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Simulating Flood Risk under Non-stationary Climate and Urban Development Conditions – Experimental Setup for Multiple Hazards and a Variety of Scenarios

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ABSTRACT

A framework for assessing economic flood damage for a large number of climate and urban development scenarios with limited computational effort is presented. Response surfaces are applied to characterize flood damage based on physical variables describing climate-driven hazards and changing vulnerability resulting from urban growth. The framework is embedded in an experimental setup where flood damage obtained from combined hydraulic-urban development simulations is approximated using kriging-metamodels. Space-filling, sequential and stratified sequential sampling strategies are tested. Reliable approximations of economic damage are obtained in a theoretical case study involving pluvial and coastal hazards, and the stratified sequential sampling strategy is most robust to irregular surface shapes. The setup is currently limited to considering only planned urban development patterns and flood adaptation options implemented over short time horizons. However, the number of simulations is reduced by up to one order of magnitude compared to scenario-based methods, highlighting the potential of the approach.

KEYWORDS

Flooding; Experimental Design; Hydraulic Modelling; Urban Development Modelling; Scenario Assessment; Deep Uncertainty

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1 INTRODUCTION

Flood risk in cities is strongly affected by climate change and urban development (Hinkel et al., 2014; Muis et al., 2015; Muller, 2007; Semadeni-Davies et al., 2008; Zhou et al., 2012).

The planning of flood risk adaptation measures therefore often relies on projections of these factors. However, both projections of climate (Hall et al., 2014; Madsen et al., 2014) and urban development (Cohen, 2004; Granger and Jeon, 2007) are subject to significant uncertainties. The design of flood adaptation options should therefore consider a variety of scenarios to identify robust measures and to identify opportunities to adapt options over time (Walker et al., 2013) and thus to gain the trust of decision makers (Leskens et al., 2014). Scenarios are in our case defined as changes of external circumstances that cannot be affected by the decision maker, i.e., different realisations of how climate and urban population develop over time.

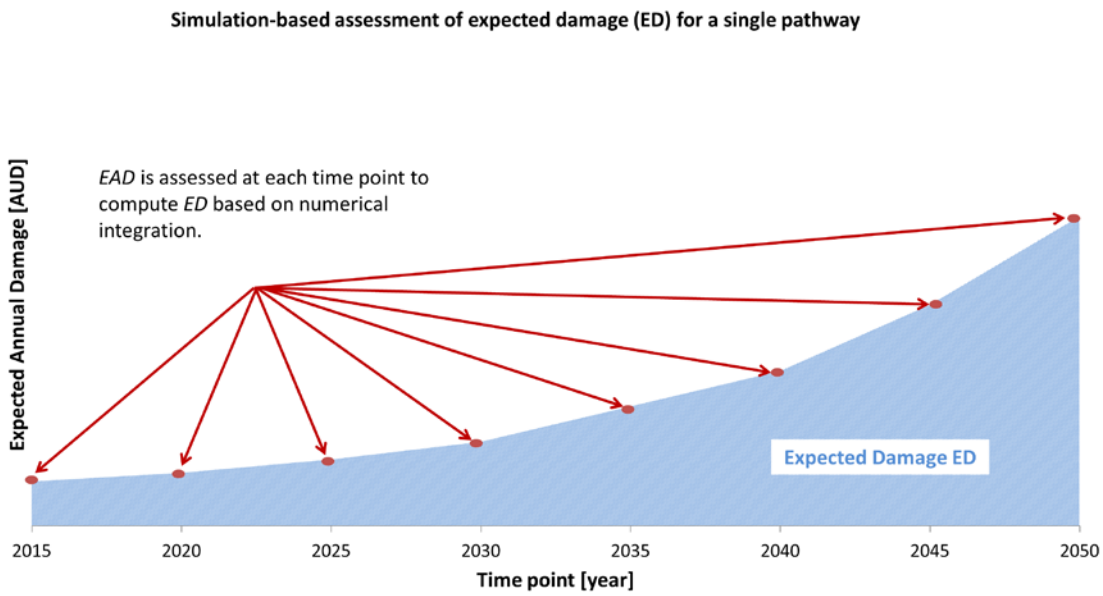

Figure 1. Illustrative development of expected annual damage (EAD) over the planning horizon for a single scenario, defined by assumptions on climate change rates and urban growth rate and assuming that a fixed set of water management options and urban planning policies is implemented.

To compare the efficiency of different adaptation measures, economic tools such as cost-benefit analysis are typically applied (GIZ, 2013). For a single scenario, the benefit from flood adaptation is the reduction in expected damages ED (Löwe et al., 2017), which can be assessed by integrating expected annual damages (EAD) (USACE, 1989) over the planning horizon. Depending on the considered scenario, EAD will often change in a nonlinear way with time. Consequently, EAD needs to be evaluated for multiple time points (Figure 1) to be able to perform numerical integration over the planning horizon (Löwe et al., 2017; Zhou et al., 2012). Similarly, the dimension and complexity of investment decisions in flood risk adaptation often means that we are also interested in the advantages and disadvantages of postponing the implementation of adaptation measures into the future (Watkiss et al., 2015) and in identifying tipping points, i.e., time points where critical values of flood risk are exceeded (Kwakkel et al., 2016). Also these analyses require an evaluation of EAD at multiple time points in the future, which then needs to be repeated for each scenario that is considered.

Detailed hydraulic simulation models are the standard tool to assess flood hazards in urban areas (Chen et al., 2012a; Şen and Kahya, 2017; Velasco et al., 2015). A number of setups have also considered the impact of urban development on urban water systems and flood hazards (Doglioni et al., 2009; Huong and Pathirana, 2013; Sekovski et al., 2015; Urich and Rauch, 2014). (Löwe et al., 2017) presented a framework that automatically links the output of an agent-based urban development model to a 1D-2D hydraulic model. This setup is illustrated in Figure 2 and forms the point of departure for this paper. It simulates flood risk for a user-selected planning option, defined by a set of water management measures implemented in the hydraulic model and an urban planning policy (i.e., the location and form in which urban development should occur), and a user-selected scenario, defined by assumed rates of change for climate and population. EAD is assessed for multiple time points along the planning horizon as illustrated in Figure 1. The simulation proceeds by

- Simulating urban development, i.e., creating new and replacing existing buildings based on the assumed population growth rate and the assumed development pattern, see (Urich and Rauch, 2014) and Appendix 1.
- Updating the 1D-2D hydraulic model with the simulated land-use layers. A separate hydraulic model is created for each time point along the planning horizon where EAD should be assessed.
- Performing 1D-2D simulations for multiple events corresponding to a relevant set of return periods for each of the considered time points for one or more hazards. In these simulations, pluvial risk is currently considered in the form of spatially uniform design storms, which is the standard approach in urban flood risk assessment.
  The simulated flood map is intersected with the simulated land-use layers and damages are computed based on depth-damage functions.

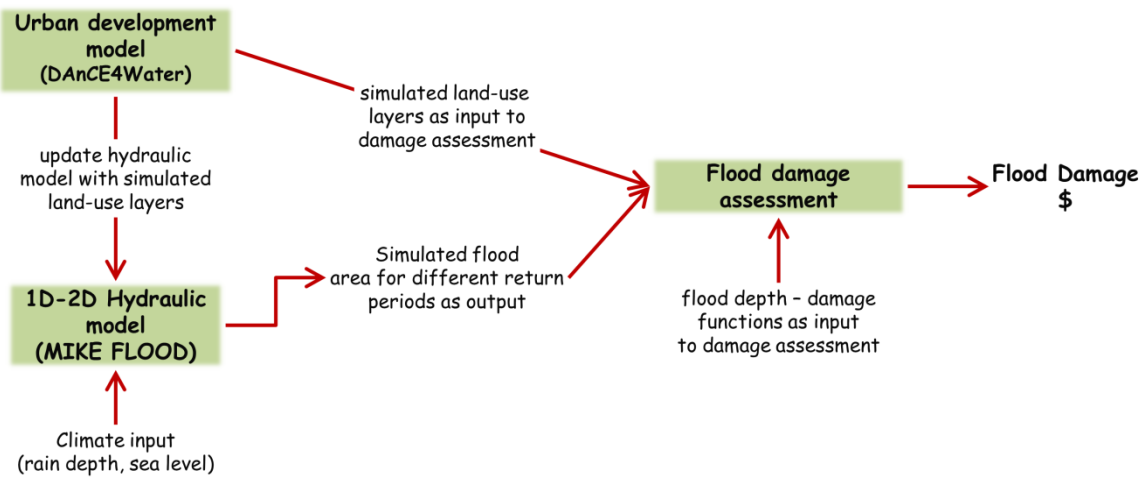

Figure 2. Setup for urban flood risk assessment in non-stationary climate and urban development.

The drawback of the detailed simulation setup is the computational demand, in particular when we consider that EAD needs to be assessed for a variety of adaptation measures, multiple scenarios, and several time points within each scenario. Even in a simple study considering only one hazard (Löwe et al., 2017) still performed more than 12,000 detailed simulations. Numerous methods for speeding up both hydraulic (Chen et al., 2012b; Davidsen et al., 2017; Guidolin et al., 2016) and urban development simulations (Jantz et al., 2010; Mikovits et al., 2015) have therefore been presented in the literature. These approaches

typically attempt to simplify the way the relevant processes are simulated, while still preserving some form of physical representation of the system.

In the work presented here, we instead focus on reducing the number of detailed simulations by using metamodels (also denoted surrogates or emulators) for the computation of flood damages. Metamodels have previously been applied in hydrology to model physical variables such as flows (Machac et al., 2016; Wolfs et al., 2015) or, as in our case, "hyper-variables" such as flood damages (Yazdi and Salehi Neyshabouri, 2014). A comprehensive review was performed by (Razavi et al., 2012a). Most applications in water-resources have considered problems related to optimization, where the meta-model is used to guide the optimizer to the optimum and the original model is then used to evaluate the objective function at the optimum. Further, in some cases (e.g., (Borgonovo et al., 2012)) meta-models were applied for the computation of sensitivity indices.

Our work instead uses metamodels to characterize the flood response of a catchment, i.e., the economic flood damages observed in the catchment given a certain magnitude of (multiple) flood hazards, and given a vulnerability of the catchment defined by the urban layout. The aim is to identify the metamodels based on a limited number of detailed simulations using sequential sampling (Kleijnen, 2015) and then to use it to compute flood damages for any scenario of interest, i.e., any combination of climate change and urban growth rate. The simulation time of the metamodel is negligible and the computational effort is thus reduced because detailed simulations no longer need to be performed for each hazard event at each time point in each scenario. (Hallegatte et al., 2011) used a similar approach by creating a functional relationship between flood damages in a city and sea level and, subsequently, using this relationship to assess expected damages for various sea level rise scenarios. In (Hallegatte et al., 2013), their approach was extended to consider socio-economic change by scaling the magnitude of the damage – sea level function and economic assessments were performed for 18 combined climate and urban growth scenarios. Similarly, (Prudhomme et al., 2010) created response surfaces for flood peaks as a function of mean annual precipitation and seasonal variability and used these to assess the effect of various climate scenarios. This paper extends previous work by

1. Including multiple flood hazards (rain depth and sea level) as input variables into metamodels that characterize economic flood damage response surfaces for a catchment,
2. Explicitly including urban growth as an input variable into the metamodels, thus allowing for the consideration of nonlinear relations between flood damages and urban growth,
3. Implementing a setup for computer experiments where multi-dimensional flood damage response surfaces are identified based on economic flood damages obtained from detailed hydraulic and urban development simulations using space-filling or sequential sampling strategies.
4. Testing the efficiency of the setup for the computation of expected damages in 4 test cases and comparing to a standard space-filling sampling strategy. The test cases are hypothetical, but derived from detailed urban development and hydraulic simulations for a catchment.

2 Framework for using Meta-Models to Calculate Expected Flood Damage Under Non-Stationary Conditions

This section outlines the conceptual basis for our setup. We illustrate how metamodels for flood response surfaces can be used to assess economic flood damages for a large number of climate and urban development scenarios in a catchment with multiple flood hazards. Technical details are provided in Section 3.

2.1 Evaluating Flood Risk for Various Scenarios and Different Adaptation Options Based on Meta-Models for Flood Response Surfaces

Computing ED as illustrated in Figure 1 for multiple scenarios quickly leads to a number of simulations that cannot be performed with detailed hydraulic simulation models, in particular if multiple flood hazards are considered (see Section 6.1). At the same time, simulations are repeatedly performed for very similar climate conditions and urban layouts (see Section 4.3. in (Löwe et al., 2017)). To reduce the computational demand, we introduce metamodels that quantify the output variable flood damage in the catchment based on input variables that characterize the magnitude of flood hazards and vulnerability and thus describe so-called flood damage response surfaces. We intend to use the metamodels in the following manner, which is also illustrated in Figure 3:

1. ***For each planning option***, a separate metamodel is identified that interpolates flood damages simulated using a detailed simulation setup (Figure 2) for a relatively small sample of the input variables. Planning options are active choices of the stakeholders, such as the implementation of a certain combination of water management measures and urban development zonings and affect the damages observed for a given hazard.
2. The metamodel for a given planning option can then be used to quantify flood damages in the catchment ***for hazard events with any return period at any future time point in any scenario***, i.e., for any trajectory of climate variables and urban population, as long as the magnitude of the input variables remains within the physical range considered by the metamodel. We can thus assess how the implementation of a set of adaptation measures affects flood risk in a large number of scenarios with the need to perform detailed simulations for each of those.

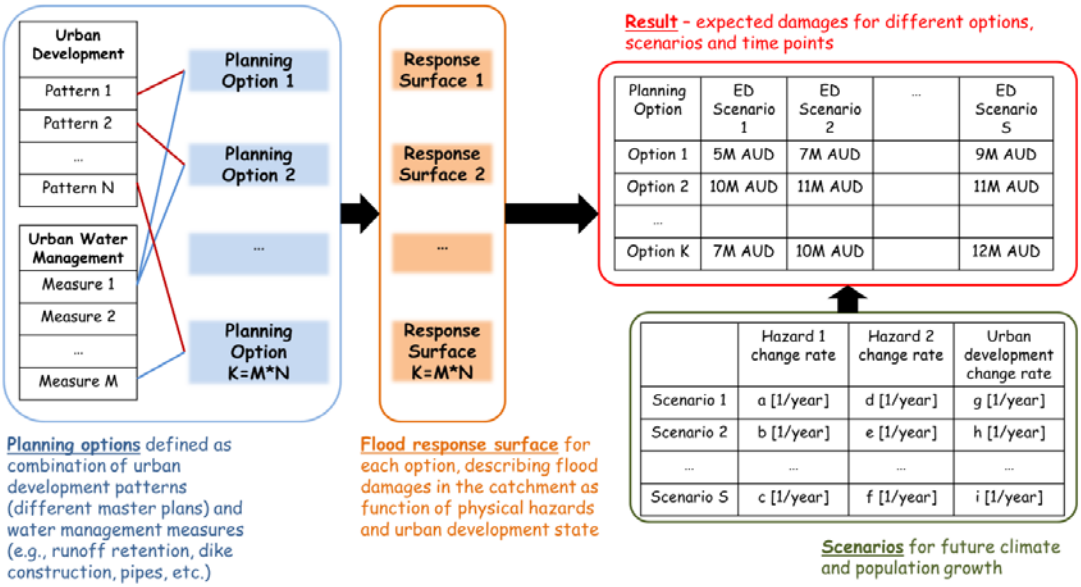

Figure 3. Schematic illustration of the application of response surfaces to assess flood risk in different scenarios. A different response surface needs to be identified for each combination of urban water management measures

and urban development masterplans. Each surface is used to compute expected damage ED for the corresponding planning option for all considered climate and population growth scenarios.

2.2 Input Variables for Characterizing Flood Risk of an Urban Catchment

In our case study, we consider an urban catchment with pluvial and coastal flood risk. We therefore chose the variables shown in Table 1 as input variables to a metamodel which characterizes flood damage. Considering the simulation setup in Figure 2, the rainfall depth P and the sea level S determine the extent and location of flood areas simulated in the catchment, while the number of households H determines how many buildings are subject to flooding. In fact, the increased number of buildings also leads to increased runoff and thus affects the simulated flood hazard. This effect is considered in the detailed simulation setup, but its impact on flood risk is small compared to the change in vulnerability (Löwe et al., 2017).

Table 1. Input variables in a metamodel that is used to quantify economic flood damage in a catchment.

Factor	Variable	Motivation
Pluvial Hazard	**P** - Total rain depth of design rain event in mm	In current practice, urban flood hazards are simulated in 1D-2D hydraulic simulations using spatially uniform design rain storms with fixed shape and duration as input. The rainfall depth is thus the only parameter affecting pluvial hazard and simulating events with different return periods simply corresponds to changing the total rain depth of the events used as input for the 1D-2D simulation.
Coastal Hazard	**S** – Sea level in m	Coastal risk is considered by applying water level boundaries with a fixed temporal pattern in the 1D-2D simulation. Assuming constant sea level during an event, we can determine the dependency of flood damage on this variable.
Changing Vulnerability	**H** – number of households in the catchment	Assuming new urban developments are simulated following a prescribed pattern of building locations and types, then the population, expressed as number of households, determines how many buildings of which type are placed in which locations in the catchment, and thus also which values are at risk of flooding for a given rain depth and sea level.

A metamodel using the variables in Table 1 to describe economic flood damage will be valid under the following principal assumptions (see Section 6.2 for a discussion of the limitations):

1. ***Urban development follows a fixed pattern and is the only factor affecting flood vulnerability of the catchment.***
   Assuming that urban development follows a fixed pattern of the form "property A is developed before property B, which is developed before property C, …" and further assuming that urban development is the only factor affecting flood vulnerability, changes of vulnerability can be linked to a variable describing the degree of urban development, for example, the number of buildings in the catchment.
   The assumption of fixed development patterns can be somewhat loosened by allowing noisy relationships between vulnerability and the variable used to measure the degree

of urban development. For example, rather than fixing an exact urban development pattern, one could require that developments should first occur in one area and then in another. The exact location of new buildings is then not known, leading to variability in the simulated flood damage. Although being more realistic, such a setup was also more difficult to implement and was therefore not yet considered in this study.

2. ***There is a unique relationship between flood damage in a catchment and the physical variables that quantify flood hazards.***
   Given a fixed vulnerability of the catchment, we can establish a relationship between the physical magnitude of flood hazards and the corresponding flood damage D obtained from a 1D-2D hydraulic simulation with subsequent damage assessment. For example, a storm surge with sea level of X meters always leads to the same simulated flood damage, irrespective of the fact that the storm surge will correspond to different return periods in different scenarios. This functional relationship is only valid as long as water management in the catchment does not change. For example, any relationship between flood damage and a magnitude of rain events would only be valid for a given layout of the stormwater pipe system.

From these assumptions, it is clear that a metamodel can only be valid for a single planning option. Different urban development zonings affect the degree to which urban development occurs in flood prone areas, while the implementation of different water management measures changes the extent and location of flooding that occurs for a given hazard event. It is important to note that the assumption of fixed water management implies that the effect of water management options does not change in time, i.e., once a decision maker chooses to implement a measure it can be assumed that it immediately reaches its full effect. This assumption is reasonable for the construction of dikes or basins, but certainly not for a gradual implementation of, for example, rainwater harvesting measures. The consideration of such measures is not addressed in this paper (see Section 6.2).

3 Experimental Setup To Assess Flood Damage Response Surfaces with Simulations

To define a flood damage response surface for a planning option, we need to

1. choose a metamodeling approach to interpolate between flood damage simulated using the detailed modelling setup shown in Figure 2, and
2. determine the combination of input variables for which detailed simulations need to be performed such that the metamodel describes flood damage in the catchment with sufficient accuracy.

Our approach to these issues is illustrated in the following two subsections.

3.1 Kriging as a Metamodel for Flood Damage Response Surfaces

A variety of meta-models have been applied in the literature. (Razavi et al., 2012a) and (Santana-Quintero et al., 2010) provide overviews of models applied in the water resources literature and the more general literature on computational intelligence, respectively. For the study presented here, a non-parametric meta-modelling technique needs to be applied, because the shape of the considered response surfaces cannot be assumed a-priori.

Kriging is a standard meta-modelling method in operational research (Kleijnen, 2015; Santner et al., 2003) and it has performed robustly in previous water resources applications (Razavi et

al., 2012b; Villa-Vialaneix et al., 2012). It allows for the consideration of different correlations along different dimensions and can thus be fitted flexibly to surfaces where the exact shape is unknown. In addition, the method is fast as long as the datasets do not exceed a few hundred observations and it was previously applied in conjunction with the sequential sampling strategy described in Section 3.2. Kriging was therefore selected as the meta-modelling approach applied in this study.

We consider a kriging model of the form

$$Y = \beta_0 + Z(\boldsymbol{x}), \tag{1}$$

where

$$Y = \frac{(D+1{,}000)^{0.25}-1}{0.25} \cdot \frac{0.25}{(D_{max}+1{,}000)^{0.25}-1}, \tag{2}$$

is the power transformed flood damage D scaled to the interval [0,1] based on an assumed maximal flood damage D_{max}. For our case study, we considered $D_{max} = \$1.5 \cdot 10^9$. In the transformation, we considered an offset of $\$1{,}000$ to address 0 values which are not defined in the transformation. The transformation was selected based on an analysis of simulated flood damage in the catchment with the aim of linearizing the relationship between output and input variables (Appendix Section 3).

We consider a constant trend function with intercept parameter β_0 which is a standard approach in deterministic simulation metamodeling (Kleijnen, 2015). Results of experiments performed with linear trend functions are detailed in the appendix (Section 5). However, we could not identify a clear improvement over the results presented for ordinary kriging metamodels in this paper.

$Z(\boldsymbol{x})$ is a second order stationary Gaussian process with zero mean and covariance function

$$C(l_p, l_s, l_h) = \sigma^2 g(l_p, \theta_p) g(l_s, \theta_s) g(l_h, \theta_h). \tag{3}$$

The input variables p, s and h correspond to P, S and H scaled linearly to [0,1], σ, θ_p, θ_s and θ_h are parameters and l_p, l_s and l_h are the 1-dimensional distances between two points with respect to the different variables. Type $Matérn\ \nu = 3/2$ was selected for the covariance kernel g based on an analysis of variograms for simulated flood damage in the catchment (Appendix Section 3).

We implemented the kriging metamodels in the R-Package DiceKriging (R-Core-Team, 2013; Roustant et al., 2012). All parameters of the kriging models are estimated using a Maximum Likelihood approach as documented by (Roustant et al., 2012).

3.2 Sampling Schemes for the Identification of Flood Response Surfaces

To identify the response surfaces, we need to determine a sample of the input variables (Table 1) for which the detailed hydraulic and urban development simulations as shown in Figure 2

should be performed. The aim is to identify a response surface that accurately describes flood damage in the catchment with as small a data sample as possible, as computational effort is minimized in this way.

Commonly, space-filling schemes (or "designs") based on latin hypercubes (Stein, 1987) and quasirandom sequences (Sobol' et al., 2011) are applied for computer experiments. (Kleijnen, 2015, 2009) argues that sequential sampling schemes are more efficient than space-filling designs with a fixed number of sample points. In this paper, we test the identifiability of flood response surfaces using a maximin space-filling scheme (Santner et al., 2003) as an efficient, easily implemented baseline (MAXIMIN) and using a sequential sampling scheme (SEQU) as described by (Kleijnen, 2015).

We observed that for non-smooth surfaces the sequential algorithm clusters data points in the regions where the gradient of the output Y is largest. While this in principle is a desirable feature, it can hinder the discovery of the rest of the surface. Therefore, we have also introduced a version of the sequential scheme (SEQUS), where sampling is performed in a stratified manner to ensure that data points are sampled in all regions of interest.

Maximin Scheme (MAXIMIN)
With this scheme, a latin hypercube sample of size n is initially generated and subsequently optimized such that the minimal distance between any 2 points in the sample becomes maximal (Santner et al., 2003). We apply the implementation from the R-package "DiceDesign" (Dupuy et al., 2015) which uses a simulated annealing algorithm for the optimization of the sample (Damblin et al., 2013).

Sequential Scheme (SEQU)
We apply a 6-step procedure for sequential sampling as proposed by (Kleijnen, 2015; Kleijnen and van Beers, 2004):

1. ***Pilot Experiment***
   The algorithm starts with a small initial sample of data points. (Kleijnen, 2015) suggests using a space-filling design. We have instead chosen to use an informed sample of 7 data points, where s and p are chosen as the centre points of the boxes shown in Figure 4, while h is generated as a stratified sample of size 7. The motivation for this approach is to ensure that all areas of interest for the computation of expected damage are represented in the pilot experiment.
   Flood damage for the selected data points is computed using the detailed simulation model.
2. ***Fit the kriging metamodel to the $m = 7$ available data points (Roustant et al., 2012)***
3. ***Create a set of candidate points and find the candidate point with the biggest metamodel predictor variance***
   We create a latin hypercube sample of 350 candidate points in the 3-dimensional unit space defined by s, p and h. For each candidate point, we compute the jack-knife variance of the metamodel prediction by generating m predictions of Y for each candidate location, removing one of the m available data points at a time from the

kriging model fitted in the previous step (Kleijnen, 2015). We select the candidate point with the biggest jack-knife variance[a].

4. ***Insert the candidate point selected in step 3 into the dataset***
   Flood damage for the new data point is computed using the detailed simulation model. The flood damage – input variable dataset now contains $m + 1$ data points.
5. ***Fit the kriging model to the new data set with $m + 1$ data points***
6. ***Return to step 3.***

Stratified Sequential Scheme (SEQUS)

This scheme proceeds in the same manner as SEQU. However, we divide the simulation space into seven boxes as shown in Figure 4. The edges of the boxes are defined by the 1 and 10 year return levels for S and P, while no subdivision is performed along the household dimension.

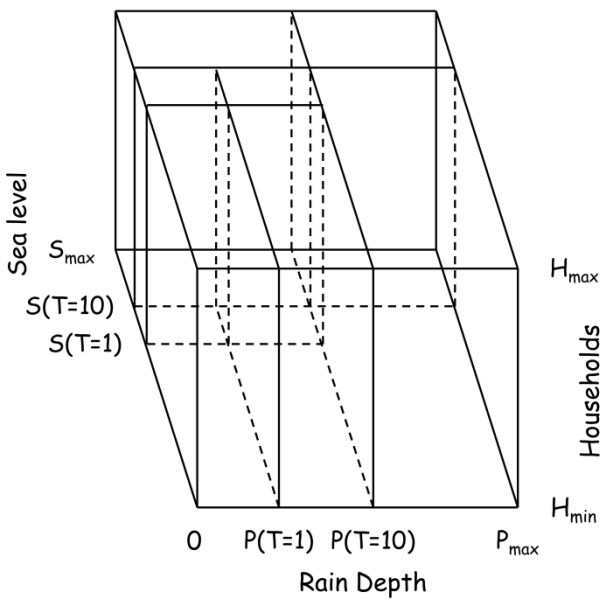

Figure 4. Division of simulation space for stratified sampling. The bounding boxes are defined by the sea level and rainfall depths occurring with return periods of 1 and 10 years in current climate. No stratification is imposed along the household axis.

Step 3 of the SEQU algorithm is then modified in such a way that 50 candidate points are selected as a latin hypercube sample in each of the boxes. We then identify the candidate point with the biggest jack-knife variance in each box. In step 4, we insert all the selected candidate points into the dataset. After each iteration of the algorithm, the number of data points thus increases to $m + 7$ rather than to $m + 1$ as in the SEQU algorithm.

[a] Note, that (Kleijnen, 2015; Kleijnen and van Beers, 2004) also consider the application of the kriging variance instead of the jackknife variance to select the candidate point which should be inserted into the design dataset. In this case, the sequential algorithm resembled a space-filling design.

The purpose of this stratification approach is to ensure that data regions corresponding to flood events with high probability of occurrence are frequently sampled, irrespective of the shape of the flood response surface. These regions have higher weight in the computation of expected flood damage and thus need to be predicted with high accuracy by the metamodel.

While our work focused on evaluating the performance of the different sampling schemes, we have also derived a potential stopping criterion for the SEQUS scheme to obtain realistic estimates for the number of sampling iterations that would be required when applying the algorithm to different catchments. The criterion is based on computing the expected damage ED^* for one scenario from the metamodel and stopping the sampling scheme when additional data points no longer affect the estimates of expected damage (see Section 6 in the Appendix).

4 CASE STUDY APPLICATION OF THE PROPOSED FRAMEWORK

The main purpose of the experimental setup presented in this paper is to reduce the computational effort required for quantifying economic flood damage. We are thus interested in the number of detailed model simulations needed to identify a flood response surface in a given case. To test the efficiency of our approach, we created reference flood response surfaces for four cases (see Section 4.2). Subsequently, we tried to identify these reference surfaces using metamodels based on different numbers $N$of sampled data points. The response surfaces for the four cases are deterministic, i.e., they are characterized by known mathematical functions, but they are inspired by detailed simulation results obtained for an Australian catchment. As a measure of accuracy we compared expected damage ED computed based on the reference surfaces and the kriging metamodels obtained for different numbers of data points N.

4.1 Case Study Area

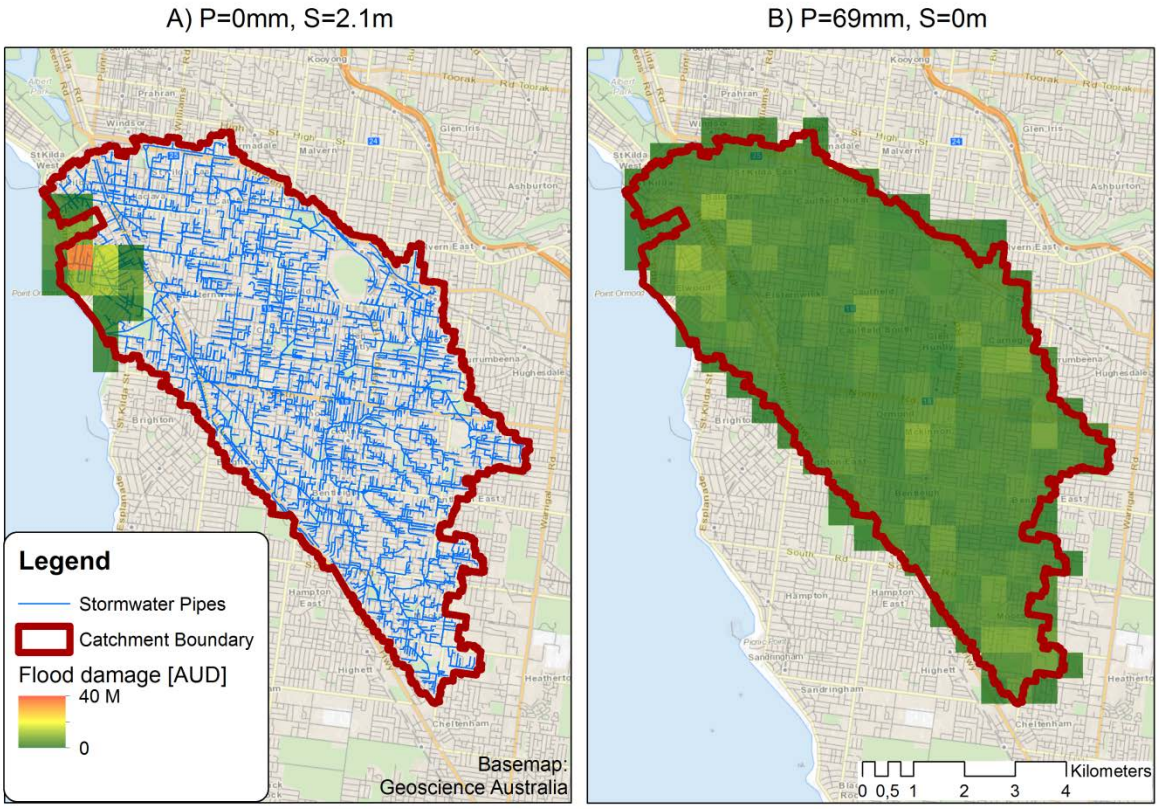

Figure 5. Elster Creek catchment in Melbourne, Australia with flood damage simulated for 100 year return levels of sea level (A) and design rainfall depth (B) projected for 2090 in RCP4.5.

The test cases described in Section 4.2 were derived based on flood damages estimates obtained from detailed hydraulic and urban development simulations for the Elster Creek catchment in Melbourne, Australia. The catchment has an extent of approximately 45km^2 and covers mostly suburban residential areas. The catchment is subject to significant pluvial risk, as well as risk of coastal flooding in the densely populated areas downstream. A 1D-2D hydraulic simulation model for the catchment is used to simulate flood hazards in the area (Davidsen et al., 2017), and both, stage-depth damage functions for flood damage assessment, as well as probability distribution for extreme rainfall and storm surges are available based on an analysis of local data (Nobre, 2015; Olesen et al., 2017). Figure 5 illustrates flood damage based on 1D-2D hydraulic simulation of the catchment for events that would have a return period of 100 years in 2090, assuming change of rain intensities and sea levels projected for RCP 4.5 (CSIRO and Bureau of Meteorology, 2015).

Rapid urban growth is projected in the area (Infrastructure Australia, 2015) and an agent-based urban development model for the catchment was implemented in the software DAnCE4Water (Urich and Rauch, 2014) to simulate the densification of the already built-up area through infill developments (Appendix Section 1).

4.2 Hypothetical Test Cases

We tested the experimental setup for identifying flood response surfaces for 4 different cases (or planning options). In all cases, we defined a hypothetical, deterministic flood response

surface for the catchment which describes the variation of flood damage with the input variables S, P and H. These surfaces are assumed to characterize the "true" flood response in the corresponding case and are in the following referred to as "reference surfaces". The experiments described in Section 4.3 aimed at identifying these reference surfaces, i.e., no detailed model simulations were performed.

In all reference surfaces, variations of design rainfall depth between 0 and 80mm are considered, sea level is varied in the range from 0 to 2.1m and the number of households in the catchment is varied between the current state of 86,500 households and a maximal considered urbanisation level of 123,900 households.

We considered the following cases:

A. ***No adaptation*** – This case characterizes the state of the catchment "as is", i.e., without implementing any flood adaptation measures.
B. ***Increase of stormwater pipe capacity*** – The capacity of the pipe system is assumed to be increased through upgrades of the existing pipe network and the installation of diversion pipes.
C. ***Flood proofing of buildings*** – It is assumed that regulations requiring a freeboard of 0.5m are introduced in the catchment, so buildings do not suffer damage for flood depth below this level.
D. ***Dike construction*** – It is assumed that a dike is installed along the coast in combination with flood gates and pumping stations, so that storm surges with water levels up to 1.5m do not result in any damage. For sea water levels above 1.5m, the dike is assumed to be overtopped.

The reference surfaces for cases A-C are based on kriging models that were fitted to power-transformed (Eq. 2) flood damage generated using the detailed modelling setup shown in Figure 2 (Appendix Sections 1-4). In case D the reference surface is based on the combination of two linear models fitted to power transformed flood damage simulated for case A, considering only pluvial ($Y = f(p)$) and only coastal hazards ($Y = f(s)$), respectively (Appendix Section 4). Flood damage resulting from the coastal hazard is set to 0 for water levels <1.5m.

Figure 6 illustrates the variation of flood damage with rain depth P and sea level S for the current urban layout with 86,500 households in all 4 cases. In case A, a step increase of flood damage is observed with both increasing rain depth and sea level. In fact, for this case significant damage was observed already for rather small rain events with return periods in the order of 1 year. In case B, the overall damage was reduced. In particular, flood damage increased less rapidly with increasing rain depth. In case C, the damage levels are generally reduced, while the response surface for case D has a pronounced discontinuity at sea level $S = 1.5$ m, which was implemented to demonstrate the limitations of the sampling algorithm.

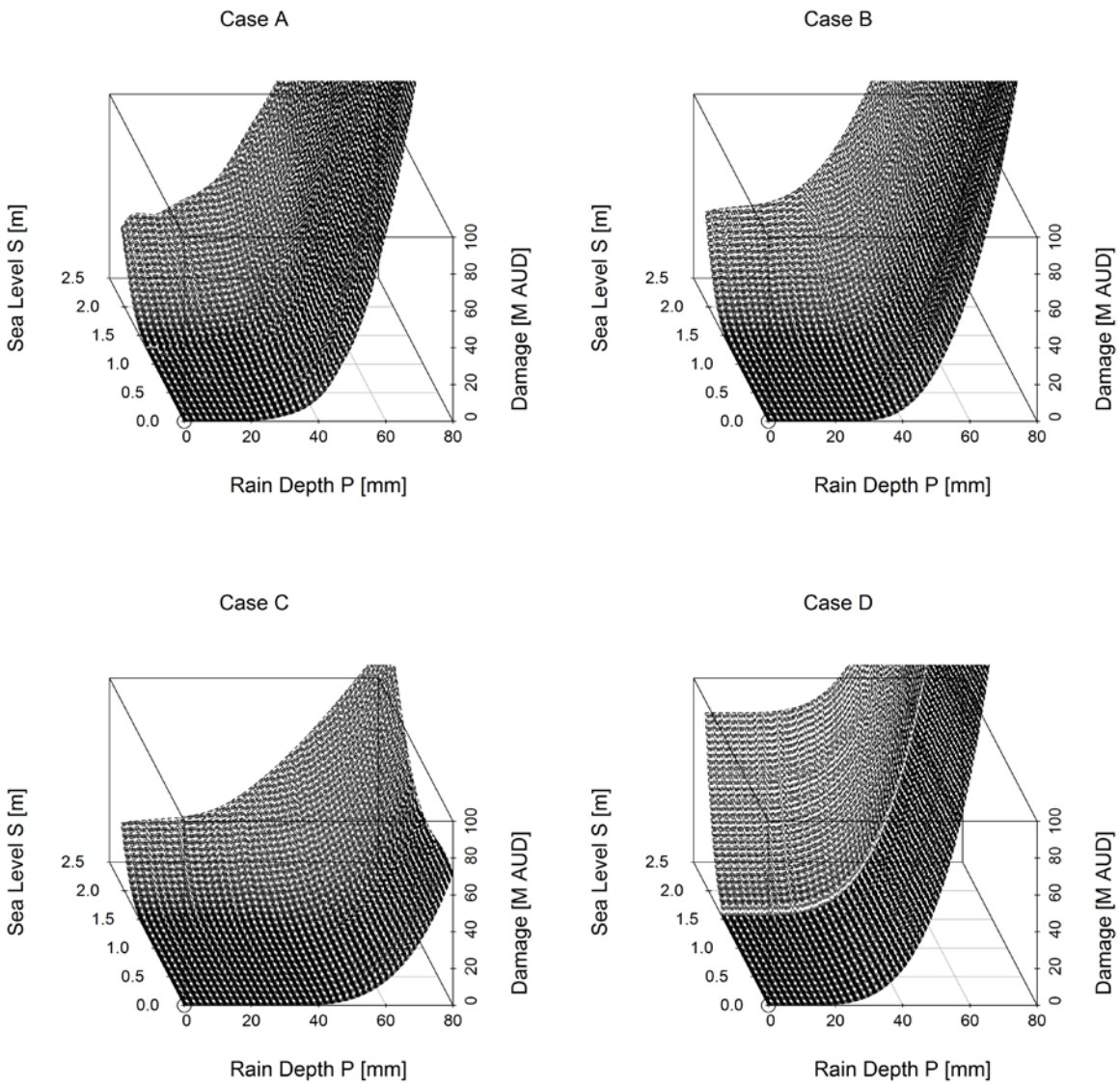

Figure 6. Flood damage for different combinations of rain depth and sea level and for a fixed number of 86,500 households in the case study catchment.

The flood damage response surfaces illustrated in Figure 6 assume a fixed number of households in the catchment. Similar trends for the dependency of damage on rain depth P and sea level S are observed when considering a denser urban layout, i.e., for increasing number of households. However the general damage level is increased. This is illustrated in Figure 7, showing how EAD (Stedinger, 1997) computed based on the hypothetical reference surfaces for cases A-D and assuming current climate depends on the number of households. The computation of EAD is detailed in Section 4.3. The figure highlights the generally reduced damage levels in cases B and C as compared to case A and the increase of EAD with the increasing number of households in the catchment.

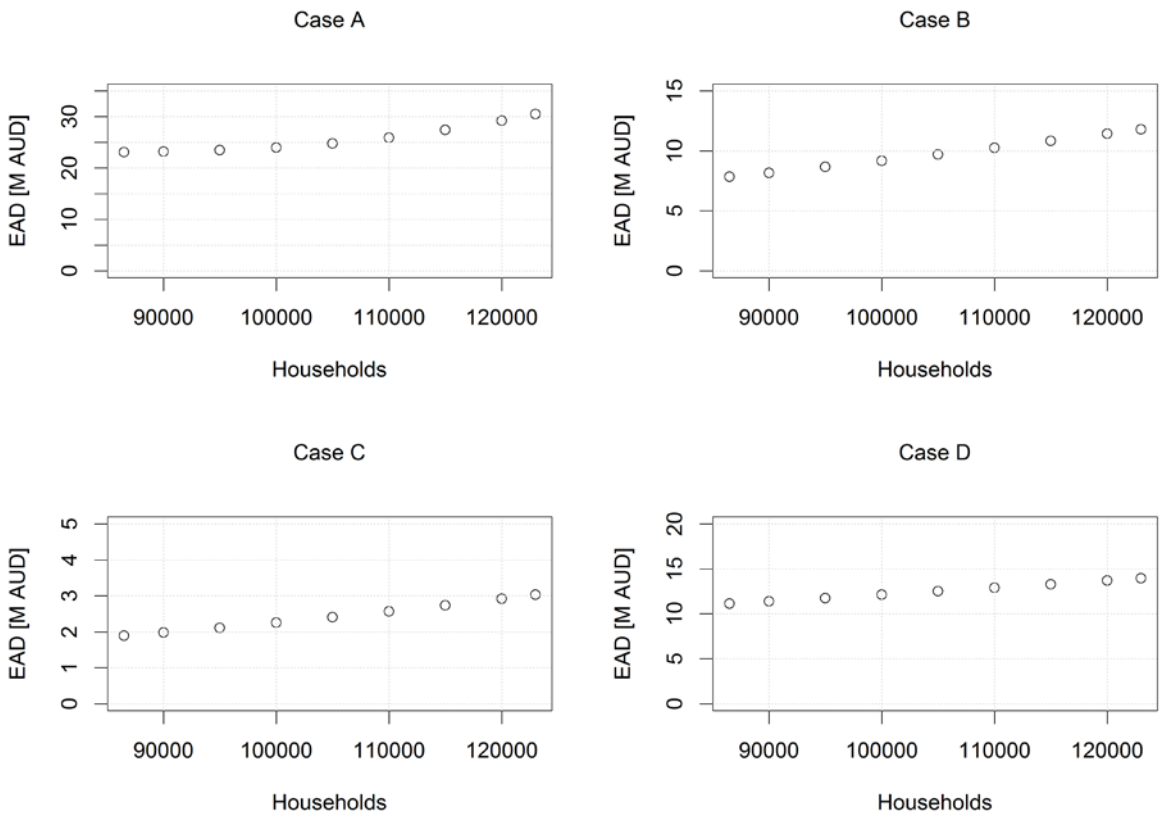

Figure 7. Variation of expected annual damage EAD with urban growth (expressed as number of households H in the case study catchment) in the hypothetical test cases A-D assuming no climate change. See Section 4.3 for details on the computation of EAD.

4.3 Performance Evaluation

We assessed the performance of the experimental setup by computing expected damage ED over a planning horizon of 30 years from both the reference surfaces, and from the kriging metamodels identified for different numbers of data points N using the sampling schemes presented in Section 3.2. Flood damage is zero for rain depth and sea levels corresponding to events with return periods smaller than 0.5 years in current climate. This region is therefore excluded from sampling in all schemes.

We considered 2 scenarios with different rates of climate change and urban growth as shown in Table 2. The first scenario represents a case where only moderate increases of flood risk are anticipated in the future, while the second scenario involves pronounced changes of flood risk.

The aim is to identify the number of data points that need to be included in the kriging metamodels, such that the expected damage computed from the metamodels deviates by only a few percent from the reference. As the considered sampling schemes are based on a random selection of new data points, we performed 50 repetitions k of the sampling process for each of the considered sampling schemes, cases and scenarios.

Table 2. Scenarios considered for computation of expected damage along the assumed planning horizon of 30 years.

Scenario	Increase design rainfall intensity [%/year]	Increase sea level [m/year]	Population growth rate [%/year]
I) moderate climate change, slow urban growth	0.02	0.005	0.3
II) pronounced climate change, fast urban growth	0.15	0.006	1.3

The computation of expected damage ED proceeds as follows:

1) Consider rainfall and sea level in 50 equally spaced intervals of 80/50=1.6mm and 2.1/50=0.04m, respectively.
2) For each year of the planning horizon compute EAD by
   a) Computing probability of occurrence for each of the 50x50=2,500 rainfall-sea level pairings based on the extreme value distributions for rainfall and sea level derived by (Nobre, 2015) and based on the climate change rates defined for the considered scenario.
   b) Computing anticipated number of households based on the population growth rate defined for the considered scenario.
   c) Computing flood damage from the considered response surface for each rainfall-sea level pairing given the considered number of households.
   d) Computing EAD for the considered year of the planning horizon based on the flood damage derived in step c) and the probability of occurrence derived in step a).
3) Sum up EAD derived for the different years of the planning horizon to obtain ED.

Computer code for the computation of EAD is available in (Löwe, 2017).

We consider the relative deviation $RDED_{i,N}$ between the expected damage $ED_{i,N}$ computed from kriging metamodels based on N data points obtained using sampling scheme i and the expected damage ED_{ref} computed from the reference surface for the considered case and scenario:

$$RDED_{i,N} = \frac{ED_{i,N} - ED_{ref}}{ED_{ref}} \tag{4}$$

5 RESULTS

5.1 EXPECTED DAMAGE COMPUTED USING DIFFERENT SAMPLING SCHEMES

Figure 8 and Figure 9 illustrate the relative deviations $RDED_{i,N}$ obtained for kriging metamodels based on N sampled data points. While Figure 8 shows the $RDED_{i,N}$ with biggest absolute value observed amongst the 50 repetitions k performed for each sampling scheme, the median of the absolute values is shown in Figure 9.

From both figures, it is clear that the SEQUS scheme performed slightly better than the SEQU scheme in cases A to C. In the 50 repetitions performed for each case, the expected damage

computed from the kriging metamodels never deviated more than 10% from the ED computed from the reference surface once 120 data points were sampled in case A and once 40 and 20 data points were sampled in cases B and C, respectively. An accuracy of at most 5% deviation was achieved with 200 data points in case A, while 45 and 25 data points were required in cases B and C. The number of data points required to achieve the same accuracy was slightly higher when applying the SEQU scheme, while both the SEQU and SEQUS schemes generally yielded small $RDED$ with significantly fewer data points than the space-filling MAXIMIN scheme. The slower convergence in case A originated from the fact that flood damage was already observed for events with small return periods in this case. This implies that the kriging metamodel needs to reproduce the reference surface more accurately in absolute terms, because relatively small damage values for events with high return frequencies receive a large weight in the computation of expected damage. Similarly, in all cases metamodels fitted with only few data points tended to overestimate expected damages (Figure 8), because they predicted small damages in the data region where damages were 0. Again, this lead to a strong overestimation of expected damages, because the events linked to this data region had high return frequencies.

Case D was the most critical test case, because

- the corresponding reference surface features a similarly steep increase of damage with rainfall depth as in case A,
- the reference surface, other than in cases B-C, is not based on a kriging model, and
- because the reference surface features a discontinuity at a sea level of 1.5m, which is a challenge for both the metamodeling approach and the sampling schemes.

Accordingly, the metamodels need to include a large number of data points to represent the reference surface with sufficient accuracy. The MAXIMIN sampling scheme returns metamodels with RDED below 5 % if at least approximately 250 data points are sampled (Figure 8). The SEQUS scheme enters this range after sampling approximately 200 data points, while the SEQU scheme in some of the repetitions does not converge at all. The latter point is indicated by a maximum $RDED$ remaining constantly above 10% in Figure 8. Interestingly, the MAXIMIN scheme converges faster and more reliably than in case A, which might suggest that the reference surface based on linear models is more easily identified by a space-filling sampling scheme. The fact that the SEQU scheme cannot guarantee convergence to the true surface in case D illustrates the limitation of this approach. The problem is mitigated by the introduction of the stratification in the SEQUS scheme.

Finally, the convergence rates derived based on Figure 8 cannot be applied to, for example, decide after how many simulations sampling should be stopped when considering a new catchment. The shape of the flood response surface is unknown in this case and a reference surface is not available. Applying the convergence criterion derived in Section 6 of the Appendix in combination with the SEQUS scheme suggests that sampling would on average be terminated once 128 data points have been sampled in case A, 98 in case B, 120 in case C and 164 in case D.

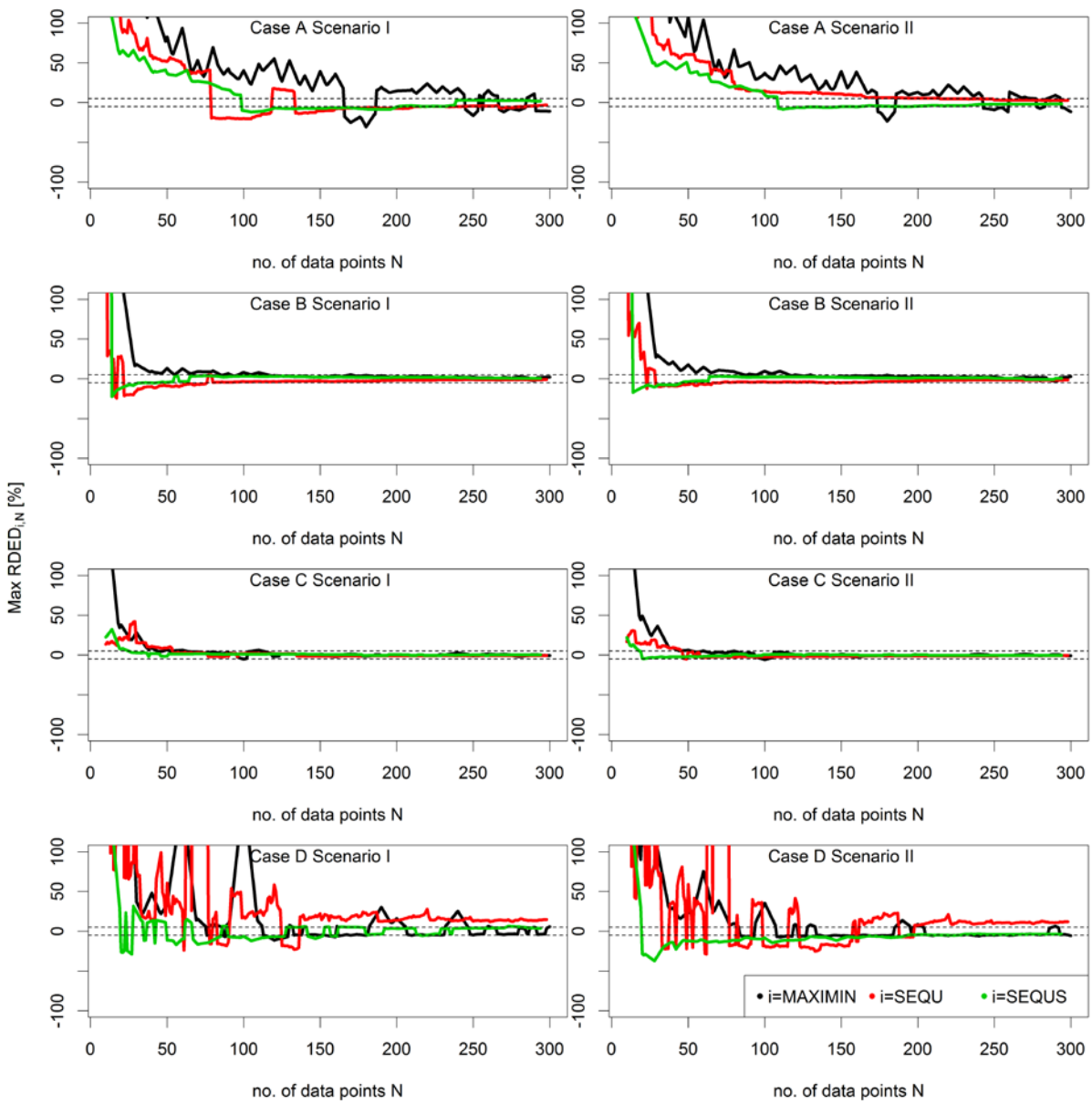

Figure 8. $RDED_{i,N}$ with largest absolute value, computed after sampling different numbers of observations N using the sampling schemes i for the different cases and scenarios (MAXIMIN=maximin sampling scheme, SEQU=sequential sampling scheme, SEQUS=stratified sequential sampling scheme). Deviations were computed for each of the 50 repetitions performed for of each sampling scheme. 5 and -5% accuracy levels are highlighted using dashed lines.

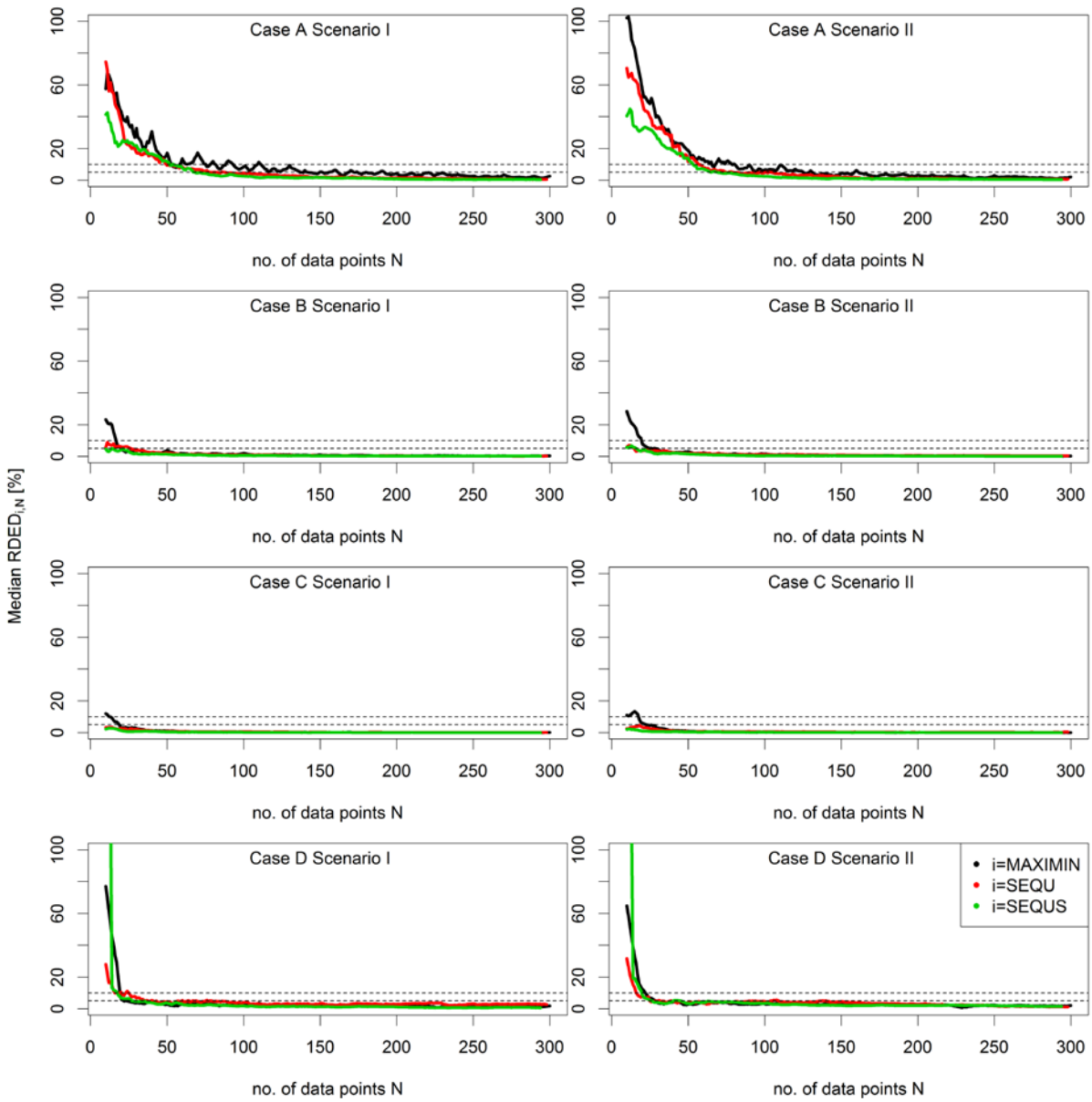

Figure 9. Median absolute $RDED_{i,N}$ computed after sampling different numbers of observations N using the sampling schemes i for the different cases and scenarios (MAXIMIN=maximin sampling scheme, SEQU=sequential sampling scheme, SEQUS=stratified sequential sampling scheme). Median errors are computed based on 50 repetitions of each sampling scheme. 5 and 10% accuracy levels are highlighted using dashed lines.

5.2 Sampling Locations Selected by the Different Sampling Schemes

Based on the results in the previous section, we can conclude that the considered sampling schemes significantly differ in the number of data points required to accurately reproduce the reference surfaces. Obviously, these differences occur because the schemes sample data points in different locations. To gain insight into the behaviour of the three schemes, we therefore analyse in Figure 10 and Figure 11 how often different regions of the simulation space are sampled.

We focus on the dimensions rainfall P and sea level S, because the most significant differences between the sampling schemes are observed along these dimensions. In the

household dimension H, the MAXIMIN scheme uniformly samples data points in the range of the variable, while the sequential schemes also sample the whole variable range, but slightly favour the extremes. This result provides little insight into the differences between the schemes and is therefore not shown here.

In Figure 10 and Figure 11 the simulation space defined by the variables S and P is divided into 25x25 intervals. In each of the 50 repetitions performed for each sampling scheme, we have counted how many of the first 100 sampled data points were located in each interval. The figures show these counts summed over the 50 repetitions k on a logarithmic scale. While Figure 10 depicts the results for Case A, Figure 11 shows the results for case D. For better reference, the figures also include the boundaries of the boxes applied for stratified sampling in scheme SEQUS as shown in Figure 4.

From both figures it is clear, that the MAXIMIN scheme samples data points more or less evenly distributed in the simulation space, not considering the region where damage is known to be zero and which was therefore excluded from sampling. In particular, data points corresponding to events with small return periods are well represented, but at the same time a lot of data points are sampled in regions with high return periods and little variation of the reference surfaces. The scheme can thus be considered robust in accurately identifying the reference surfaces, but it is also inefficient as more points are sampled than necessary to identify the surface.

Schemes SEQU and SEQS sample relatively more data points in data regions with rather small return periods around the edges of the simulation space and in the data region where the sea level variable S starts to have an impact on the observed damage. In case A, the SEQU scheme samples most data points in the region with rain depths smaller than 40mm, while the SEQUS scheme distributes data points evenly amongst the boxes used for stratification, leading to a concentration of data points in the small boxes for sea levels between 1.3 and 1.5m.

The tendency of both schemes to sample data points corresponding to events with small return periods can be explained by the fact that the kriging metamodels are applied to power-transformed flood damage Y (Eq. 2), which implies that prediction errors for small flood damage is punished more severely in comparison to prediction errors for large damage. This feature is very much desirable, as data regions with minimal flood damage typically have a higher probability of occurrence and thus, receive larger weight in the computation of expected damage.

In Figure 11 the impact of the discontinuity in the reference surface for case D on the SEQU scheme can be observed. The scheme places the majority of data points in the region around the discontinuity as the metamodel cannot properly describe the surface in this region. The rest of the data region is not properly sampled anymore, and in some of the repetitions the scheme does not place any data points in the other regions. This leads to the large errors in the computation of ED seen in Figure 8 and Figure 9. In the SEQUS scheme, a similar tendency to sample around the discontinuity can be observed. However, the effect is mitigated by the stratification which forces the scheme to also place data points in other data regions.

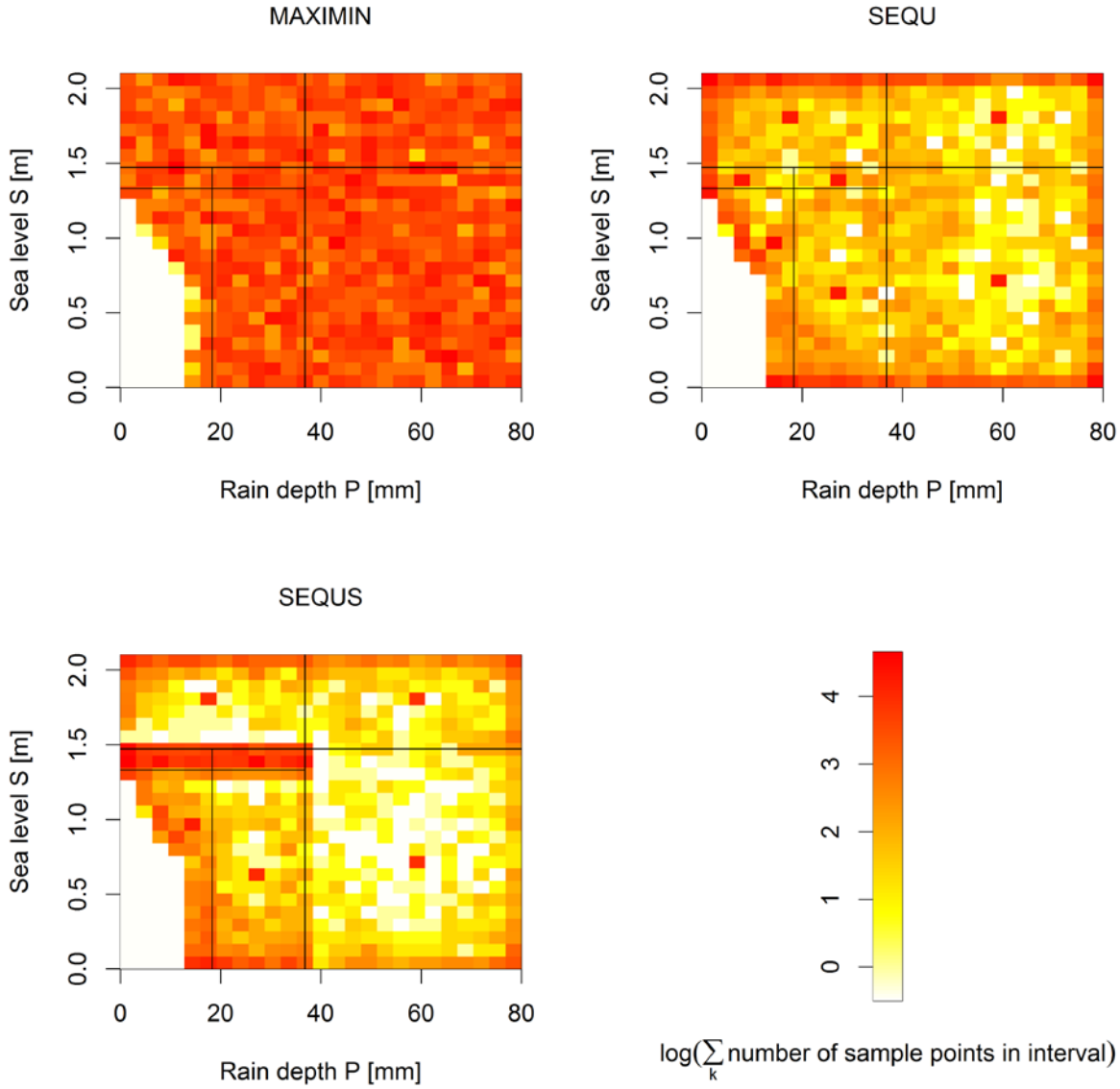

Figure 10. Number of data points that were sampled in different intervals of rainfall *P* and sea level *S* during 50 repetitions *k* after sampling 100 data points using the different sampling schemes (MAXIMIN=maximin sampling scheme, SEQU=sequential sampling scheme, SEQUS=stratified sequential sampling scheme). Results are shown on a logarithmic scale for case A.

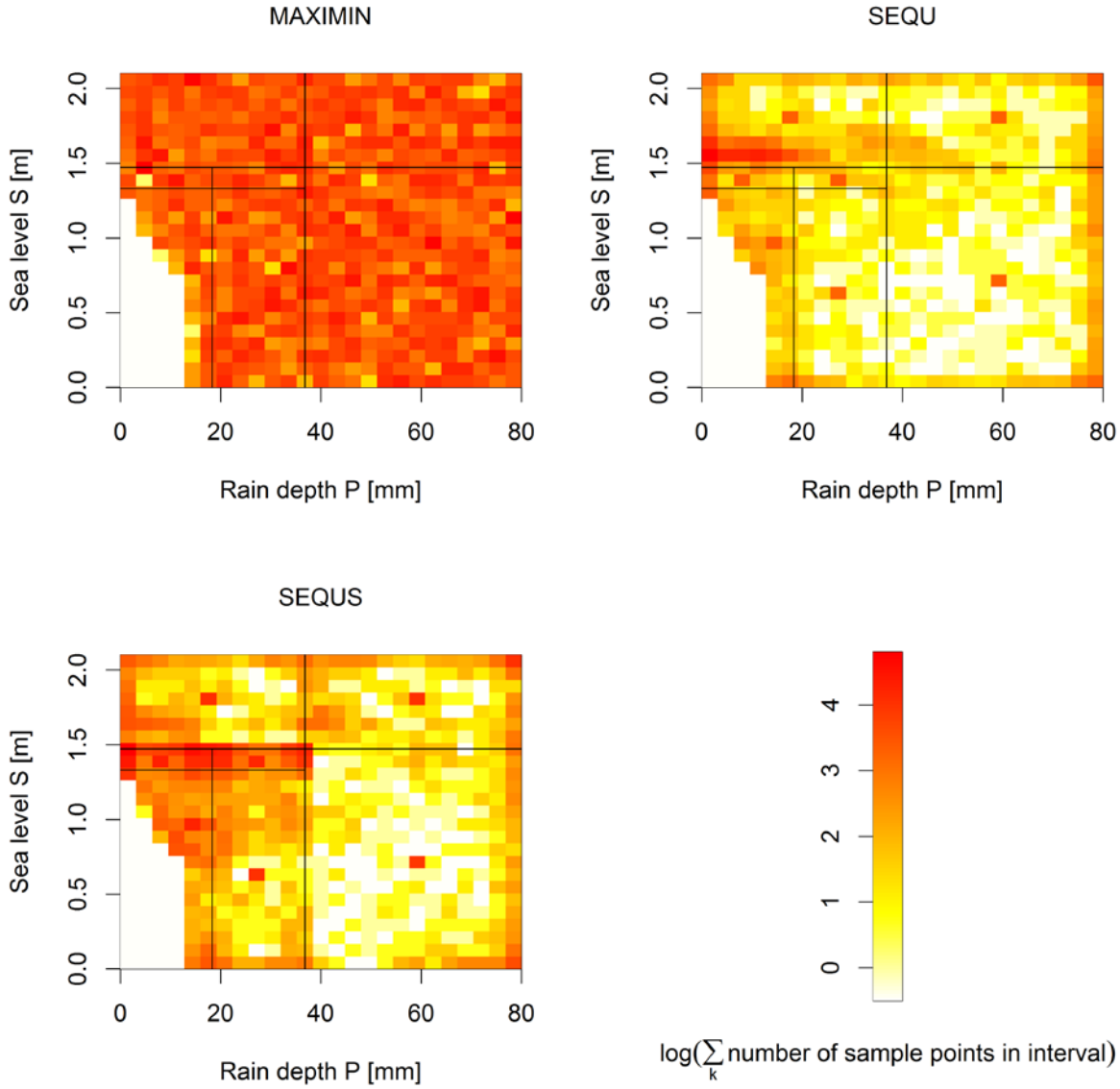

Figure 11. Number of data points that were sampled in different intervals of rainfall P and sea level S during 50 repetitions k after sampling 100 data points using the different sampling schemes (MAXIMIN=maximin sampling scheme, SEQU=sequential sampling scheme, SEQUS=stratified sequential sampling scheme). Results are shown on a logarithmic scale for case D.

6 Discussion

6.1 Identification of Reference Surfaces and Computational Efficiency

The main purpose of the setup presented in this article is to reduce the computational effort for assessing expected flood damages ED for numerous climate and urban growth scenarios, in comparison to a setup where only detailed simulation models are applied. Table 3 compares the simulation efforts between a setup based on detailed simulations only and a setup which combines detailed simulations with the metamodelling approach proposed in this paper. Following the reasoning of (Razavi et al., 2012b), we should also consider the additional analyst efforts required for handling the metamodelling setup. This part is not detailed in

Table 3, because we would expect additional efforts in the order of one week in a new case study, which is negligible compared to the months of work typically spent on setting up detailed simulation models.

Table 3. Comparison of metamodelling time and number of detailed urban-development and hydraulic simulations (Figure 2) required for assessing ED for 12 scenarios in a given catchment using A) a detailed modelling setup only, or B) a combined detailed and metamodelling setup. The number of detailed simulations required in A depends on the specific requirements of the analysis and we thus provided both an average and a lower estimate (in brackets).

	A) Detailed setup	B) Detailed setup + metamodel	
	No. of detailed simulations (min. number of simulations required)	Meta-modelling time	No. of detailed simulations
Identification of response surface using the SEQUS scheme	-	1 hour	130
Simulation of EAD for 1 time point in a catchment with 2 hazards	36 (20)	1 minute	-
Compute ED for 1 scenario based on EAD for 5 time points in planning horizon	5*36=180 (2*20=40)	5*1=5 minutes	-
Compute ED for 12 scenarios (e.g., 4 climate scenarios and 3 urban growth rates)	12*180=2160 (12*40=480)	5*12=60 minutes	-
Total	**2,160 (480)**	**some hours**	**130**

In Table 3 we assumed that 36 events need to be simulated to compute EAD for a catchment with pluvial and coastal hazard, based on the experiences in (Pedersen et al., 2012). This is a rough estimate, but given that 5-7 different design storms are typically considered to compute EAD if only pluvial hazard is present (Löwe et al., 2017; Olsen et al., 2015), we would expect that no less than 20 combined hazard events need to be considered. The computation of ED in (Löwe et al., 2017) was based on evaluating EAD every 10th year along the planning horizon. Assuming a planning horizon of 50 years, EAD would need to be computed 5 times to evaluate which impact flood adaptation has at varying time points during one scenario. In a simple case, the evaluation of 2 time points, e.g., in the middle and at the end of the planning horizon, might be sufficient. Finally, as in (Löwe et al., 2017), we assumed that the analyst wants to consider 12 combined climate and urban growth scenarios, which is in line with the 18 scenarios considered by (Hallegatte et al., 2013). Thus, a total of 480 to 2,160 events need to be simulated when applying detailed models only.

Applying a combined detailed and metamodelling setup, we assumed that the kriging metamodel on average predicts flood damages with sufficient accuracy once 130 data points have been sampled (Appendix Section 6), i.e., with 3 to 16 times fewer detailed simulations than the setup not applying metamodels. The reduction factor strongly depends on the number of scenarios considered. The meta-modelling setup was developed to allow the consideration of a variety of urban growth and climate scenarios and thus also becomes more attractive the more scenarios are considered.

The convergence rates estimated in Section 5 and in Section 6 of the Appendix may be optimistic for cases A, B and C. In these cases, our experiments aim at identifying reference surfaces based on kriging models with the same covariance structure as the kriging-metamodels used in our experimental setup. On the other hand, the flood response considered in case A is unusual with damages already occurring for small events with return periods in the order of one year. This behaviour implies that the metamodel needs to predict flood damages with high accuracy, as relatively small errors in predicting small events can have large impact on the computation of expected damages. In addition, case D includes a discontinuity in the reference surface and was designed as a critical test case to identify the limitations of the setup. In this case, the SEQUS scheme converged after, on average, 160 data points were sampled.

The computational effort for metamodelling is negligible, as long as the computation time required for detailed simulations is in the order of one hour or more for a single simulation on a single core. In our case, the detailed simulations took approximately 5 hours for one event. An iteration of the sequential sampling algorithm described in Section 3.2 is typically executed within 1 to 2 minutes, even for relatively large design datasets with a few hundred data points.

6.2 LIMITATIONS

While our setup demonstrates that the concept of flood response surfaces has significant potential to reduce computational effort in scenario-based assessment of expected economic flood damage, there are several limitations that need to be addressed.

We have made a basic assumption that the (reference) response surfaces identified by our setup are deterministic, i.e., free of noise. This assumption implies that the urban development pattern produced by the urban development model (see Figure 2) must be pre-defined with a high level of detail, i.e., we need to define in advance which buildings are developed in which order and at which location and that there must be an exact relationship between flood damage and the variables describing flood hazard. These assumptions are not very compatible with reality. Typically, we would be able to make assumptions on some overall regions and generic types of development, while the actual location and time point of redevelopments would be random. Similarly, spatial variability of rainfall would, for example, lead to a noisy relationship between rain intensity and damages. The consideration of these uncertainties would provide valuable information to the decision maker but is a challenge for the meta-modelling approach (see Section 6.3)

Another basic assumption of our approach is that the water management in a catchment does not change over time. Again, this assumption is not valid for all flood adaptation strategies, since some of them require gradual implementation. This problem could be addressed by either directly including variables that describe the degree of implementation of such time-dependent measures (for example, the percentage of buildings with rainwater harvesting tanks installed) in the metamodel, or by identifying separate metamodels for varying degrees of implementation. Also this feature would require the ability to handle noisy observations of flood damage. For example, if 10% of the buildings in a catchment have rainwater harvesting tanks installed, these tanks can be installed at different locations and the flood damage simulated for this installation percentage would thus be subject to some degree of variation.

6.3 GENERALIZATION AND OUTLOOK

We have tested our approach in four hypothetical test cases that were derived based on detailed simulations performed for the Elster Creek catchment. The same kriging metamodel structure in combination with the SEQUS sampling scheme was applicable in all four test cases without modification. We would expect to find flood damage response surfaces of similar shape in other catchments, and our approach should thus also be applicable to other catchments in the form presented here.

There may be potential for improved convergence rates by fine-tuning hyper-parameters of the setup. However, initial tests with pilot experiments where the data points were placed in the corners of the sampling space instead of the centre of the boxes shown in Figure 4, as well as with different numbers of candidate points did not suggest a significant impact on the convergence of the sampling scheme. Other parameters that could be investigated are the number of data points in the pilot experiment and the number and location of the stratification boxes considered (Figure 4). Identifying optimal values for these parameters requires more experience with the method in other studies.

As discussed in Section 6.2, the main limitation of our experimental setup is its inability to handle situations where the flood damage data obtained from the detailed simulation models are noisy. To address this issue, it would be beneficial to impose monotonicity constraints to ensure that results obtained from meta-models fitted to noisy data are physically meaningful (e.g., damages increase with increasing hazard). In addition, an improved metamodelling approach would need to fulfil the requirements named in Section 3.1, i.e., it should be able to describe surfaces with unknown functional shape and different, unknown correlations between the response and the input variables, and it would need to be fast enough to be applied in a cross-validation procedure. A model type which potentially fulfils these conditions are monotonic splines (Wood, 1994). Alternatively, it could be an option to apply stochastic kriging meta-models (Ankenman et al., 2010; Roustant et al., 2012) in the sampling scheme and to subsequently fit a suitable parametric model to the sampled data points.

Finally, further work should investigate the potential of “re-using” detailed simulation results across different planning options to further reduce computational demand. For example, different urban development patterns could be included as a parameter in the meta-models, because the relation between flood damages and hazards might still exhibit similar trends. Similarly, meta-models for planning options using flood proofing of buildings could to a large degree be based on the hydraulic simulations performed for planning options without flood proofing by simply replacing the depth-damage function used for damage computation.

7 CONCLUSIONS

We present a setup for efficient assessment of economic flood damage for a variety of climate and urban development scenarios. The setup is based on the concept of “flood damage response surfaces”, where flood damage in a catchment is modelled based on physical variables describing flood hazards and vulnerability. Using this concept, a limited number of combined urban development and hydraulic simulations can be performed to compute flood damage and the results of these simulations are interpolated using a kriging metamodelling approach, and the metamodel is subsequently applied to compute flood damages for a variety of scenarios. Several sampling schemes were tested to identify how the number of detailed

model simulations can be best reduced, compared to a traditional, scenario-based simulation approach.

Based on an experimental test of the setup in a case study with both coastal and pluvial risk, we draw the following conclusions:

1. The concept of flood response surfaces is indeed suitable to model economic flood damage in a catchment.
2. Depending on the considered case and the number of scenarios that need to be considered in the decision making process, the proposed methodology has the potential to reduce the number of detailed simulations required for assessment of expected damage by one order of magnitude.
3. Sequential sampling schemes can significantly reduce the number of detailed simulations required as compared to a space-filling scheme. However, a stratification procedure should be applied to avoid clustering of sample points at discontinuities of the flood response surface.

Our setup currently has two limitations:

1. We are not able to address noise in the observed flood damage.
2. We assume that water management in the considered catchment is constant over time.

To address these issues, future work should focus on the investigation of improved metamodelling approaches, as well as the combined application of detailed and simplified flood hazard models for the identification of response surfaces.

8 ACKNOWLEDGEMENTS

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The contribution of the authors to this article was as follows:
Roland Löwe scoped the paper, executed the simulations and prepared the manuscript. Christian Urich performed the urban development simulations used to inform the considered test cases and, together with Ana Deletic, supported the identification of potential implementations of combined urban development and hydraulic simulations through discussions. Murat Kulahci provided assistance in framing the experimental setup through suggestions for metamodelling approaches and sampling schemes, as well as through frequent discussion of the results. Mohanasundar Radhakrishnan supported the creation of the hydraulic model used to inform the considered test cases and participated in discussions on scoping the study. Karsten Arnbjerg-Nielsen supported the scoping of the study and provided detailed feedback on the experimental setup, the computation of expected damage in a catchment with multiple hazards and on the test case to consider in the article. All co-authors have revised multiple versions of the manuscript.

9 SOFTWARE AVAILABILITY

The reference datasets applied in our case study, the R code used for the identification of response surfaces with the different sampling schemes and an R script for the computation of expected damages from the response surface models are available for download under the GNU GPL3 license from https://zenodo.org/record/809829. We refer to the instructions provided in the included Readme file for details (Löwe, 2017).

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