Natural Hazards
and Earth System
Sciences

Discussions

Open Access

Uncertainty in flood damage estimates and its potential effect on investment decisions

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Abstract

This paper addresses the large differences that are found between damage estimates of different flood damage models. It explains how implicit assumptions in flood damage models can lead to large uncertainties in flood damage estimates. This explanation
5 is used to quantify this uncertainty with a Monte Carlo Analysis. As input the Monte Carlo analysis uses a damage function library with 272 functions from 7 different flood damage models. This results in uncertainties in the order of magnitude of a factor 2 to 5. The resulting uncertainty is typically larger for small water depths and for smaller flood events.
10 The implications of the uncertainty in damage estimates for flood risk management are illustrated by a case study in which the economic optimal investment strategy for a dike segment in the Netherlands is determined. The case study shows that the uncertainty in flood damage estimates can lead to significant over- or under-investments.

1 Introduction

15 Flood damage assessment is an essential aspect of flood risk management. It is used for supporting policy analysis and flood insurance. In the Netherlands flood damage estimates are used, for example, to determine economic optimal protection standards for flood defenses, prioritize investments or to compare the impact of different flood risk management strategies.

20 The most commonly used method for flood damage assessment is the unit loss method (de Bruijn, 2005). This method assesses the damage for each unit separately. This assessment is based on a maximum damage per object and a damage function. A damage function describes the relationship between a flood characteristic (most often water depth) and the fraction of the economic loss that occurs to the object that is
25 damaged.

Most flood damage models that exist are based on the unit loss method (e.g. HIS-SSM for the Netherlands (Kok et al., 2005), Multi Coloured Manual in the UK (Penning-Rowsell et al., 2010), HAZUS in the USA (Scawthorn et al., 2006) and FLEMO in Germany, Thieken et al., 2008; Kreibich et al., 2010). These models are developed for a specific country, region and/or flood type. They are often based on either expert judgment (synthetic models) or data from a few flood events, or combinations. Different models can give significantly different results when applied to the same event (De Moel and Aerts, 2011; Jongman et al., 2012; Chatterton et al., 2014). This is because models are often tailored to characteristics of the flooding and objects in the considered region.

Jongman et al. (2012) compared the damage outcomes of seven different flood damage models with the recorded flood damages from events in the UK and Germany. The difference between the smallest and largest estimate/recording was a factor 5 for the German event and a factor 10 for the event in the UK. Chatterton et al. (2014) compared two different damage assessments for a region in the UK. The damage estimates differed about a factor 5 to 6 for both residential and commercial damages. These large differences indicate that flood damage models are prone to large uncertainties.

These large differences also show that potentially large errors can occur when flood damage models are applied. To correctly interpreted results of flood damage models, it is, therefore, important to understand these uncertainties and their implications for decision making. A quantification of the uncertainty can help to get an insight in the potential error that can occur in a decision based on the flood damage estimate. US-ACE (1992) and Peterman and Anderson (1999) both showed that taking into account the uncertainty can lead to different decisions. Furthermore, uncertainty quantification is useful to expose key focus points for the improvement of flood damage models. Knowing the potential costs of a decision based on a wrong damage estimate can help making decisions about the effort to be spent on improving the flood damage estimation. It could also be a motivation to collect more or different data.

Generally, uncertainty in flood damage assessment is quantified with forward uncertainty propagation models which use Monte Carlo simulations (Merz et al., 2004;

Egorova et al., 2008, Apel et al., 2008; De Moel et al., 2012). The results of Egorova et al. (2008) indicate moderate uncertainties, which is in contrast with the large differences between models that were found by De Moel and Aerts (2011), Jongman et al. (2012) and Chatterton et al. (2014). This difference in results indicates a need for a better understanding of uncertainties involved in flood damage modeling.

The first aim of this study is to provide a method to get a robust estimate of the uncertainty in damage estimates. For this a damage function library is created with 272 functions from 7 different models. Furthermore, an explanation is provided for the large differences between existing flood damage models, based on an analysis of how the different models are created. This explanation is used as foundation for estimates about the correlation between several input parameters used in the Monte Carlo simulations. The assessment of these correlation factors is crucial for the analysis of the degree of uncertainty.

The second aim of the paper is to show the quantified implications of the uncertainty in flood damage models on flood risk management decisions. These implications are illustrated by deriving economic optimal flood protection strategy for a dike segment. The paper shows the potential costs of wrong or uncertain estimates of flood damages.

The paper focuses on direct material damage. Indirect damages including damages due to business interruption are not considered here, since their analysis requires different methods. The paper starts with a qualitative analysis of the uncertainty found in flood damage models. This qualitative analysis is the basis for the assumptions made in the Monte Carlo analysis model which is used to quantify uncertainty. Next, the Monte Carlo analysis model is described and discussed in detail. Finally, the Monte Carlo analysis model is applied and the resulting uncertainties in damage estimates and the effects on flood risk management decisions are discussed.

2 Qualitative uncertainty analysis

2.1 The unit loss method for flood damage assessment

The unit loss method uses relationships between flood characteristics and damages to a unit. In the unit loss method four elements are crucial: the maximum damage s_i for each category, the flood characteristics (such as water depth d at all locations j, the damage functions ($f(d)$) for all categories which determine the damage fraction and the number of objects affected (n). Damage of an area is assessed as the sum of all damage categories i for all grid cells n by the following formula (Egorova et al., 2008):

$$\text{Damage} = \sum_{i=1}^{m} s_i \sum_{j=1}^{n} f_{ij}\left(d_j\right) n_{ij} \tag{1}$$

Potentially relevant flood characteristics are the maximum water depth, flood duration, flow velocity, pollution, warning time and other possible aspects of the flood. In general, only the water depth is used in flood damage modeling, occasionally supplemented by one or two other parameters. The uncertainties in the flood characteristics which are used as input for the damage estimation are not part of this paper.

Damage is usually calculated for categories such as houses, industries, and commercial companies, roads, and agriculture. These object categories differ in maximum damage and flood damage functions. The object and flood characteristics are linked by damage functions which give the fraction of the maximum damage which occurs as a function of the flood intensity[1]. The damage fraction is then multiplied with the maximum damage to get the damage.

The maximum damage can be defined in different ways. In this analysis we define the maximum damage as the expected damage corresponding with an extreme water

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[1]Some models use absolute damage functions which relate the flood intensity directly to the damage and not to a fraction of the maximum damage. An example of such a model is the Multicoloured Manual (Penning-Rowsell et al., 2010).

depth. This means that the damage function will reach one for the most extreme water depths and it means that the maximum damage already holds information about what part of the total value is susceptible to flood damage. The maximum damage does not include value which is not or unlikely to be susceptible to floods, such as the value of the ground, the costs of building the foundation or the value present on high floors in buildings that are unlikely to collapse. Other models, such as SSM2015 also use this definition (De Bruijn et al., 2014). However, also models exist which include more items in the maximum damage and apply damage functions which never reach one if part of that value is on average not susceptible to flooding. When comparing different models, the definitions of maximum damage and damage functions first need to be aligned to make a fair comparison.

2.2 Types of uncertainty

In the uncertainty analysis in flood damage assessment two types of uncertainty are distinguished: aleatory and epistemic uncertainty (Merz et al., 2009).

Aleatory uncertainty is related to the variability or heterogeneity within a population which can be expressed by statistic parameters such as the mean, variance, and skewness. This uncertainty is introduced by using average data: we use the maximum damage value of an average residence, although we know that some houses will suffer more, and other will suffer less damage. In small flood events which only affect a few houses, these few houses may differ significantly from the "average house" and therefore the damage estimate for these houses is uncertain. In large flood events which affect many houses it is likely that deviations from the mean damage cancel out. This means that for large floods this type of uncertainty is of lesser importance.

Uncertainty by using averages can sometimes be reduced by applying more differentiation. E.g. the uncertainty within the maximum damage of a residence is reduced by using more differentiation in house types. The variation in maximum damage per house type is then less than if all houses together would be considered as one category "houses".

Epistemic uncertainty is the lack of understanding of a system and can in theory be reduced by further study or more data. In other words, also the average damage itself is not certain. For flood damage assessments, data is only available for a small number of events and those events often differ significantly from each other. This variation
5 between events is still very little understood and is therefore related to epistemic uncertainty. The epistemic uncertainty as stated above is not reduced when many objects are flooded. Therefore, it is the dominant uncertainty type for large flood events.

This type of uncertainty is especially relevant when a damage module made for another area is used. In such a case, for example the maximum damage values within
10 the model related to houses, may be valid for other types of houses than present in the area of consideration. It would therefore be good not to mix up models from different areas. However, given the data scarcity this leaves many modelers with the difficult choice between a foreign model based on some recorded data or a synthetic local estimate.

15 ## 2.3 Uncertainty in unit loss method

Uncertainty in the unit loss method consists of uncertainty in object data, in maximum damage figures and in the damage functions. Table 1 shows an overview of the uncertainties present in these aspects of the unit loss method.

2.3.1 Uncertainty in object/land use data

20 Uncertainties are found in the location data and the quantity of objects at the location. The precise location of objects is important, since the hazard may differ from location to location. Each object should be linked to the hazard value present at the location of the object (e.g. water depth). The effect of the uncertainty on the precise location of objects on damage estimates is smaller for more homogeneous hazards. For exam-
25 ple, in a deep flat polder the exact location of an object is not important because the water depth is the same everywhere. When a hazard becomes more heterogeneous

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the uncertainty in the geographical data is relevant. Geographical data uncertainties are especially significant in areas which flood frequently, but with small water depths, because in such areas typically all valuable objects are placed at safe local elevations. Damage estimates may be very wrong if the approach used was too coarse to see
5 these local elevations. For example, the Dutch standard damage model HIS-SSM estimated EUR 100 million damage for an event in an unprotected area that in reality had only caused about EUR 30 000 in damages (Slager et al., 2013).

Such errors are, however, unlikely when objects are not on purpose elevated, placed on safe locations or protected in other ways. Without this local protection for some
10 objects the damage will be overestimated and for others it will be underestimated. If many objects are affected, these errors compensate each other which reduces the uncertainty in the total area damage. Use of high resolution elevation information is also very useful to reduce this uncertainty (Koivumaki et al., 2010).

Uncertainty in the quantity of objects can be caused by errors in data, or by using
15 data sources that are inappropriate for the intended application. This uncertainty depends on the quality of the dataset that is used. De Moel and Aerts (2011) illustrated that this type of uncertainty may be small as they showed that different types of land use maps for the same area only have a small impact on the resulting damage estimate. In the uncertainty quantification for this paper the uncertainty in the geographical
20 data is neglected.

2.3.2 Uncertainty in maximum damage figure

The uncertainty in the maximum damage figure can be divided into two parts: the uncertainty in the value of the object and in the part of that value that is susceptible to flood damage.
25 There are generally two ways to obtain the maximum damage for a flood damage model: deriving this from economic data or by looking at synthetic (hypothetical) buildings.

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Economic data typically provides a total value per sector of all physical assets in the economy. To obtain a maximum damage figure per unit, this total value can be divided by the number of units within that sector. Next, the part of this total value which is susceptible to flooding must be identified. The strength of this method is that the mean value will be accurate. However, uncertainty is still present in the part of the maximum damage that is susceptible to flood damage. A similar method is to use average construction costs and to correct this for the fraction that is actually susceptible to flooding.

Alternatively, the maximum damage of a category can be obtained by defining a "hypothetical" average company or object, and assessing the damage of all parts/aspects within that hypothetical company. The strength of this method is that the damage function and the maximum damage are well connected. Furthermore, the part of the value that is susceptible to flood damage is determined in a systematic way. The disadvantage of this approach is that epistemic uncertainty is introduced in the value of the object as the assumptions about this may be wrong.

2.3.3 Uncertainty in damage functions

Damage functions can be obtained in two ways: by analyzing data on observed damages to objects in past flood events, or by defining hypothetical "average" objects and assessing their damage corresponding with different flood intensities. Also a combination of both approaches may be used.

Flood damage data is rarely collected in a systematic way, and not always available for research. When it is available it is often limited to a single or a few events. These events are often not representative for other types of floods or other countries or areas. Cultural or geographical differences can cause the use of different building or interior materials between regions and events, making one dataset not applicable to other areas. Another problem is that data is often limited to certain ranges of a flood parameter. For example, data may be only available for low water depths or the flood that was the

source of the data may have coincided with a storm. In such cases the data cannot be used for events with larger water depths or no storm.

In general, transferring data from one event to another is error-prone. This makes it very difficult to apply knowledge derived from one event on another. Even when the data is applied to the same area as the data was taken from, problems may arise. Different flood events in the same area may lead to very different damages due to different human responses. For example, the same area in the Netherlands flooded in 1993 and 1995 with approximately the same water levels. The second time the damage to housing content was about 80 % less (Wind et al., 1999). Also the damages due to Rhine floods of 1995 were less than half of the damages that occurred in 1993, as a result of precaution measures taken by households (Bubeck et al., 2012). This shows the sensitivity of flood damage to other factors than water depth. These other factors (in this case flood experience) are often neglected in the recordings. This example shows that a dataset based on a small number of events is too small to catch all possible variable values.

Synthetic damage functions solve many of the problems of having too little empirical data on actual damages. In this method a hypothetical building is defined and flood damage is assessed for each building part. The hypothetical building should be representative for the average building in the area. When it is not, or when the damage estimates for the different building parts are not right, the damage function is wrong.

Damage data can also be combined with synthetic knowledge. Probably the most common method to create a damage model is by picking and choosing damage functions from other models based on an analysis of which existing damage function best represents the area considered. Or, the average between different functions could be used as a damage function, this was for example done for this paper. The challenge with this combined method is to understand the background assumptions between the models that are brought together or compared. For example, a common challenge may be that the maximum damage definitions do not match.

The ideal case is to combine the best of the two methods. The damage data available should be used to calibrate a synthetic model. This limits the possibility that large errors are made in the interpretation of the damage data (e.g. wrong definition of the maximum damage), by forcing the modeler to think about the processes. Furthermore, it gives the modeler the freedom to diverge from the observed data in situations that do not match any of the recorded events.

A common problem in constructing damage functions is that it is difficult to include the large number of parameters that may influence the flood damage. The parameters that are not used are implicitly considered. Each model based on a limited number of parameters is therefore making assumptions on the effect of the non-explicitly considered parameters. Those non-considered parameters have been very significant in a subset of the events. For example, in the 2002 Elbe floods contamination was critical (Thieken et al., 2005), in the Meuse floods flood experience was critical (Wind et al., 1999) and in the 1945 floods in the Wieringermeerpolder in the Netherlands the waves in the flood water were critical (Duiser, 1982). This last example is complicated by a study of Roos (2003) who showed that the findings of the 1945 Wieringermeerpolder flood are not valid for modern buildings. So also the construction year of a building can in some cases be a critical parameter. Other possibly significant parameters are, for example: building style, flow velocity, flood duration, warning time and preparation.

Parameters that are not used can have a correlation with parameters that are used. For example, the water depth is correlated with the flood duration for floods in the Netherlands (Duiser, 1982; Wagenaar, 2012). Because of this correlation, the uncertainty caused by not knowing the flood duration is limited for a Dutch model. This relationship between two parameters may, however, be completely different for other types of floods (e.g. flash floods). A generally applicable damage model therefore needs all parameters.

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3 Methodology

3.1 Overview of the method

For the quantitative uncertainty analysis a Monte Carlo analysis is used, in which the uncertainty of the inputs is propagated into uncertainty in the output. The qualitative uncertainty analysis discussed in the previous section is used to estimate the uncertainty in the inputs and the correlations between the different input parameters.

The damage analysis in this paper is limited to two damage categories: houses and companies; as they are represented in the different models on which this research is based. Both damage categories are divided into damage to buildings and damage to content. Many individual models provide several more detailed sub categories for these basic categories. Our approach may therefore lead to slightly larger uncertainties than present in such more detailed models.

A crucial aspect of this Monte Carlo simulation is the correlation amongst the uncertainty of the different input parameters, such as the maximum damages of houses. If the maximum damage of for example house X is overestimated, the maximum damage of house Y may also be overestimated. The parameters that are homogeneous within one event, but vary between events will have a strongly correlated uncertainty value: e.g. if damage depends on warning time and in one particular event the warning time is unusual short, this is more or less the case for all houses which were affected in that event. Such aspects are therefore sampled for the entire area at once. Other parameters vary between neighborhoods, or from place to place, such as for example the building type. Those need to be sampled on a smaller level then the entire area at once. Sampling will therefore be done at two different levels: for the entire event and on a more detailed sub-event level.

Figure 1 gives an overview of the calculations process which is repeated ten thousand times. This results in ten thousand different damage estimates which together make up the distribution of possible damages.

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3.1.1 Input information

Flood damage library

A damage function library was constructed containing 262 different damage functions from 7 different models. These functions were the basis for the damage fraction and the susceptibility to flooding. The damage fraction was sampled by picking functions from a model. These functions were individually all scaled to one to ensure that the same maximum damage definition is applied everywhere. Table 2 gives an overview of the models included in the damage function library. The Tebodin model only has damage functions for companies and the Billah (2007) model only has damage functions for houses.

Land-use maps

The model needs input about the number of houses and jobs affected. For the case study the number of houses was taken from the geographical database BAG. This database is made by the Dutch Cadastre, Land Registry and Mapping Agency. For the number of jobs the background data of HIS-SSM was used (Kok et al., 2005).

Water depth map

This model works for a particular flood scenario, represented as a water depth map. For the case study a water depth map was used from the VNK project (VNK, 2014). For the model behavior tests a table was used showing the number of objects/jobs per water depth class.

3.1.2 Step 1: event-level sampling (epistemic uncertainty)

The sampling on the event level is done by sampling a damage model and using that throughout that damage calculation. This sampled model will be applied to all cate-

gories and will be used as source for the damage functions and for the susceptibility to flooding of the maximum damages. The advantage of this is that a realistic combination of inputs will be sampled. This procedure prevents that on average a higher damage for small water depths than for large water depths are sampled or that functions with different implicit assumptions are merged.

3.1.3 Step 2: sub-event level sampling (aleatory uncertainty)

Group size and dependency

For the sub-event level sampling, uncertainty values are sampled for small groups of houses or for a company. Houses and jobs are grouped because in reality also often similar houses are built near each other and also a company is expected to be relatively homogeneous in damage per job. It is therefore not realistic to sample all houses and all individual jobs in an area completely independent from each other. By sampling in small groups of houses/jobs total dependency is assumed within the group and total independency between the groups.

The way in which the area is grouped determines the dependency for this aleatory uncertainty. This buildup of groups is therefore also sampled again for each Monte Carlo simulation. This sampling should therefore be seen as a sampling of the dependencies between the damage of different objects. For houses the area is split in groups of 1, 10 or 100 houses for every simulation. Houses are only grouped when they have a similar water depth. This is done to keep the calculation simple but also because similar water depths typically occur in locations that are geographical close. Furthermore, the group sizes are so small that for medium, or larger, sized events this assumption has no influence on the results. For companies, the jobs are grouped per company.

Damage curves

Within each group every house/job receives the same damage fraction and maximum object value. Sampling for the damage fraction is done based on the set of damage functions within the model sampled in step 1. For example, if the model sampled has 3 damage functions for houses, for each group one of the three damage functions is randomly used.

Maximum damages

The values are based on De Bruijn et al. (2014) and Gauderis (2012). De Bruijn et al. (2014) estimated the structural value of a house on EUR 125 000. The minimum and maximum from the triangular distribution are estimated at ±EUR 75 000 for structural damage. For content damage De Bruijn et al. (2014) estimated a maximum damage of EUR 70 000, for which also a triangular distribution is assumed, with ±EUR 50 000. These assumptions lead to a symmetric probability distribution, while it is probably in reality positively skewed. This is neglected in this study because the impact is expected to be very small.

Gauderis (2012) estimated physical value per job for 62 different categories of companies. These estimates are taken together to produce a distribution of the physical value of a company per job. Because not all company categories are equally common, the values were weighted in the distribution based on their quantity in the Netherlands. The results are shown in Fig. 2. These values include both the structure and the content. It was assumed that 50 % of the value is content and 50 % structure.

4   Model behavior: trial of the method on hypothetical flood maps

To gain understanding in the model behavior it was tried on hypothetical flood depth maps, one with small water depths (< 0.5 m), one with medium water depths (0.5–2 m) and one with large water depths (2–3 m). These had average water depths of 0.35,

1.25 and 2.5 m. These maps were used for calculations with 150 and 15 000 houses and jobs. In total thus 6 different trials were carried out and the resulting uncertainty values were compared.

The uncertainties in the damage estimates are expressed with the coefficient of variation. This is the standard deviation of the damage divided by the mean of the damage. It has no unit and is therefore independent of the size of the flood event. This makes it a good measure to compare the uncertainties in different areas.

Figure 3 shows the results of this hypothetical analysis. It stands out that both a smaller water depth and a smaller area increase the uncertainty significantly. This is because at small water depths the different models differ significantly more from each other than at large water depths. This indicates that the uncertainty in damage estimates for events like for example small regional levee failures is much larger than the uncertainty in damage estimates for large scale floods with large water depths.

Another observation is that the distribution of the damage for small events looks very different from the distributions of the damage of large events. The main reason for this is that for large events the aleatory uncertainty in the damages within models can be reduced significantly by the law of large numbers, but not the epistemic uncertainty.

Epistemic uncertainty is therefore the significant uncertainty for larger events. The frequency distributions therefore show then clearly separate peaks related to the damage functions of the separate damage models.

It is difficult to determine for what event size the variation between the models becomes more important than the variation within models. For the uncertainty model created in this paper this point is somewhere between 100 and 3000 houses plus jobs. This critical size depends on the dependencies between individual objects. These dependencies determine how fast the law of large numbers will reduce the aleatory uncertainty. For this paper this was estimated by sampling in groups instead of in individual objects. The size of these groups therefore determines when the epistemic uncertainty becomes dominant. These group sizes were based on a rough estimate in this paper and should be calibrated for better results.

5 Case study

A case study is done in the Betuwe, Tieler-en Culemborgerwaarden area (dike ring 43) in the Netherlands to show the effect of the uncertainty in the flood damage estimation on investment decisions for flood risk management. Dike ring 43 is located between Rhine branches in the Netherlands. In the west the area is closed with a high dike (border to next dike ring area). The area slopes down to the west. The difference in height between the eastern and western part is about 10 m.

The uncertainty model is applied on a water depth map resulting from a simulated dike breach (VNK, 2014) along the Rhine river near Bemmel in the Netherlands (see Fig. 4 for its location). This dike section is about 26 km long. Bemmel is situated in the eastern upstream part of the Betuwe area. When the dike breaches, water flows through the Betuwe area to the west where it is stopped after about 70 km by the western embankment. The maximum water depths due to this dike breach vary from less than 50 cm in the east to over 5 m in the west. In this dike-breach scenario a total area of 626 km^2 is inundated. This area contains several small cities and villages, with a total population of around 300 000 people. The large flood extent and the large number of affected residences and companies and the large variation in water depths are expected to have a reducing effect on the aleatory uncertainty in the total damage of the dike-ring area.

The damage assessed for this flood scenario was EUR 16 billion with a standard deviation of EUR 5.6 billion based on 10 000 simulations. The resulting damage outcomes are shown in the Fig. 5. The peaks in Fig. 5 are related to the damage models and illustrates the large differences between the different damage models.

The results in Fig. 5 are used to find the optimum flood protection standard and investment strategy for the dike segment from an economic viewpoint. The optimum flood protection standard and investment strategy is calculated using a simplified version of the approach of Kind (2013). Kind (2013) assesses which investment strategy has the smallest total costs. These total costs consist of the present value of the EAD (ex-

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pected annual damage) and the present value of all future investments. In this paper we assess the effects of uncertainty in damage estimates on the economic optimal flood protection standard and the total investment costs. We do that by determining the investment strategy for five different damage estimates. The first four estimates relate to the first four peaks. For the highest damage estimate the 98 % percentile of the damage outcomes was used.

The optimal investment strategy depends not only on the flood damage, but also on the current protection level, consolidation of the dike, correction factor for indirect damages, fixed and variable costs of dike improvements, climate change predictions, economic growth predictions for the area protected by the dike segment and the discount rate to calculate the present value. These parameters were all taken from the WV21 project (Kind, 2011).

The analysis in this paper focuses on the first investment made. In all five alternatives this investment is done in 2015. The second investment is in all alternatives planned about 75 years later and a third investment is suggested about 50 years after the second one (around the end of the time span considered). The total investment costs are mainly determined by the first investment, because the weight of later investments is very small due to the use of the net present value which gives future costs and benefits a much lower weight than current costs and benefits. The calculations assumed a discount rate of 5.5 % (based on WV21 Kind, 2011).

The results in Table 3 show that the optimal investment strategy is at first glance not very sensitive to the precise damage estimate. The difference between the five alternatives in required dike heightening is only 18 cm (88–70 cm). This small difference is partly explained by the strong sensitivity of the flood probability to the precise height of the dike. The dike segment in this case study becomes 10 × safer by raising it with only 34 cm. If the flood probability would be less sensitive to height changes the differences in dike height between a low and a high damage estimate could be much larger. If the dike should be increased with 1 m to reduce the flood probability with a factor 10, the difference between the top and lower damage estimate would be 47 cm.

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If the flood damage applied in the cost benefit analysis differs from the flood damage that would actually occur, a suboptimal investment strategy would be applied. Table 4 shows the costs of using a wrong damage estimate. It gives the unneeded cost made by assuming a certain damage for different "real damage values". This cost varies in this case study between EUR 0 and 12 million and is on average about EUR 2 million, which is 1.4 % of the total costs and for this case study about EUR 75 000 km^{-1}. The maximum error is 9 % of the total costs and for this case study EUR 500 000 km^{-1}.

This case study illustrates how the uncertainty model may be used to assess the uncertainty in damage assessments, and how the effect of this uncertainty on invest-ment costs may be determined. In the case study here, the effect is small. However, if we take into account the fact that in the Netherlands we have about 3000 km of em-bankments and that EUR 12 million might be unnecessary spend per 26 km, the total amount of money spend unnecessary may then be large. It is also likely that in cases with lower flood probability standards, or with smaller flood events the effects of this uncertainty are much larger.

A striking observation in the results of Table 4 is that the costs of overestimating the damage are significantly lower than the costs of underestimating the damage. The difference in costs is on average a factor 2 (see Table 4). This can be explained by the non-linear relationship between the flood probability reduction and the investment costs. The flood probability can be reduced a lot with a small extra investment, thus when too little is invested the EAD goes up faster than the investment costs go down. This implies that under uncertainty it would be economically efficient to add a safety factor to avoid investing too little.

6 Discussion

This paper discusses a new method for the quantification of uncertainties and applied this method in a case study. The case study is a good illustration of the method and its use, but the calculated uncertainty, the damage frequency distribution and the effect

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of uncertainty on investment decisions, may not be representative for all situations. First of all, because several damage determining aspects were neglected in the case study. The damage is assumed to consist only of damage to buildings and companies. Other damage categories, such as affected persons and fatalities may also be relevant to quantify and can be taken into account in a CBA. Another simplification is that the entire cost benefit analysis in the case study is based on only one flood scenario at one breach location and at one water level (at the design water level of the dike). A more precise way would have been to include multiple breach locations and water levels, these effects are however assumed to be negligible for the conclusions of this paper.

Secondly, because the exact location and number of peaks in the damage frequency distribution depend on the input damage models in the uncertainty analysis. The set of 7 damage models used does not cover all possible damage models. If an extra model would have been added to the damage function library an entire new peak could ap-pear. The frequency distributions of the outcomes must therefore be considered as an example of what a frequency distribution could look like and how far the peaks are ap-proximately apart from each other. It is impossible to make a real frequency distribution because the major uncertainties are epistemic uncertainties. Epistemic uncertainties are by definition not understood and can therefore not be represented by a frequency distribution (Helton and Oberkampf, 2004).

Thirdly, the costs of a wrong estimate which were estimated for the case as about 1 % and at maximum 10 % may also be different for other cases. It depends amongst others on the costs required to reduce the failure probability with a factor 10, on the damage itself and on the uncertainty in the damage interaction (which will be larger for small areas and areas with little flood water depths).

Finally, the uncertainty in the damage estimate was, in this case study, directly linked to an error in the investment strategy. However, in the determination of the optimal investment strategy not only uncertainties in the damage estimate, but also in other components play an important role. Uncertainty in the costs of dike strengthening, in the discount rate, in the future economic growth, in the flood pattern and so on, all add

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to the uncertainty in the optimal investment strategy. These uncertainties may partly compensate each other, but can also aggregate each other. Their relative importance differs per case depending on local characteristics (De Moel et al., 2014).

We tried to combine information from different damage models to get a better quantification of uncertainties in damage outcomes. This can only be done when the damage models may all be applicable to the flood scenario which is being modeled. Whether flood models are equally applicable is sometimes difficult to establish. Metadata of the source of the damage models is not always available and sometimes information on the event on which the model is based, is also lacking. This makes it difficult to compare damage models and to understand why they have different estimates for the same flood patterns. Relevant metadata on parameters which may be obvious for a certain event, but vary from event to event are needed. Examples of such parameters are for example flood experience of the population, building style, flood duration, contamination of the flood water, etc.

Metadata for flood damage functions should give clear instructions about the type of events for which damage functions are applicable and for what events they are not. This could lead to a classification of different flood types with their own damage functions. This would first lead to a better transferability of models and could eventually lead to generally applicable models.

7 Conclusions

Uncertainties in flood damage estimates can be large. This study showed uncertainties of an order of magnitude of 2–5. This uncertainty is mainly caused by a lack of knowledge. Most flood damage models are based on data resulting from a small number of events. Because flooding can occur in many different ways (water depths, contamination, flow velocities, flood durations, etc.) and in many different types of areas (building types, flood experience local population) any model will miss considerable parts of the spectrum of possible options. Data from one event therefore is often not transferrable

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to other areas or events. Since only data representative for the event under consideration can be used, little data is available and hence large uncertainties are introduced in flood damage modeling.

This study introduced a method to quantify these uncertainties using a set of damage models which have all been applied in the past to river floods (not flash floods) or storm surges in developed countries. To quantify the uncertainty a distinction was made between epistemic and aleatory uncertainties. Epistemic uncertainties are introduced by a lack of knowledge about the spectrum of possible flood events and areas in which they could occur. The size of this spectrum was for this study estimated by using the difference between flood damage models. Aleatory uncertainties are introduced by local variations between objects and circumstances. These uncertainties were for this study estimated with the variations within different flood damage models.

These aleatory uncertainties are large for small flood events and much smaller for large flood events affecting many objects. Epistemic uncertainties are not smaller for large areas, since they are not related to deviations of single objects from the average object for which the damage functions were derived. Epistemic uncertainties can only be reduced with new knowledge. The resulting uncertainty estimation model therefore shows larger uncertainties for small areas. However, at a certain event size the epistemic uncertainties become dominant.

These uncertainties in flood damage modeling can potentially have a significant effect on investment decisions. In this study a case study was carried out to calculate the economic optimal investment strategy for a dike segment. This case study showed that uncertainties in damage estimates can lead to sub-optimal investment decisions. In the worst case scenario (maximum error in damage estimate), the difference between the total costs (remaining risks and investment costs) may be as high as EUR 500 000 per km dike. The expected difference between the optimal and sub-optimal investment strategy was, however, significantly lower (EUR 75 000 km^{-1}). These findings need to be verified with further research in other areas.

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The paper provides <mark>a good first approach</mark> for uncertainty quantification in damage estimates and shows how this approach can be used to improve investment decisions. Further research including other areas and more flood events is recommended to develop the approach further.

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Table 1. Overview of the uncertainties in flood damage modeling.

Element	Uncertainty	Type	Expected significance
Object data	Quantity	Both	Depends on input data expected to be often insignificant
	Location	Both	Depends on area, often insignificant
Maximum damage	Value of the object	Mostly aleatory	Varies
	Susceptible to flood damage	Mostly epistemic	Significant
Damage function	Parameter representation	Both	Significant
	Knowledge	Epistemic	Significant

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Table 2. Overview of the damage models from which damage functions are included in the damage function library.

Model	Description
HIS-SSM	The standard Dutch flood damage model (Kok et al., 2005). It is based on several earlier Dutch flood damage studies (Duiser, 1982; Briene et al., 2002). The functions are based on expert estimates combined with data from the 1953 flood in Zeeland and the 1945 flood of the Wieringermeerpolder.
HAZUS-MH	An American disaster impact model with a flood module. This model was created by the federal government agency FEMA. It is described in FEMA (2008) and Scrawthorn et al. (2006). HAZUS provides a large set of American flood damage functions. From the HAZUS library a subset was used in the library presented here. The functions taken for houses were based on American insurance data and the functions for companies are based on expert judgment from the USACE.
MCM	The Multi Coloured Manual (MCM) is a British flood damage model. For the library presented in this document the version of Penning-Roswell (2005) was used. MCM-based on a systematic expert judgment approach were a hypothetical building is split up in smaller parts, with each part being evaluated separately. The model has a large number of functions for different types of company buildings.
FLEMO	A German flood damage model based on data from the Elbe floods of 2002. The functions were derived from FLEMOps for houses (Thieken et al., 2008) and FLEMOcs for companies (Kreibich et al., 2010). The functions include a low and a high estimate.
Rhine Atlas	This second German model is based on expert judgement taking into account ~~and~~ data from an earlier German damage database (HOWAS). More information about these functions is available in Jongman et al. (2012).
Tebodin	This is a Dutch study, based on a detailed, systematic and well documented expert judgement approach. This study only provides damage functions for industry. It is detailed: it provides functions for many different industrial types and it has separate functions for areas protected by flood defences and for unprotected areas (Snuverink et al., 1998; Sluijs et al., 2000).
Billah, 2007	This is a research project in which the systematic expert judgment approach as used in MCM was applied to Dutch houses.

Table 3. Optimal investment strategy given different damage estimates. The flood protection standard is a return period based on the direct method described in Kind (2011), note that the actual return period of the investment strategy differs per year.

Damage (EUR in million)	Extra height for the investment (cm)	Flood protection standard (year)	PV Investment cost (EUR in million)	PV EAD (EUR in million)	PV Total cost (investment cost +EAD) (EUR in million)
8000	70	25 000	109	11	121
12 000	77	40 000	114	11	126
15 000	80	50 000	117	11	128
18 000	82	58 000	118	12	130
25 000	88	83 000	122	12	134

Table 4. Cost of a damage estimate error for this dike segment in EUR million.

		Damage estimate for calculation investment strategy				
		8000	12 000	15 000	18 000	25 000
Damage estimate Reality	8000	0	1.1	2.1	2.7	5.5
	12 000	1.3	0	0.2	0.5	2.3
	15 000	3.2	0.3	0	0	1.2
	18 000	5.2	0.9	0.2	0	0.7
	25 000	12.2	3.8	1.8	0.9	0
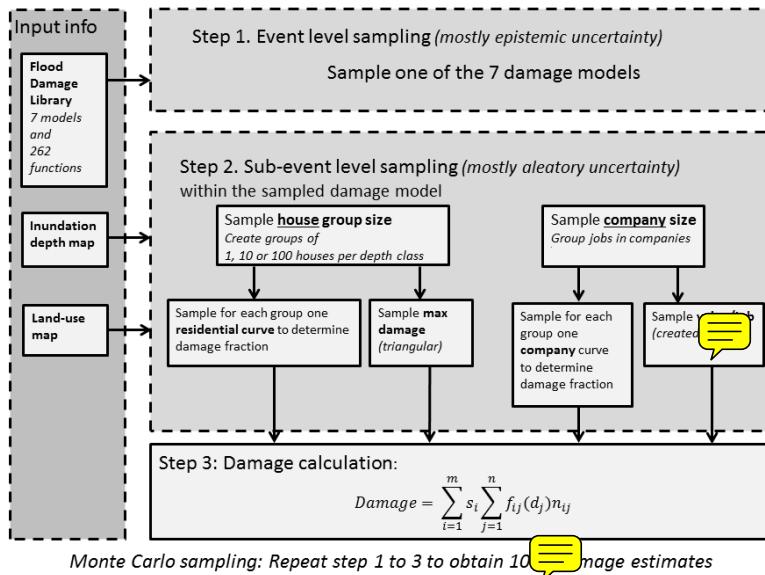
Figure 1. Overview of the different sample steps undertaken in the Monte Carlo analysis.

$$Damage = \sum_{i=1}^{m} s_i \sum_{j=1}^{n} f_{ij}(d_j) n_{ij}$$
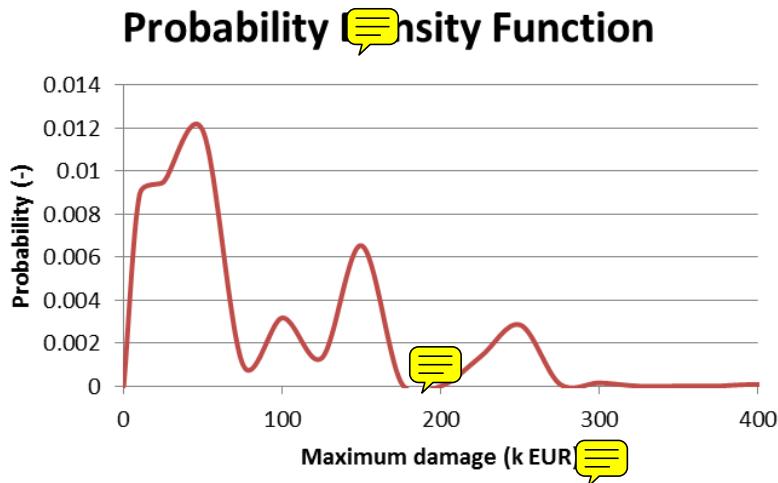
Figure 2. Probability density function of the average company value per job based on 62 different categories as defined in Gauderis (2012).
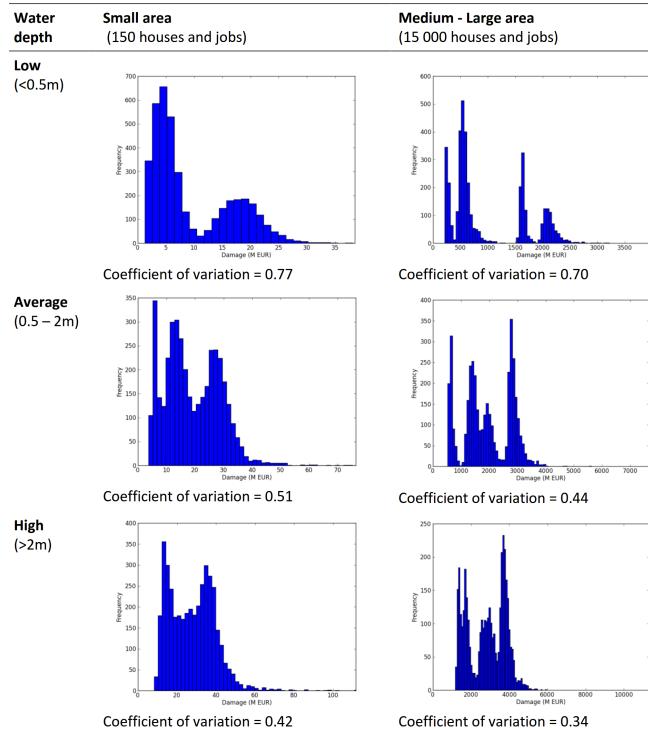
Figure 3. Results of the Monte Carlo simulations applied on synthetic flood maps shown as frequency distributions and coefficient of variations for different types of hypothetical areas based on 4000 samples. The *x* axis is equal to four times the mean damage.
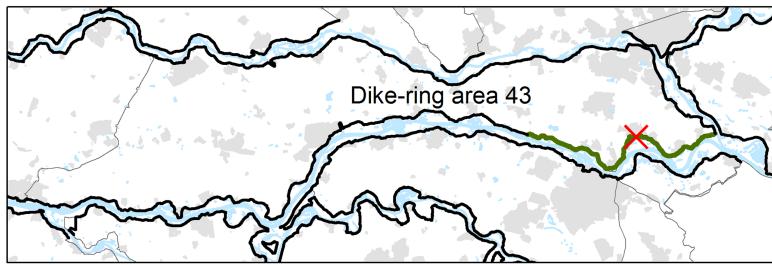
Figure 4. Map of the casestudy area. The green line is the dike segment that is looked at, the cross indicates the location of the breach scenario which was used.
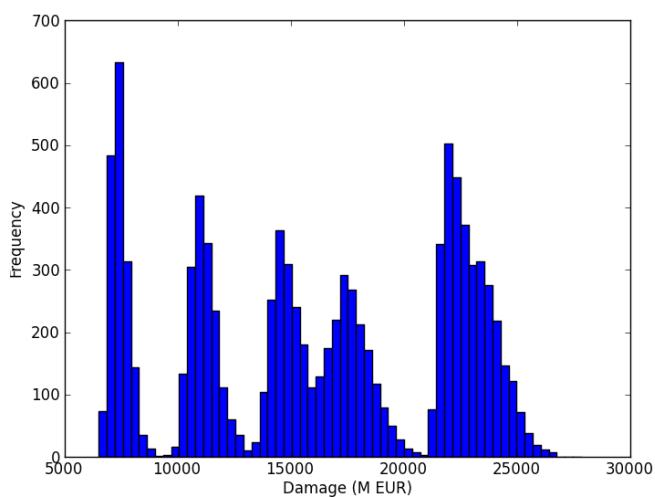
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Figure 5. Frequency distribution of the damage in the case study area (based on 10 000 Monte Carlo simulations).

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