood damage function obtained for the case study Kalundborg (DK) (Boettle et al., 2011, 2013). **(c)** Relative storm damage function for a German district (Prahl et al., 2012). **(d)** Damage function for the city of Bologna, relating mortality increase to apparent temperatures (data extracted from Stafoggia et al., 2006). The shaded areas in **(c)** and **(d)** represent uncertainty bands.

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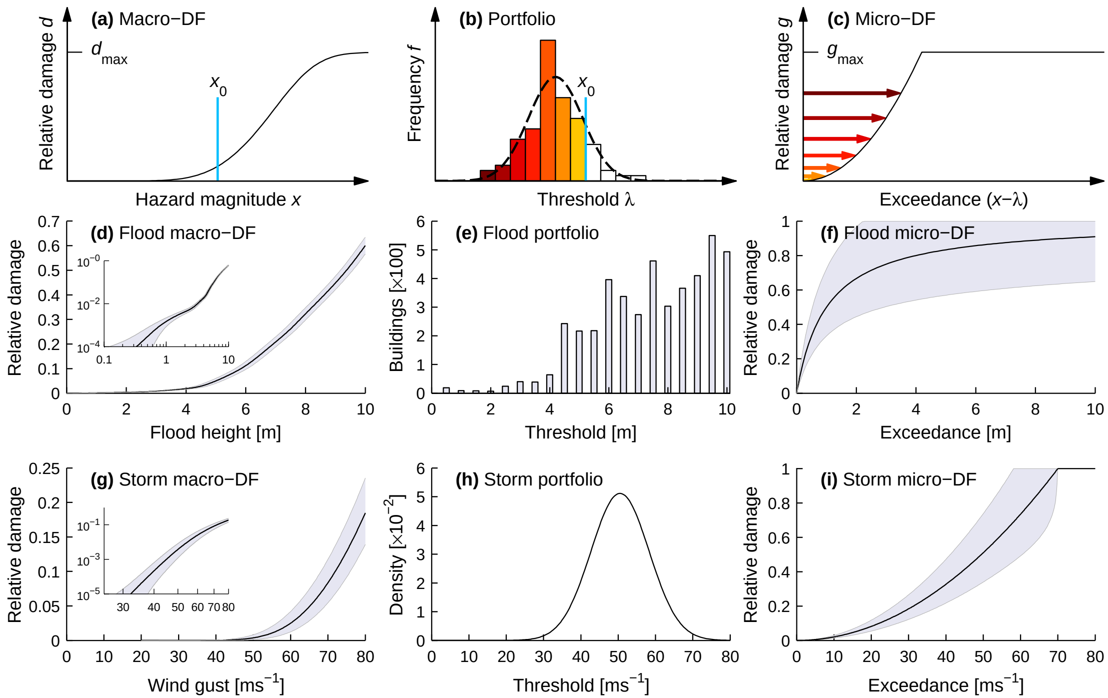

Figure 2. Schematically, **(a)** shows a macroscale damage function based on a building portfolio with a distribution of hazard thresholds as shown in **(b)**, where coloured bars indicate portfolio segments affected at hazard magnitude x_0. **(c)** shows the applied microscale damage function. Accordingly, the coloured arrows indicate the damage inflicted on the respective portfolio segments at x_0. Analogously, **(d–f)** show the damage function components for the case study of coastal flooding in Lisbon, Portugal. **(g–i)** demonstrate the methodology for storm damage within a building portfolio of 5000 individual buildings, based on the study by Heneka and Ruck (2008). The shaded areas around the damage functions indicate 95 % confidence intervals. The insets in **(d)** and **(g)** show the macroscale damage function on a log-log scale.

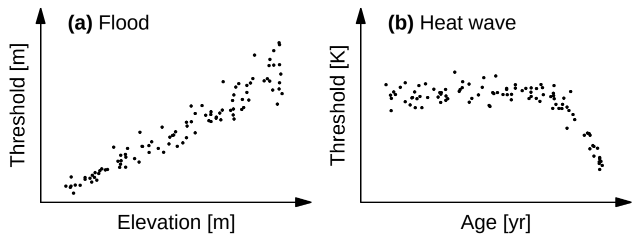

Figure 3. (a) Illustrative example of the relationship between elevation and flood hazard threshold. **(b)** Illustrative figure showing the potential relationship between the hazard threshold for heat mortality and age (cf. Hajat et al., 2007; Basagaña et al., 2011).

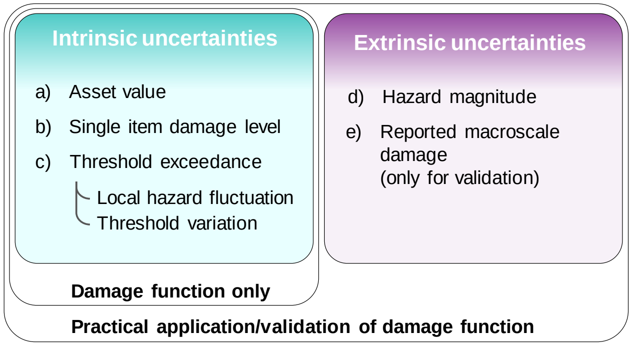

Figure 4. Classification of data uncertainties into intrinsic and extrinsic, including the circumstances for their consideration.

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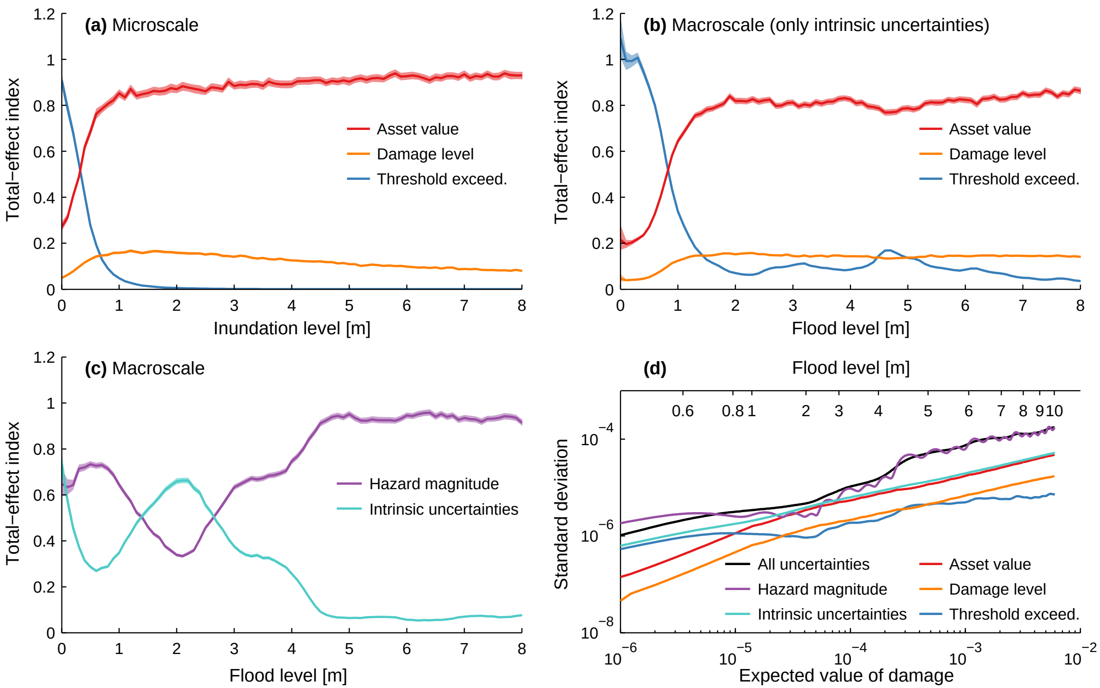

Figure 5. (a–c) show the results of variance-based sensitivity analysis (total-effect index) for the Lisbon case study on different scales. Shaded areas indicate boot-strapped confidence bands. For microscale damages, **(a)** shows the attributable effect of intrinsic uncertainty in asset value, damage, and threshold exceedance on the total variance. Similarly, **(b)** shows the effect of the intrinsic uncertainties on the variance of the aggregated portfolio. In **(c)**, the portfolio-aggregated microscale uncertainties are weighed against the hazard uncertainty, i.e. error in estimated flood level. **(d)** shows the increasing standard deviation of Lisbon flood damages against their expected value. Each curve includes only those uncertainty sources that are indicated by the legend.

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