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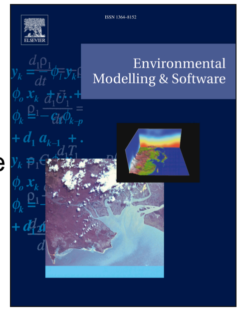

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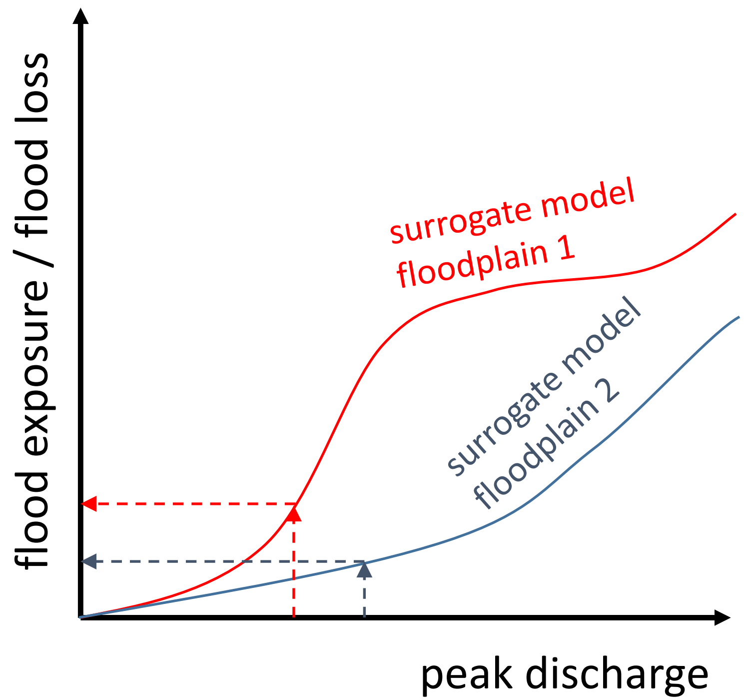
flood exposure / flood loss
surrogate model
floodplain 1
surrogate model
floodplain 2
peak discharge

Extending coupled hydrological-hydraulic model chains with a surrogate model for the estimation of flood losses

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Keywords: model coupling, surrogate model, flood loss estimation, complex river system, river basin-scale

Abstract. In comparison to a local-scale flood risk analysis, modeling flood losses and risks at the river basin scale is challenging. Particularly in mountainous watersheds, extreme precipitation can be distributed spatially and temporally with remarkable variability. Depending on the topography of the river basin and the topological characteristics of the river network, certain rainfall patterns can lead to a synchronization of the flood peaks between tributaries and the main river. Thus, these complex interactions can lead to high variability in flood losses. In addition, flood inundation modeling at the river basin scale is computationally resource-intensive and the simulation of multiple scenarios is not always feasible. In this study, we present an approach for reducing complexity in flood-risk modeling at the river basin scale. We developed a surrogate model for flood loss analysis in the river basin by decomposing the river system into a number of subsystems. A relationship between flood magnitude and flood losses is computed for each floodplain in the river basin by means of a flood inundation and flood loss model at sub-meter resolution. This surrogate model for flood-loss estimation can be coupled with a hydrological-hydraulic model cascade, allowing to compute a high number of flood scenarios for the whole river system. The application of this model to a complex mountain river basin showed that the surrogate model approach leads to a reliable and computationally fast analysis of flood losses in a set of probable maximum precipitation scenarios. Hence, this approach offers new possibilities for stress test analyses and Monte-Carlo simulations in the analysis of system behavior under different system loads.

1 Introduction

Floods are one of the most damaging natural hazards, accounting for a majority of all economic losses from natural events worldwide (UNISDR, 2015). Managing flood-risk requires knowledge about hazardous processes and the impact of floods. Although flood-risk management practice is rapidly changing, the primary approach at present is the prevention of floods by means of constructing flood defense works, such as lateral dams along rivers. Flood protection measures are typically designed on a local-basis and the most optimized solution in terms of cost-benefit analysis (Mechler, 2016; Shreve and Kelman, 2014). The insurance of flood risks is also part of flood-risk management practices. Both the design of flood prevention measures and portfolio risk analyses require sound knowledge of flood hazards within a particular area (Burke et al., 2016). The complex processes occurring in river basins that lead to flooding can be simulated with a cascade of dedicated models (Biancamaria et al., 2009, Felder et al., 2017, Wagner et al., 2016). Thus atmospheric, hydrological, flood inundation and flood-loss models are run subsequently on the basis of precipitation scenarios (with a certain probability). Recently, remarkable progress was made for developing model chains from atmospheric to hydrological and hydraulic models, either on global-scale (Sampson et al., 2015), continental-scale (e.g., Trigg et al., 2016) or river basin-scale (Lian et al., 2007; Biancamaria et al., 2009; Paiva et al., 2013; Laganier et al., 2014; Falter et al., 2015; Nguyen et al., 2016; Felder et al., 2017).

However, the coupling of atmospheric, hydrological and hydraulic models mostly ends with the hydraulic model. The extension of a model cascade with flood impact models has been rare to date. Thus, only a small number of studies extend the model chains towards a coupled-component model from rainfall to flood-losses. Examples of full model chains from rainfall to flood losses are shown by Alfieri et al. (2016a), Ward et al. (2013, 2015) at global scale, by Alfieri et al. (2016b) at continental scale, by Falter et al. (2014), Falter et al. (2015), Qiu et al. (2017), Schumann et al. (2013), van Dyck and Willems (2013) at large river basin scale, and by McMillan and Brasington (2008), Foudi et al. (2015), Koivumäki et al. (2010) at regional and local scale. In most cases, of risk analysis, a cascading modeling approach is followed.

The complexity of the processes triggering floods is determined by spatio-temporal patterns in precipitation (Emmanuel et al., 2015), by the geomorphic characteristics of the sub-catchments of the river basin, and by the synchronization of the flood peaks between the tributaries and the main river channel (Pattison et al., 2014). Particularly in mountainous catchments with a high topographical complexity, the storm track and the precipitation pattern are influenced by the mountain ranges. Thus, the relative timing of peak discharges in river confluences as a consequence of the spatio-temporal distribution of the rainfall pattern have to be addressed (Emmanuel et al., 2016; Zoccatelli et al., 2011). Furthermore, in mountainous areas, the runoff is also determined by the 0°C isothermal altitude and thus by the share of areas with snowfall rather than rainfall (Zeimetz et al., 2017). Hence, an integrated modelling approach and the coupling of specific simulation models is needed to assess the processes leading to floods in river basins with a complex river topology. In addition, if the impacts of floods have to be assessed, the simulation models have to be extended with impact models.

Feasible solutions for impact modeling address the interactions between natural and social/technological systems and include integrated modeling approaches (Kelly et al., 2013; Laniak et al., 2013; Welsh et al., 2013), coupled natural and human systems (Liu et al., 2007; O'Connell and O'Donnell, 2014), or coupled component models (Strasser et al., 2014).

In the case of flood impact modeling, there is a lack of computationally efficient flood-loss models that can be coupled with hydrologic models and used in wider areas at a higher spatial resolution. However, the availability of data needed for flood risk analysis at the river basin scale is constantly improving and with it, the level of detail is rising. Consequently, this non-linearly increases the required computing power. In many cases, probabilistic approaches are required to simulate a high number of flood scenarios (e.g., in Monte-Carlo simulations). Here, a model chain from atmosphere to rainfall-runoff, flood inundation and flood losses reaches its limits due to the lengthy amount of computing time necessary. In addition to the computationally demanding inundation models, the flood loss models require computational resources too, if targeted at single-object scale but applied in a whole river basin. Therefore, the study design of flood risk analysis at the river basin scale has always required a trade-off between the level of detail (spatial resolution) and the size of the study area (Fewtrell et al., 2008; Savage et al., 2016). Usually, with an increasing size of the study area, the spatial resolution decreases (Savage et al., 2015). Thus, there is a gap in methods available for representing a river basin system at a high spatial resolution while contemporaneously maintaining the ability to study the complex interactions between the physical processes and the impact on the values at risk.

However, there are other approaches for dealing with computational demands in integrated environmental models than the variation of the model's spatial resolution. Such approaches include metamodeling strategies, the use of model emulators and surrogate models. Metamodels, model emulators, response surface modelling and surrogate modelling are often used as synonyms (Ratto et al., 2012; Razavi et al., 2012a). The principal idea behind surrogate models is emulate and to replace the complex simulation model requiring high computational resources with a simplified and fast-to-run model (Castelletti et al., 2012; Yazdi and Salehi Neyshabouri, 2014). A surrogate model can be derived by simplifying the process-based model structure, or by generalizing the studied system's behavior with a low-order approximation of a set of outcomes of a model experiment with the complex model (Castelletti et al., 2012). Dynamic emulation modelling aims at preserving the dynamic nature of the original process-based model and is, thus, preferably used for reducing complexity (Castelletti et al., 2012). Surrogate models are often used in applications that require a large number of model runs, e.g. in sensitivity analysis, in scenario analysis, and in optimization. In flood management applications, surrogate models have been used for reservoir operation (Castro-Gama et al., 2014; Tsoukalas and Makropoulos, 2015), water resources management (Tsoukalas et al., 2016) and for reducing the complexity in hydraulic simulations (Gama et al., 2014; Meert et al., 2016; Wolfs et al., 2015). A review of surrogate modeling in hydrology is given by Razavi et al. (2012b). Nevertheless, Saint-Geours et al. (2014) and Marrel et al. (2011) stated that the development of surrogate models with spatially distributed inputs and outputs is still an open research question. This also applies to object-based flood loss modelling, where a 2D inundation model computes flow depths for each affected building and the loss model computes the damages on the basis of the flow depths, a vulnerability function, and the building value.

Hence, the question arises if a surrogate modeling approach is suitable to represent the inherent complexities of flood processes that lead to flood losses within a river basin. Specifically, we aim to assess whether the surrogate modelling approach is able to represent the flood processes and their impacts at the river basin scale with a spatial resolution at street level. Thus, the main aim of this work is to develop a surrogate model for flood loss analysis and to evaluate its applicability in the context of a model experiment with multiple scenarios covering different spatiotemporal patterns of rainfall over a river basin with a complex topography. Within this context, the hypothesis is that a river system can be divided into subsystems which are connected within a topological river network (Wolfs et al., 2015). The reaction of the whole system to a flood scenario can then be deduced from the reactions and interactions of the subsystems. Thereby, we aim at contributing to the discussion about the use of surrogate models in model simplification (Crout et al., 2009; van Nes, Egbert H. and Scheffer, 2005) and in flood risk analyses (Wolfs et al., 2015; Wolfs and Willems, 2013).

2 Methods

The main goal of flood risk analysis at the river basin scale is to analyze the potential consequences of a selected precipitation scenario or a set of scenarios. This is done by a model cascade of rainfall-runoff models with 2D hydraulic models producing the flow depths for the flood loss models. Here, we propose a different method, where the last two models are substituted. The 2D hydraulic model and the flood loss model are replaced by a 1D hydraulic model with a surrogate model for flood loss computation nested into the 1D hydraulic model. This requires two main steps. First, the surrogate model has to be developed. Then, the surrogate model is introduced into the model chain with reduced complexity. We tested this method on the Aare River basin, located upstream of Bern, Switzerland.

This chapter is organized as follows. First, the case study and the definition of the system under consideration are described in detail. Second, the development of the surrogate model is described. The interrelation between the two main steps is shown in figure 1. Third, we describe the model evaluation procedure. The methods chapter is concluded with a description of the setup and the application of the model chain for flood loss analyses.

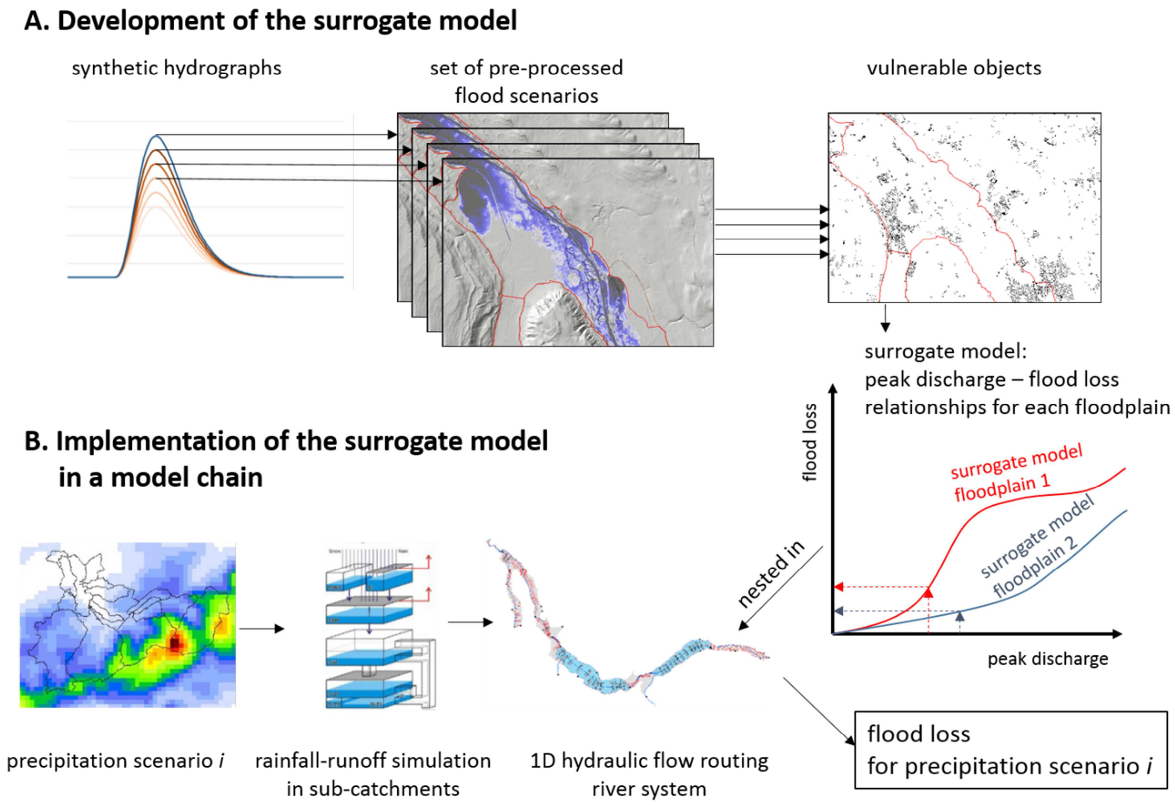

Figure 1: Overview of the method. The first step is to develop the surrogate model. The second step is to nest the surrogate model into a model chain from the meteorological model to a rainfall-runoff and 1D hydraulic routing model.

2.1 System definition and system delimitation

The study area is the watershed of the Aare River located upstream of Bern, Switzerland (see figure 2). The river basin has an area of approximately 3000 km^2 and thus is defined as a mesoscale catchment. The river network consists of 26 tributary catchments (sub-catchments), with confluence into the floodplains of the main valley. The main valley is divided into seven floodplains. These are the floodplains of the river reaches “Hasliaare”, between Meiringen and Lake Brienz (1), the coastal areas of “Lake Brienz” (2), the flood plain of the city “Interlaken” and the river Lütschine (3), the coastal areas of “Lake Thun” (4), the floodplain of the city “Thun” (5), the river “Aare”, between Thun and Bern (6), and the tributary “Gürbe”, between Burgistein and Belp (7). The flooding processes in the Aare River basin are dominated by both riverine and lake flooding. The

Hasliaare floodplain is dominated mainly by riverine flooding. However, the delta of the Hasliaare floodplain is also affected by flooding from Lake Brienz. The lateral shorelines of Lake Brienz and Lake Thun are exposed to lake flooding only. In contrast, the city of Interlaken is exposed to four different flooding processes. In the eastern part, this floodplain is exposed to lake flooding from Lake Brienz. The western part is exposed to lake flooding from Lake Thun. A high water-level in Lake Brienz leads to a high discharge in the Aare River, between the two lakes. Consequently, the central part of the city of Interlaken is exposed to riverine flooding. From the southern boundary of the floodplain, the tributary Lütschine River flows into Lake Brienz with the occurrence of riverine flooding possible. The city of Thun is exposed to both lake flooding from Lake Thun and riverine flooding from the Aare River at high lake levels. The floodplain of the Aare River between Thun and Bern and the floodplain of the Gürbe River are exposed to riverine flooding. The discharge of the Aare River downstream of Thun is dominated mainly by the outflow from Lake Thun and secondarily by its tributaries. Transport and deposition of sediment and woody debris were not considered in this analysis.

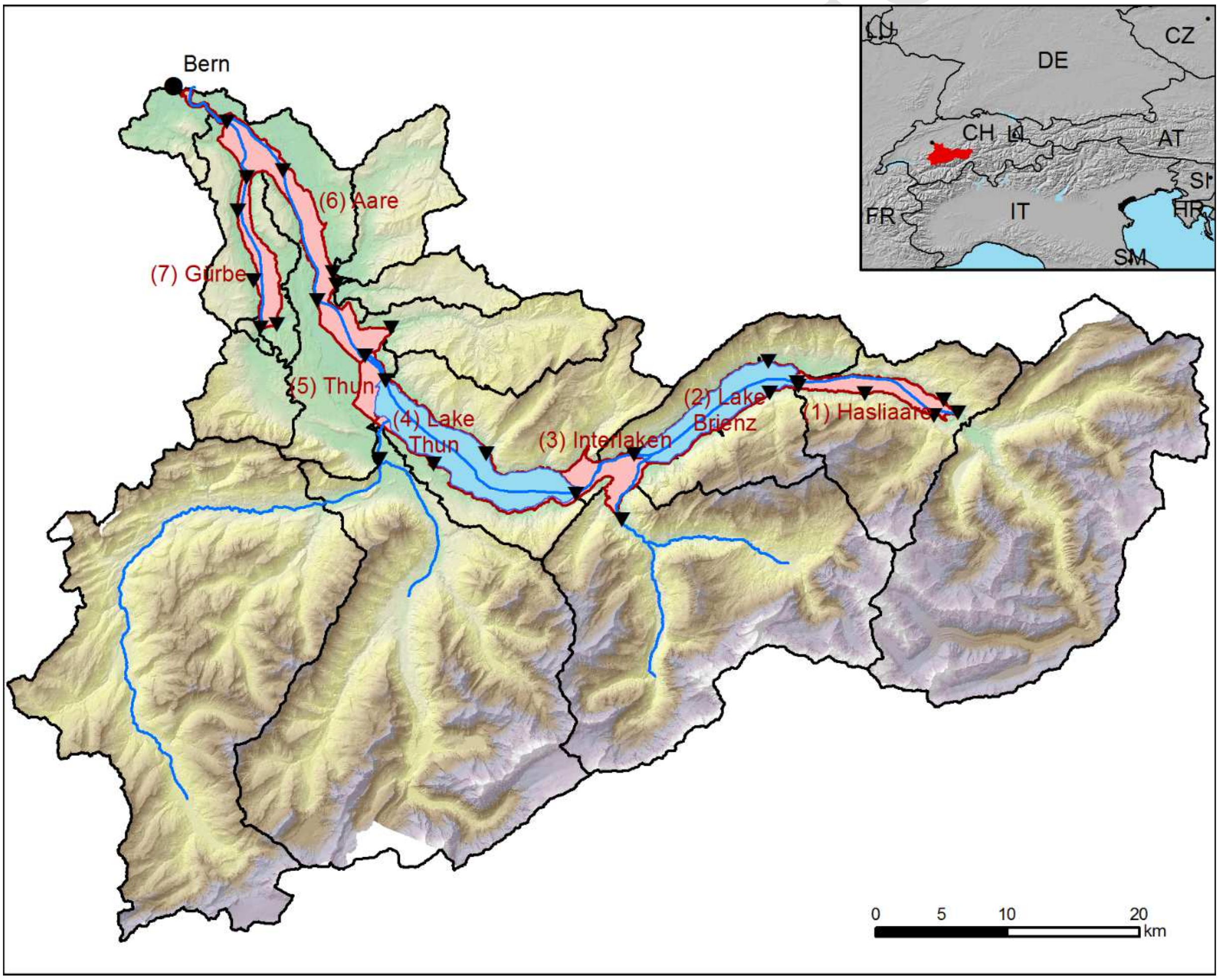

Figure 2: Aare river basin upstream of Bern, Switzerland. The sub-catchments of the hydrological model are divided by black lines. The black triangles are indicating the points where the outflow from the subcatchments is used as a system load at the upper boundary conditions of the floodplains. The floodplains that are represented by the surrogate model are marked in red.

The physical processes in the river system considered here are principally defined as flood processes leading to losses at buildings. The main driver for the amount of losses due to flooding is the flood magnitude (i.e., peak discharge and lake level), with the related flow depths at the location of the exposed buildings. Thus, we assume here that there is a relevant relationship between the flood magnitude and the values at risk. In addition to the flood magnitude, this relationship also depends upon the hydromorphic characteristics of the floodplain (i.e., how the building stock is topographically and topologically located within or outside the flooded areas) and the characteristics of the building stock (economic values and vulnerabilities). This relationship can also be named as the exposure "footprint" of a floodplain (Rougier et al., 2013). This approach was described by Hubbard et al. (2014) for an urban area exposed to flooding. Here, this approach is extended to a number of floodplains. Each floodplain is defined as a subsystem of the whole river basin. The input of the upper boundary condition of a subsystem is the inflow of water. The magnitude of the boundary condition is defined by the peak discharge in a river reach in the case of riverine flooding and by the lake level in case of lake flooding. The fluxes (flood flows) between the subsystems are modeled with the hydrodynamic model BASEMENT in 1D (BASEchain, Vetsch et al., 2017). Figure 3 shows the spatial setup of the river system and the topology between the subsystems.

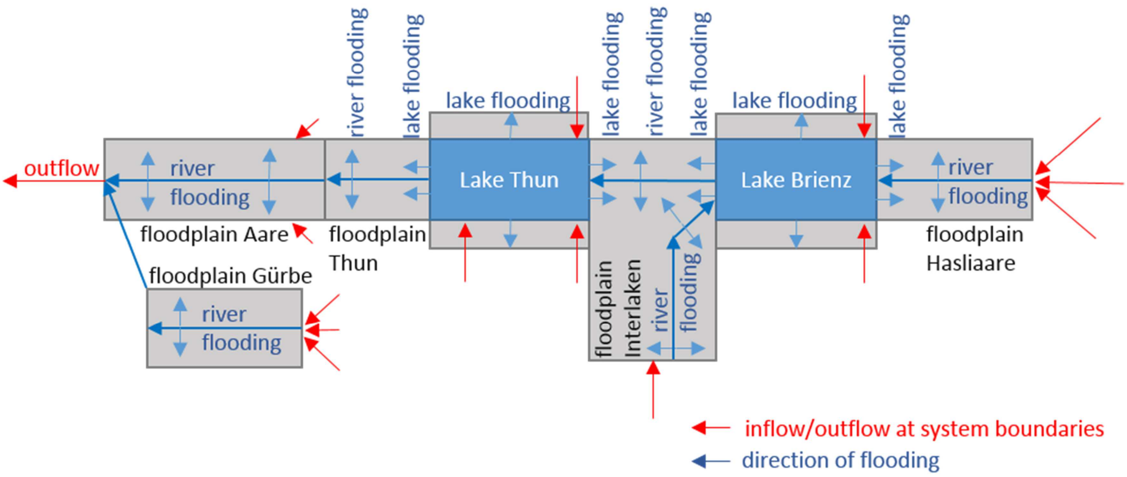

Figure 3: Simplified representation of the river system. The floodplains are represented in gray. The type of flooding process is represented by blue arrows.

2.2 Development of the surrogate model

The surrogate model is built in three steps. First, for each subsystem (i.e., floodplain), the range of system loads at the upper boundary condition were defined. On the basis of an observed discharge time-series, typical flood hydrographs, i.e. a synthetic design hydrograph, were derived using the guidelines proposed by Serinaldi and Grimaldi (2011). For each river gauging station in the study area, observed hydrographs were normalized in terms of event duration and peak discharge. The resulting dimensionless event hydrographs were superimposed, and centered around the peak position. A two parametric gamma distribution function was fitted to represent the typical shape of the event hydrographs, as described by Nadarajah (2007) and Rai et al. (2009). This resulted in a synthetic unit hydrograph that represents a typical hydrograph shape of flood events in the corresponding catchment. The synthetic unit hydrograph was scaled to various peak discharges, whereas an empirical peak-volume-ratio was used to determine the corresponding event duration. Recently developed techniques for the determination of flood-type-specific synthetic design hydrographs, as for example proposed by Brunner et al. (2017), were not considered in this study. The procedure was applied to generate synthetic design hydrographs for a continuous series of peak discharges for each of the floodplains affected by riverine flooding (Hasliaare River, Lütschine River, Aare River between Thun and Bern, Gürbe River). The synthetic design hydrographs were used as upper boundary conditions for the 2D inundation model of each floodplain.

In the second step, we developed a flood inundation model in 2D for each floodplain. We used the flood inundation model BASEMENT in 2D (BASEplane) to represent the water fluxes through the river systems (Vetsch et al., 2017). It is a numerical model solving the shallow water equations on the basis of an irregular mesh. The mesh was generated on the basis of a digital terrain model (DTM) of the year 2015, with a spatial resolution of 0.5 m and a maximum error of +/- 0.2 m in the z-axis orientation. In the river courses, the DTM was corrected on the basis of topographical surveys of the riverbed. These data were delivered by the Federal Office for the Environment, FOEN. The heights and location of the lateral dams were surveyed by dGPS. Together, all data sources result in a high-resolution terrain model. In the flood models, the roughness coefficients in the river channels were calibrated with existing stage-discharge relationships. The roughness coefficients in the floodplains were estimated based on literature. The floodplains are delimited by the lateral dimensions of the floodplains (i.e., the confining hillslopes). The upper system boundaries are the main river courses flowing into the floodplains. The lower system boundary is determined by the lakes, or other topographic or geomorphologic constraints delimiting the floodplains.

The 2D hydrodynamic model provides the basis for the flood-loss model. In this study, we focus only on structural damages to buildings (i.e., residential, public and industrial buildings). Damages to mobile assets, building content, movables and infrastructure are not considered here. The loss model consists of a dataset of buildings with attributes and a set of vulnerability functions. Each building is represented by a polygon and classified by type, functionality, construction period, volume, reconstruction costs, altitude level of ground floor and number of residents. The dataset of the values at risk was elaborated on the basis of the SwissBuildings^{3D} dataset of the Federal Office for Topography SWISSTOPO, based on the approaches of Fuchs et al. (2017); Röthlisberger et al. (2017), and Röthlisberger et al. (2016). The reconstruction values of the buildings were calculated on the basis of the volume (derived by the Lidar surface and terrain models) and the mean prices per cubic meter and building function (SVKG-SEK/SVIT, 2012), accordingly to the practice in Switzerland. The flood intensity maps (flow depths), resulting from the hydrodynamic models, lead to the calculation of the object-specific vulnerability and therefore to the estimation of object-specific losses (Fuchs et al., 2012). Vulnerability functions provide a degree of loss on the basis of the flow depth at the location of the house. The value ranges from 0 (no damage) to 1 (total loss). This degree of loss is subsequently multiplied by the specific reconstruction value of the building. Currently, three vulnerability functions are considered in the damage calculation procedure. We used the functions of Hydrotec (2001), Jonkman et al. (2008), and Dutta et al. (2003), shown in figure 4. The multiplication of the reconstruction value of the house with the degree of loss leads to the flood-loss for a specific exposed object (e.g., a single house). The sum of all losses in the floodplain enters into the “flood peak – flood loss” relationship of the floodplain.

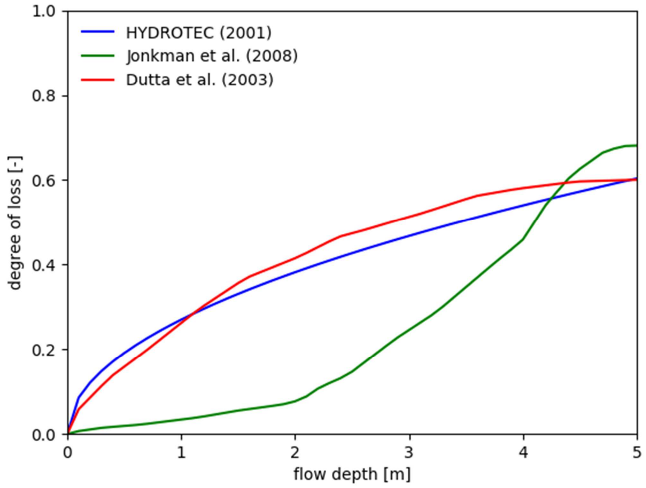

Figure 4: Vulnerability functions used for flood loss estimation

We modeled the inundation for each floodplain and specific set of synthetic hydrographs. This results in a number of simulations ranging from the river discharge capacity to a worst case flood. Each model run was overlain with the building dataset and the degree of loss was calculated for each single building on the basis of the flow depth at the building, as well as the resulting loss. Thus, for each synthetic hydrograph, a sum of flood losses in the floodplain is computed. Furthermore, the number of exposed buildings and the number of exposed residents are summarized. Generally speaking, this follows the dynamic emulation modelling approach of Castelletti et al. (2012). With peak discharge (flood magnitude), the resulting flood losses and exposed buildings/residents increases. For each floodplain, the shape of this relationship between flood magnitude and flood losses is calculated. These floodplain-specific curves are the basis of the meta-model, or surrogate model for further analyses. The surrogate model can then be used to extend coupled hydrological-hydraulic model chains by nesting it into the 1D hydrodynamic model.

2.3 Model evaluation

The complexity of the model chain requires a validation of the surrogate model and of the surrogate model coupled with the hydrologic/hydraulic model. In addition, the 2D inundation model used for the elaboration of the surrogate model has also to be validated separately. Thus, the coupled hydrologic-hydraulic model, the 2D inundation model, and the surrogate model were validated separately and in the coupled version.

First, the coupled hydrologic hydraulic model (1D) was validated against the observed discharge at the catchment outlet in the validation period from 2011 to 2014. For this, we computed the Nash-Sutcliffe-Efficiency NSE (Nash and Sutcliffe, 1970) and the Kling-Gupta-Efficiency KGE (Gupta et al., 2009; Kling et al., 2012).

Second, the 2D inundation models used to elaborate the surrogate model were validated with post-event data of the floods in May 1999, and August 2005 (table 1). The main purpose of the 2D inundation model is to predict the number of affected buildings and to predict the flow depths at the buildings. Thus, a validation of this model should weight the populated areas higher than the areas without values at risk (Stephens et al., 2014). As the surrogate model gives the number of exposed buildings and the flood losses as outputs, we adapted a validation approach proposed by (Zischg et al., 2018) that explicitly focuses on the validity of the flood models in populated areas. They proposed to adapt binary performance measures to be used with insurance claims for validating flood models. Hence, we validated the model performance with the model fit measure F (Bennett et al., 2013, eq. 1, also defined as critical success index CSI or flood area index FAI). This measure can be computed by either considering the predicted and observed flooded areas or the number of affected and not affected buildings. If based on the flooded areas, this performance measure requires a comparison of the spatial pattern of the observed and the modelled wet and dry areas. If the populated areas should be weighted higher, this performance measure can be computed by overlaying the map of the observed flood extent with the dataset of the buildings. The buildings within the observed flood extent represent the reference observation dataset. Subsequently, these buildings are compared with the buildings located in the modelled flood extent. Buildings correctly predicted as inundated, count as hits. Buildings predicted as dry by the model and observed as inundated, are counted as misses. Buildings predicted as wet by the model but observed as dry are defined as false alarms. Correct negatives are buildings that are predicted and observed as dry (outside of observed flood extent). The validation of the 2D inundation model of the floodplains of Interlaken and Thun is described in Zischg et al. (2018).

$$F = \frac{\text{hits}}{\text{hits+false alarms+misses}} \quad (1)$$

Third, the surrogate model was coupled with the hydrologic/hydraulic model chain and validated with event documentations from three past flood events based on the number of affected buildings. We counted the number of buildings that are located within the areas that were reportedly flooded during the flood events in May 1999 August 2005, and October 2011, respectively. The characteristics of these reference flood events are summarized in table 1. Subsequently, we computed the number of affected buildings in these three flood events with the surrogate model. For the flood event of 1999, we used the observed discharges for calculating the number of affected buildings with the surrogate model. In contrast, we used both the observed and modelled discharges of the hydrologic/hydraulic model chain to calculate the number of affected buildings during the flood events of 2005 and 2011. Consequently, we compared the modelled number of affected buildings with the observed ones.

Table 1: Peak discharges and return levels of the flood events used for model evaluation. Source: FOEN (2018)

River reach	May 12-16, 1999	August 22-23, 2005	October 10-11, 2011	Peak discharge of a 100-year flood
Hasliaare River	228 m^3/s <10 yy	444 m^3/s 47 yy	367 m^3/s 22 yy	538 m^3/s
Lütschine River	126 m^3/s <2 yy	254 m^3/s >150 yy	226 m^3/s 68 yy	239 m^3/s
Aare River at Bern	613 m^3/s >150 yy	605 m^3/s >150 years	416 m^3/s <10 yy	551 m^3/s
Gürbe River	44.6 m^3/s <10 yy	52.1 m^3/s 20 yy	8.08 m^3/s <1 yy	60.7 m^3/s

Fourth, we analyzed the relative error of the surrogate model. Depending on the range of peak discharges - from the river conveyance to the probable maximum flood - we selected different intervals of the synthetic hydrographs used for computing the surrogate model. In the Aare River reach, we used intervals of 100 m^3/s to compute the surrogate model, while in the other floodplains we used intervals of 50 m^3/s, except in the Gürbe River reach. In this floodplain, we used intervals of 5 m^3/s. To estimate the interpolation error, we doubled the intervals of the peak discharges for deriving the surrogate model and compared the interpolated value of the coarser surrogate model with the values of the original surrogate model. The interpolation error is represented here by the root mean square error (RSME). However, the surrogate models of the lakes are based on a continuous simulation and thus we did not analyze the sensitivity of these models to an increase of the interval.

Fifth, we modelled one out of the 150 model runs with the full 2D simulation model. We selected the model run with the highest peak discharge at the river basin outlet at Bern, corresponding to the probable maximum flood. This model run was used as a benchmark to evaluate the performance of the surrogate model for this scenario.

A validation of the loss module was not possible, as corresponding loss data are protected by privacy regulations of the corresponding Cantonal insurance company. However, the predicted flood losses where validated in another case study using the same model setup with observed loss data delivered by the Cantonal insurance company for buildings (Zischg et al., 2018). In the river reach of the Engelberger Aa River in in the Canton of Nidwalden, the flood event of August 2005 led to losses of around 22 million Swiss Francs. The vulnerability function of Jonkman et al. (2008) underestimated the losses (26% of documented losses), whereas the vulnerability function of Hydrotec (2001) overestimated the losses by a factor of 2.7, and the vulnerability function of Dutta et al. (2003) by a factor of 2.1. Thus, we assume that the three different vulnerability functions should quantify a range of possible outcomes and the most reliable loss estimation lays in between different outcomes.

2.4 Computing the system behavior and the flood losses during probable maximum precipitation scenarios

We tested the applicability of the surrogate model with a set of extreme flood scenarios based on the probable maximum precipitation (PMP). The PMP is often used for the analysis of residual risks and furthermore for identifying the probable maximum flood (PMF) in a river basin. The PMP in the study area was estimated after the guidelines of WMO (World Meteorological Organization, 2009). To consider the spatio-temporal patterns of precipitation in the river basin, the same amount of areal precipitation in the PMP scenario (300 mm in 3 days) was distributed in different spatio-temporal patterns across the entire river basin in a Monte-Carlo-simulation framework after Felder and Weingartner (2016). In a first step, a random temporal distribution of the total precipitation for the chosen duration was generated. In a second step, the temporal pattern of the rainfall was distributed spatially in three meteorological regions, and in five sub-catchments within each meteorological region. The sub-catchments and the meteorological regions were defined to consider the relatively independent behavior of specific parts of the catchment, e.g. lowlands and mountainous regions, in terms of precipitation amount and intensity. A set of plausibility criteria evaluates the physical reliability of the randomly generated rainfall pattern. For further details we refer to Felder and Weingartner (2016). From a set of physically valid 10^6 iterations, we extracted 150 scenarios that lead to the highest discharge at the catchment outlet. These rainfall scenarios were fed subsequently into the hydrological model (Felder et al., 2017). The rainfall scenarios were modeled in 15 sub-catchments with the hydrological model PREVAH (Viviroli et al., 2009). The discharge at the outlets of the sub-catchments was routed through the river system with the hydraulic model BASEMENT in 1D (Vetsch et al., 2017). The hydrodynamic model is based on the St. Venant equations and computes the water fluxes in 1D. This model allows for simulation of the weirs at the outlets of the lakes within the river network and thus is able to simulate lake levels. The 1D hydrodynamic model was calibrated by empirically adjusting the friction coefficients in the river channels with particular regard to the water surface elevation in the main channel at peak discharge. The setup of this system is described in detail by Felder et al. (2017) and Felder and Weingartner (2017). The surrogate model described in chapter 2.2 is nested into this 1D hydraulic model. The 1D hydraulic model provides the upper boundary conditions for the single floodplain models. The peak discharge is then extracted from the modeled inflow hydrographs and used for interpolating the flood losses from the surrogate models of each floodplain. The losses of the single sub-models are then summed up for each precipitation scenario. We computed the number of exposed buildings and residents and the flood losses for 150 scenarios. Out of 10^6 simulations, these scenarios had the highest discharge at the outlet of the river basin in Bern. Thus, this can be assumed as a set of extreme floods. The scenario with the highest discharge at Bern was modeled with the 2D simulation model as a reference run. In the 2D simulation, the tributaries flowing into the floodplains from the lateral boundaries are considered, as well as in the loss model. The same scenario was then simulated with the surrogate model. Finally, the reliability of the surrogate model was evaluated by comparing it with the reference model run.

3 Results

Surrogate model

The primary result of the first part is the "flood magnitude – flood exposure" relationship for each floodplain. In figure 5, these relationships are presented for riverine floods. Here, the sensitivity of the floodplain against peak discharges is shown in terms of the number of exposed buildings and people. The figure shows that the floodplain of the Lütschine River reach is the sub-model with the highest sensitivity to an increasing peak discharge. The Lake Thun sub-model is that which has the highest sensitivity against a rising lake level (figure 6). It is shown that the exposure of residents is increasing, on average, by 38 residents per cm of rising lake level.

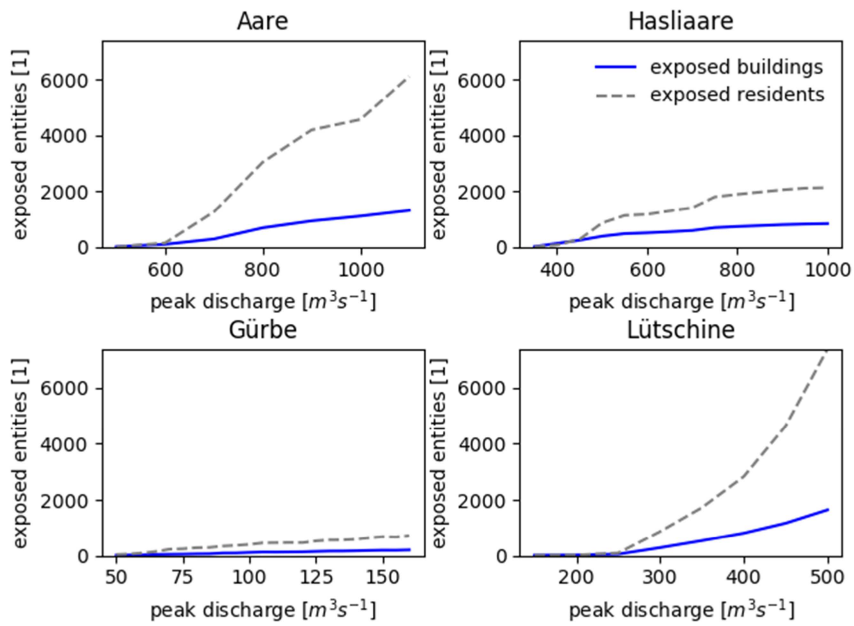

Figure 5: "Peak discharge – flood exposure" relationships for the floodplains with riverine flooding

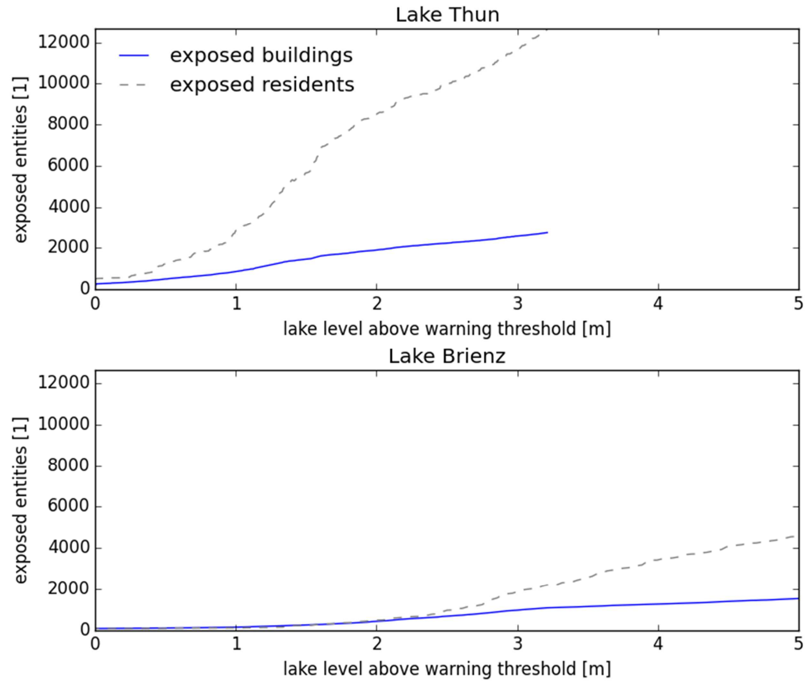

Figure 6: "Lake level – flood exposure" relationships for the floodplains with lake flooding. Warning thresholds for Lake Thun: 558.3 m a.s.l.; warning threshold for Lake Brienz: 563.9 m a.s.l.

Regarding flood losses, the "flood magnitude – flood loss" relationships exhibit shapes similar to that of the "flood magnitude – flood exposure" relationships. In contrast to the exposed buildings and residents, the figures for the losses show the uncertainty in flood loss estimation in relation to the vulnerability functions. The vulnerability function of Jonkman et al. (2008) results in remarkably low losses (figures 7 and 8). Figure 8 shows that the floodplain of Thun is the subsystem with the highest sensitivity to increasing flood magnitudes.

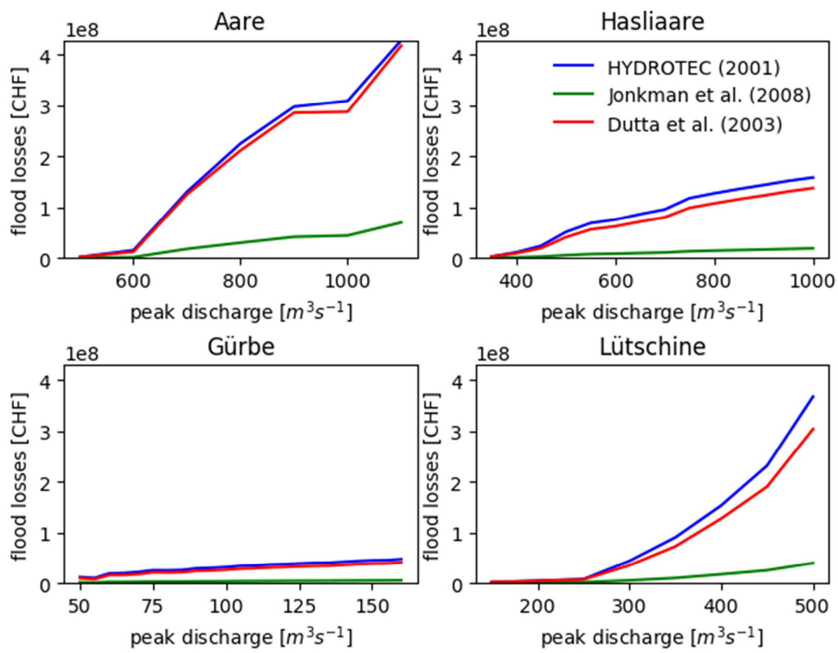

Figure 7: "Peak discharge – flood loss" relationships for the floodplains with riverine flooding

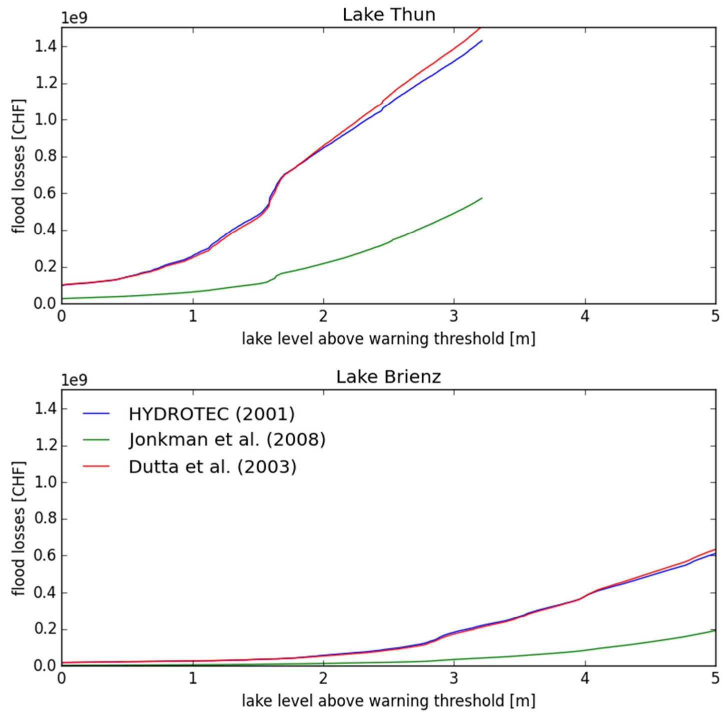

Figure 8: "Lake level – flood loss" relationships for the floodplains with lake flooding. Warning thresholds for Lake Thun: 558.3 m a.s.l.; warning threshold for Lake Brienz: 563.9 m a.s.l.

Model evaluation

The model evaluation showed that both the single modules and the model chain can be used reliably in this study. The coupled hydrologic-hydraulic model has a NSE value of 0.85 and a KGE value of 0.85 in the validation period 2011-2014.

The 2D inundation model was validated with the flood event in August 2005. Based on the observed discharges and flooded areas of the flood event in August 2005, the 2D flood model of the Aare and Gürbe river reaches exhibit a model fit of 0.62, the model of the floodplain in Thun has a model fit of 0.61, and the model of the floodplain in Interlaken has a model fit of 0.68 (with consideration of the dam break in the Lütschine River). In the Hasliaare river reach, a dam break occurred and thus the observed flooded areas are remarkably higher than the modelled ones. In contrast to the Lütschine river reach, this dam break was not modelled in the validation run and thus no validation was possible for this river reach and this flood event. Calculating the model fit on the basis of the modelled discharges (model chain of the coupled hydrological–hydraulic model based on precipitation as the model input, and whole study area), gives a model fit of 0.46 when considering flooded areas in the validation metric and a model fit of 0.49 when considering the number of exposed buildings, respectively.

The output of the surrogate model in terms of number of exposed buildings was compared with the observed number of affected buildings. However, in the corresponding simulation, the dam breaks that occurred in the Hasliaare river reach and in the floodplain of the Lütschine river during the flood event in 2005 were not considered and, thus, the surrogate model underestimates the number of exposed buildings. The surrogate model nested into the full model chain predicted 1643 affected buildings, while 2366 buildings were actually located in the flooded areas of the 2005 event (table 2). In contrast, when run with the observed discharges of the flood event in May 1999, the surrogate model predicts 995 affected buildings, while 1059 buildings were actually located in the flooded areas. This corresponds to an underestimation of 6%. However, the surrogate model neglects a dam break in the Aare River reach during the flood event in 1999 and, thus, underestimates the exposed buildings in this area. For the 2011 flood event, the surrogate model predicts 132 and 38 affected buildings with observed and modelled discharges, respectively. At river basin scale, the full 2D model nearly predicts the exact number of buildings affected by the 2011 flood. However, when looking at the detail, there is a slight underestimation in the Hasliaare River reach and a slight overestimation in the Lütschine River reach. The hydrological model underestimates the peak discharges during this rain-on-snow flood event (Rössler et al., 2014) and thus the surrogate model underestimates the number of affected buildings when implemented into the full model chain.

Table 2: Number of exposed buildings in the flooded areas of the flood events of May 1999, August 2005, and October 2011. *surrogate model based on observed discharges and lake levels. **surrogate model based on observed precipitation and, thus, based on modelled discharges and lake levels. ***No consideration of levee breaches.

floodplain	1999 obs.	1999 surrogate model*	2005 obs.	2005 surrogate model*	2005 surrogate model**	2011 obs.	2011 2D*	2011 surrogate model*	2011 surrogate model**
Hasliaare River and Lake Brienz	3	33	412	***265	***191	31	16	60	1
Interlaken (Lütschine River and both Lakes)	110	93	941	***161	***141	13	33	38	12
Thun (Aare River and Lake Thun)	308	353	408	397	723	0	0	0	0
Aare River between Thun and Bern	258	***126	111	110	137	0	0	0	0
Gürbe River	0	0	14	16	0	0	0	0	0
lateral lake shorelines	380	390	480	406	451	31	34	34	25
whole study area	1059	995	2366	1355	1643	86	83	132	38

A comparison of the presented surrogate models with coarsened surrogate models shows that the number of simulations for elaborating the surrogate model and thus the intervals between the considered flood magnitudes is relevant for the robustness. The submodels have an RMSE of 54 buildings in the Aare River reach, 16 in the Hasliaare River reach, 28 in the Lütschine River reach, and 7 in the Gürbe River reach. For the 2005 flood event, the RSME lays in the order of 48% of the exposed buildings in the Aare River reach and of 0.5-3.9% in the other river reaches. In terms of flood losses, the RMSE is 43.5, 1.5, 1.8, and 1.4 million Swiss Francs, respectively. While the RMSE is highly relevant for the Aare River reach, it is less relevant for the other river reaches. The surrogate model of the Aare River reach is already based on wide intervals of the peak discharges and thus a coarsening of the intervals leads to remarkable model errors. In contrast, narrow intervals increase the robustness. This is especially relevant for peak discharges around the river conveyance capacity.

The benchmark test with the selected scenario run in full 2D mode shows the applicability of the surrogate model in the case of extreme floods. The surrogate model predicts 3294 exposed buildings and 15413 residents, whereas the full 2D simulation predicts 3720 exposed buildings and 17261 residents. Thus, the losses are underestimated in the surrogate model in comparison to a full 2D simulation. The simplified model underestimates the number of exposed buildings and the number of exposed residents by 11%, and the computed losses by 13-23%, depending on the vulnerability function. The deviation can be explained by the flooding of smaller lateral tributaries, which the reference model considers in contrast to the surrogate model. These smaller tributaries did not lead to flooding in the validation runs. In the Hasliaare River reach, the reference model run simulates flooding that is mainly due to the tributaries. Thus, in this river reach, the surrogate model does not consider the flooding of more than 200 buildings. In the Aare River and Gürbe River reaches, the surrogate model underestimates the exposure of 188 and 275 buildings respectively for the same reason.

Model application

The combination of the single surrogate models was used in a Monte-Carlo framework for modeling flood losses of probable maximum precipitation scenarios. This results in a high number of outcomes, rather than a single value in a deterministic framework (figure 9). The number of exposed buildings range from 2181 to 3661 depending on the precipitation scenario, with a median of 2768. Thereby, a minimum of 8569 and a maximum of 16175 residents are exposed as a result. The median of the exposed residents is 11079. However, the histogram of the losses (figure 9) shows a double peak. This double peak is a consequence of the different vulnerability functions. While two vulnerability functions (Dutta et al., 2003; Hydrotec, 2001) have relatively similar shapes, the third vulnerability function (Jonkman et al., 2008) shows remarkable differences to the others up to flow depths of 3 m. The left peak in the histogram at the right of figure 9 shows the losses calculated with the vulnerability function of Jonkman et al. (2008), the right peak in the histogram shows the losses of the other two vulnerability functions. Consequently, the losses range from 129 to 1499 million Swiss Francs, with a median of 782 million Swiss Francs. The loss footprint of the floodplains allows us to understand which precipitation pattern leads to the highest losses. High losses are associated with a high level of Lake Thun and a high discharge in the Lütschine River.

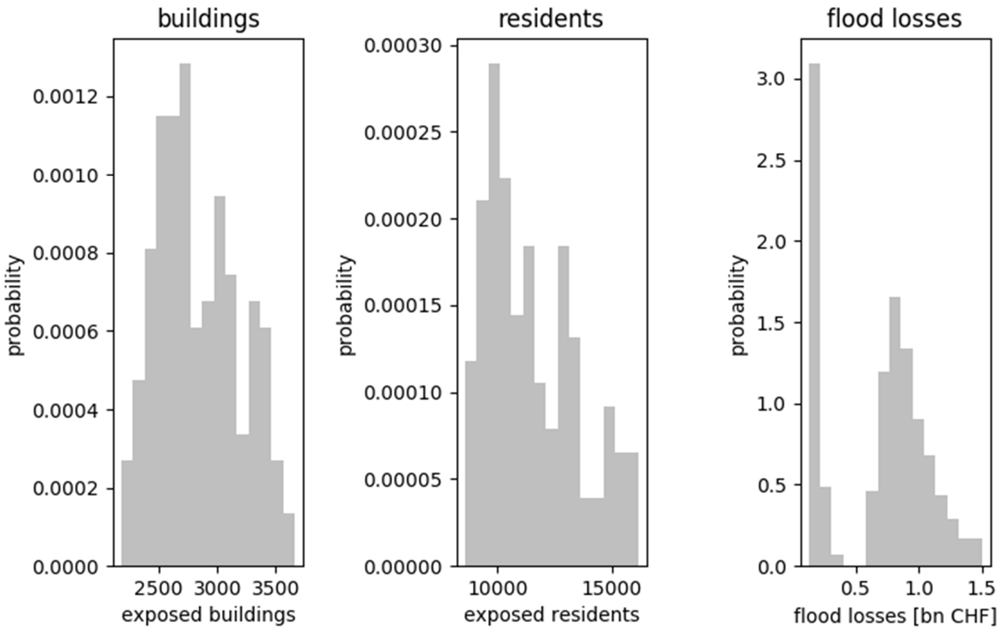

Figure 9: Histograms of exposed buildings and residents, and flood losses in 150 PMP scenarios

4 Discussion

The presented meta-modeling approach in a river basin is a combination of surrogate models. The main benefit of this approach is that it enables analysis of the behavior of a complex river system under varying system loads. The basis of the model is a 1D hydrodynamic routing model (Vetsch et al., 2017) that routes the inflow fluxes from the sub-catchments, provided by the hydrological model through the connected floodplains. The flood loss sub-models are nested into this hydrodynamic routing model, similar to Alarcon et al. (2014), Mani et al. (2014) and Bermúdez et al. (2017), except in the form of surrogate models. Since the 1D hydrodynamic routing model is remarkably (~2000-4000 times) faster than the 2D flood inundation model with a high spatial resolution, the combination of the 1D hydrodynamic model with the surrogate for flood loss computation offers a high potential in scenario-based flood risk analyses and in other applications that demand low computational costs. This is in line with the conclusions of Wolfs and Willems (2013) and Wolfs et al. (2015). Because the meta-model is derived from a flood inundation model in a very high spatial resolution (accuracy at the sub-meter resolution), the high spatial accuracy can be brought to the river basin scale in a computationally efficient framework. Hence, the presented model can be used in Monte-Carlo simulations, targeting flood loss analyses, as shown in the example of probable maximum precipitation scenarios. If the number of scenarios to be simulated remarkably exceeds the number of synthetic hydrographs required for building the surrogate model, the simplified model is able to reduce the computational costs.

However, the presented surrogate model has still notable uncertainties. In comparison to a full 2D simulation, it introduces an interpolation error. This error depends on the intervals of flood magnitudes that are as reference simulations needed for elaborating the meta-model. This is especially relevant for flood events with a high frequency but it can be solved by increasing the number of simulations with a magnitude slightly below and above river conveyance capacity. Furthermore, the surrogate model represents the errors of the 2D model and the loss model. A crucial factor is the spatial representation and attribution of the buildings. Uncertainties in the building dataset are directly relevant for the prediction capability of the surrogate model. Both errors, either caused by the model simplification or by the 2D inundation and flood loss models, contribute to the total error. While the first is more easily to consider by increasing the number of simulations in the pre-processing and elaboration of the surrogate model, the errors in the inundation and flood loss models are in many cases difficult to detect and to quantify because of lacking documentation of historic flood events and their impacts. Last but not least, the surrogate model depends on reliable predictions of peak discharges and thus it heavily depends on the reliability of the coupled hydrologic/hydraulic model. A comparison of the loss estimations that are based either on observed or modelled discharges showed that the uncertainty in the prediction of the peak discharges is still the one of the most relevant contributions to the overall uncertainty.

In general, the surrogate models show the effects of an increase in river discharge on the flood exposure. Nevertheless, the surrogate models do not consider the smaller tributaries yet. The reference run shows that, in the study area, the lateral tributaries play a relevant role in causing flood losses and producing the peak discharge in the main river reach. In other cases than those presented, the lateral tributaries may be a less significant driver for flood losses than the main river reach. With the consideration of more tributaries, the system could potentially be better represented by surrogate models. In principle, the presented approach can be extended with consideration of the tributaries. However, the problem of duple exposures arises, i.e., buildings that are affected by both the main river and a tributary should not be counted twofold. This remains to be addressed. It could be solved by developing spatially distributed surrogate models, e.g. meta-models that show the relationship between the peak-discharge of the main river or the nearby tributary and the flow depths for each single building. In such a simulation, duple exposure of buildings from the main river and the tributary can be identified and considered. However, the level of complexity increases and with it the required pre-processing work needs to be considered. Consequently, one has to ask for the practicability and efficiency of the approach (Crout et al., 2009; Wolfs et al., 2015). Furthermore, discharge time series, which are needed for the elaboration of the tributaries' synthetic design hydrographs are often not available. Moreover, at the confluence of two river reaches, the synchronization of the peak discharges in both rivers plays a determinant role in flood loss estimation (Neal et al., 2013). Thus, the surrogate modeling approach must be extended by considering multiple scenarios that depend upon each other. Another approach to overcome this critical issue is to scrupulously define the validity of the model predictions by a rigorously dedicated spatial delimitation of the study area. This can be done either by bounding the system to the floodplains in the valley bottoms only, by inserting the flood hydrographs directly into the main river rather than in the lateral border of the floodplains, or by restricting the data containing the buildings explicitly to the ones the flood prediction should be valid for.

The loss computation model was not validated on the basis of loss data in the study area. For this purpose, another study area had to be chosen, where reliable data about flood losses was available. However, the vulnerability functions used in this work can easily be exchanged with other ones, as presented by Jongman et al. (2012) or Merz et al. (2013). The uncertainty inherent in the chosen vulnerability function has to be estimated (Merz et al., 2004; Merz and Thieken, 2009; Wagenaar et al., 2016), as this appears to be one of the most sensitive factors in flood loss estimations (Moel and Aerts, 2011). Furthermore, the transferability of vulnerability functions from one region to another is questionable (Cammerer et al., 2013) but is out of the scope of this study.

The results of the scenario runs show a high variability in the resulting numbers of exposed buildings and residents, as well as flood losses. The high variability is in line with the findings of Sampson et al. (2014). Furthermore, it must be mentioned that the floodplains in the case study do not show a very high sensitivity to the volume of a flood event in terms of flood loss estimation. High flood volumes are represented in this study by high lake levels. In cases where the volume of a flood is a remarkable factor for the amount of flood losses, the presented approach has to be extended with different forms of synthetic hydrographs. Other points are not discussed here, such as the propagation of the uncertainties in the model cascade framework, as discussed by McMillan and Brasington (2008) and Rodríguez-Rincón et al. (2015). This, as well as the questions regarding the limitations of the use of surrogate models must be analyzed next.

5 Conclusions

With the development and application of a surrogate model, we present an approach for reducing complexity in flood risk modeling at the river basin scale without losing the ability to study the complex interactions between the physical processes and the impacts on the values at risk. We can verify our hypothesis of decomposing the river system into a number of subsystems and deriving the reaction of the whole system to a rainfall scenario by modeling the behavior of the subsystems in the form of relationships between flood magnitude and flood exposure/losses for each subsystem. The presented approach is a feasible way to overcome the trade-off between the spatial resolution of the inundation model and the accuracy of flood loss prediction. We have shown that the use of a surrogate model can bridge different scales by maintaining a high spatial resolution, while simultaneously allowing the simulation of a high number of flood scenarios. This approach offers new possibilities for stress test analyses and Monte-Carlo simulations demanding low computational resources in order to analyze the system behavior under different system loads. It has been shown that the surrogate model approach leads to a reliable and computationally fast analysis of flood losses in a set of probable maximum precipitation scenarios in a river basin. Thus, the approach may be implemented in coupled-component models, in portfolio risk assessments, and in the identification of the hot spots in a river basin. Furthermore, the presented approach may offer a high potential to couple it with real-time discharge forecast systems. Thus, this approach may be a basis for making a step forward from short-term discharge forecast towards short-term loss forecasts. In addition, the sensitivity analyses of the subsystem may also provide a basis for an inverse modeling approach that searches for the spatio-temporal precipitation pattern and leads to the worst-case scenario losses.

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Highlights

- A novel approach for coupling flood loss models with hydrological-hydraulic models
- Simulation of complex river systems at high spatial resolution
- Surrogate model based on the “flood magnitude – flood loss” relationship of floodplain
- An alternative approach for flood loss computation with demanding computational costs
- High potential for integration in Monte Carlo simulations and short-term flood loss forecasts