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REPORT

Application of Spatial Exploratory Global Uncertainty-Sensitivity Analysis for Flood Damage Assessment Scenarios

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Abstract

Eco-hydrological modeling of flood risk and damage assessment often employs spatially explicit models, which are prone to uncertainty in their input and output data. A modeling approach, which quantifies both uncertainty and sensitivity, is a mandatory step to increase the quality of model and dependability in spatially explicit models. This research on flood damage assessment model aims to provide an effective tool for assessment of the quality in output and therefore leading an optimization for the resource allocation problems for flood damage assessment.

The spatially-explicit integrated Uncertainty-Sensitivity Analysis (iUSA) framework (Ligmann-Zielinska & Jankowski, 2014) will be used in the proposed research to investigate the relationship between model input and output. The uncertainty analysis will focus on the input data by exploring the effect of spatial relationships in input factors on model output. For the sensitivity analysis, a variance-based decomposition will be used to understand the contribution of input factor variances on the output variance as the first and total order indices. The extended spatially-explicit iUSA framework will be tested in flood damage assessment model used in Carinthia, Austria.

1. Introduction

According to the 2015 Global Assessment Report on Disaster Risk Reduction Report of the United Nations International Strategy for Disaster Reduction (UNISDR), floods are the most frequently and costly occurring natural disasters and expected to increase due to the climate change (UNISDR, 2015). This is not an exception in many European cities where old infrastructures, growing urbanization and climate conditions are mostly common (Ugarelli, et al., 2005, Freni, La Loggia, & Notaro, 2010). Therefore, failure of preparedness and protection from such a catastrophic event may result in severe consequences considering the high concentration of population and valued assets in flood prone zones (Barredo, 2009).

Flood damage can be defined as the sum of losses or harm caused by the flooding incident and flood damage assessment is the process of evaluation of extent and content of damage and estimates the cost and time required for the replacement and restoration of the disaster. Many government agencies, research institutes or insurance companies are putting effort to develop models to understand the extend and severity of flood damage and assess the expected impact after the event (Jongman et al., 2012). The primary aim of flood damage assessments is to help decreasing the vulnerability in case of flood hazard by providing reasonably accurate information to the researchers and policy makers. Therefore, the dependability and quality of the output of the flood damage assessment models has paramount importance.

In spatially-explicit modeling of flood damage assessment, presence of uncertainty is always inevitable due to nature of geographical data. Additionally, an input variable regarded as non-influential could appear in the result of the analysis at a larger scale. Therefore, understanding the relationship and the dependence between a model output and its input is critical in terms of confidence in the model results. In this sense, analysis of uncertainty together with sensitivity will contribute to resource allocation and risk mitigation processes for spatially-explicit models such as flood damage assessment.

In this study, an iUSA framework is proposed to investigate the relation between model input and output for flood damage assessment model provided by Carinthia municipality. The proposed method for the flood damage assessment model is expected to support the decision making process in resource allocation policy making and risk mitigation for floods in Carinthia region.

2. Literature Review

2.1 Background for Uncertainty and Sensitivity Analysis Methods

Models are numerical representations of complex phenomena which produce output values based on a set of input variables. The output of models is valuable in describing, understanding, predicting or forecasting complex phenomena or helping decision or policy making processes. However, uncertainty is an inextricable part of representing complex real-world phenomena in especially environmental models where model depends on spatially distributed data. With the increase of variety in data sources, the degree of the complexity of model tends to increase since the interactions between these inputs can be amplified (Crosetto & Tarantola, 2001). For example, in spatially explicit models a variable considered as non-influential at some scale and kept fixed in model simulations could appear influential at a larger scale. Moreover, in case of multiple operations combined, errors are compounded making it difficult to evaluate the final results. Therefore, understanding the relationship and the dependence between model output and its inputs becomes critical in terms of confidence and robustness in the model results.

Uncertainty in spatially explicit models can be analyzed by implementing methods for comparing the importance of the input uncertainties in terms of their relative contributions to uncertainty in the outputs. The result of uncertainty analysis can be in the form of mean and standard deviation to visualize for the target end-users. However, due to non-linear nature of most models, sometimes the output of a model may have much greater uncertainty compared to input data. Therefore, the uncertainties could be compounded rather than being enhanced. Given this case, it is important to have some information about the impact of input uncertainty to the output. Consequently, an integrated usage of sensitivity analysis together with uncertainty analysis will help to reveal the influence of various input factors. By this way, we can better advocate to our models.

Sensitivity analysis (SA) analyses the variation in the output of a model and its dependence on input by defining it qualitatively and/or quantitatively. With its basic definition made by Morgan and Henrion (1992), for a model, sensitivity analysis (SA) is the measure of change of the output y of a model with respect to variation in an input x of the model (Morgan & Henrion, 1992). Unlike uncertainty analysis, which measures the uncertainty in a model's results (forward-looking), sensitivity analysis backtracks the relationship between inputs and outputs of the model (backward-looking) (Saltelli, Chan, & Scott, 2000 ;Gómez-Delgado & Bosque-Sendra, 2004; Chu-Agor, Munõz-Carpena, Kiker, Emanuelsson, & Linkov, 2011). Therefore every component of the model and the effects of their interaction on the variability of model output can be examined and quantified. Information about the dependence of model output variability on model input may lead to model simplification through fixing of non-influential model input factors and reducing model uncertainty through procurement of higher accuracy data for influential model input factors.

There is a variety of methods for applying SA for spatial models, depending on the particular problem under consideration (Saltelli et al, 2000; Helton & Davis, 2003). Behavior and effectiveness of different sensitivity analysis techniques could be different from one another. Therefore, one should consider the model structure, input data dependence, and computational cost before selection one technique. For example, local approaches investigate the input perturbations at specific points by estimating partial derivatives (Iooss & Lemaitre, 2015). As one of the widely used local SA methods in spatially inexplicit models, the one-at-a-time approach evaluates one model parameter at a time in order to determine a given parameter's effect on the model output (Lilburne et al. 2006; Ligmann-Zielinska & Jankowski 2008; Saltelli et al. 2010; Anderson et al. 2014) . As illustrated in Kocabas and Dragicevic's study (2006), this technique can be applied to define the degree of similarity between outputs when varying different input parameters (Kocabas & Dragicevic, 2006). The OAT is computationally efficient and does not need a large number of model executions. However, besides its advantages, the OAT approach has some drawbacks. First of all, it fails to identify the interactions among exogenous variables, therefore understanding of the significance of interactions is underestimated (Butler et al. 1997; Anderson et al. 2014). Secondly, the OAT only gives reliable results where the model input-output relation is linear. However, as stated by Ligmann-Zielinska and Jankowski (2008) the majority of spatial decision problems are non-linear. Moreover, the OAT is vulnerable to sudden change of parameter values due to its interactive environment (Crosetto, Tarantola, & Saltelli, 2000). This could result in vagueness in the magnitude of the input value change. These disadvantages limit the OAT usage in problems where model parameters can be spatially autocorrolated (Ligmann-Zielinska & Jankowski, 2014).

Variance-based techniques can also be defined as global sensitivity measures since they consider the full ranges of uncertainty of the inputs. However, a distinction should be made here since not all of SA methods, which used variance as a sensitivity indicator, are regarded as global. Regression-based methods such as correlation coefficients (CCs), standardized regression coefficients (SRC), partial correlation coefficients (PCC) and their rank transformations such as rank correlation coefficients (RCCs), standardized rank regression coefficients (SRRC), and partial rank correlation coefficient (PRCC) rely on the idea of using variance as an indicator of importance for input factors. These regression-based models are stronger in linear models. Comparison of a test set examples of these models with random and LHS sampling methods is thoroughly discussed in Helton and Davis (2002). According to their finding, for linear models, CC and RCC can identify the important parameters for even small sample sets for both random and LHS sampling. Moreover, in the complete absence of correlation, CC and SRC or RCC and SRCC would give the same results whereas neither PCC nor PRCC can provide information regarding to importance of individual inputs(Helton & Davis, 2002).

Other variance-based method in SA such as FAST, E-FAST and Sobol design, considered as global SA (GSA) where the influence of the variation of model components (called model factors) on the model output is studied. (Homma & Saltelli, 1996; Saltelli, Tarantola, & Chan, 1999a; Sobol, 2001). GSA helps to improve the overall quality of model and input parameters by improving reliability, enabling transparency and building credibility by showing the variations of the output in terms of input. In recent years, the investigations of variance-based GSA approaches in the complex models have been on the rise due to their multiparametric nature. Saltelli and his co-authors (1999b) recommended in their study GSA methods for spatial problem analysis. They proposed Fourier Amplitude Sensitivity Test (FAST) as a model independent method effective for both monotonic and non-monotonic models (Saltelli, Tarantola, & Chan, 1999b). Tarantola and his co-authors (2002) advanced GSA by using Extended-FAST method and tested it in an environmental assessment case study. This new technique is an extension of FAST by introducing a resampling technique. It also introduces the computation of first-order (S) and total sensitivity (ST) indices, which are instrumental to understand the influence of model's factors on model output variability. However, for inputs which are not continuous in their ranges, FAST fails to make good predictions. Saisana, Saltelli and Tarantola (2005) argued that composite indicators (similar to aggregation functions in MCDA models), commonly used in many policy studies, could be the massive source of uncertainty due to the large amount of data used in deriving index values. Research conducted by Saisana and her colleagues has been aimed at increasing robustness and quality of composite indicators by using GSA methods. Gomez-Delgado and Tarantola (2006) proposed an integrated approach for Extended-FAST method, which assumes uncorrelated input factors. In 2010, Saltelli and his co-authors presented another GSA approach, which is superior to FAST and Extended-FAST by easing the computational cost of higher-order model factor interactions. This method of Sobol' decomposes the output variance into fractions so that the fractional composition of each input can be traced with first order and total effects (Saltelli, et al., 2010).

The importance of variance-based GSA is that they provide higher order effects which give the information about interactions among input factors. Therefore, factor prioritization and factor fixing becomes possible after USA. In particular, they are recommended due to their model-independent approach with supporting nonlinear models and spatially explicit data. A well-developed technique of GSA uses variance-based measures that can deal with nonlinear models and measure the effect of interactions of model components (Ligmann-Zielinska & Jankowski, 2008; Saisana, Saltelli, & Tarantola, 2005; Saltelli, Tarantola, & Chan, 1999a). Differing from correlation ratios and rank coefficients which similarly use variance as an indicator of importance for input factors, GSA variance-based methods are independent of any assumptions about model structure. Therefore, GSA variance-based methods can be applicable for non-monotonic and monotonic models as well as nonlinear models.

As stated in many application of USA in complex models, the selection of the method always depends on the particular problem (Saltelli et al, 2000; Helton & Davis, 2003). Behavior and effectives of different sensitivity analysis techniques could be different from one another. Therefore, one should consider the model structure, input data dependence, and computational cost before selecting a particular technique. Of course, for some of the models, more than one technique could be applied. In such cases, one can implement selected subset of methods to a smaller test problem rather than the full-size problem. Therefore, without spending more energy on the computation side, researcher can have the comparison of results of selected techniques. In addition, the model's additivity or linearity could also influence the accuracy of the SA, which may require a test with a model-independent SA method. However, the most influential limit could be the number of factors to be investigated in the model. For the larger sets of input factors, the computational cost becomes high and SA is difficult to accomplish.

In general, quantitative SA methods give accurate and exact percentages of the variance in the output, whereas qualitative methods rank the input factors in terms of importance. However the quantitative methods are more complex to solve due to this computational exactness, therefore they are computationally more expensive. One possible comprise might be first to apply parameter screening and then evaluate sensitivity and uncertainty by using a quantitative SA method with the simplified version of the model (Gan et al., 2014).

Considering its importance for model evaluation, SA becomes a requirement for any model whether it is going to be used for analytical or predictive purposes. Various research applied SA in various spatial models including ***hydrological models*** (Dixon, 2005; Estrada & Diaz, 2010; Saint-Geours & Lilburne, 2010; Marrel, Iooss, Jullien, Laurent, & Volkova, 2011; Chen, Yu, & Khan, 2013; Baroni & Tarantola, 2014; Gan, et al., 2014; Massmann, Wagener, & Holzmann, 2014), ***environmental models*** (Diebel, Maxted, Nowak, & Vander Zanden, 2008; Pantus, Ellis, Possingham, & Venables, 2008; Li, Brimicombe, & Ralphs, 2000; Roura-

Pascual, Krug, Richardson, & Hui, 2010; Chu-Agor et al , 2011; Yang, 2011), ***land suitability and land allocation*** (Humphries, Bourgeron, & Reynolds, 2010; Verburg, Tabeau, & Hatna, 2013; Ligmann-Zielinska & Jankowski, 2014) and spatially explicit resource allocation decisions developed by means of ***multi-criteria evaluation*** (Alexander, 1989; Jankowski, Nyerges, Smith, Moore, & Horvath, 1997; Butler, Jia, & Dyer, 1997; Butler & Olson, 1999; Tarantola, Giglioli, Jesinghaus, & Saltelli, 2002; Feick & Hall, 2004; Gómez-Delgado & Bosque-Sendra, 2004; Feizizadeh, Jankowski, & Blaschke, 2014).

Spatially-explicit sensitivity analysis for eco-hydrological modeling also applied in various domains such as ***flood monitoring*** and ***flood prediction*** (Hossain, Anagnostou, & Dinku, 2004;Akbari, Nezhad, & Rema, 2012); ***flood risk assessment*** (Islam & Sado, 2000) and ***flood retention*** (Chen et al., 2012). Regarding the especially economic assessment in ***flood damage assessment*** models, to increase the robustness and improvement in confidence, SA is a strong mechanism in flood risk assessment chain (Saint-Geours, 2012).

2.2 Uncertainty and Sensitivity Analysis in Flood Damage Assessment

Most of the studies in the literature for flood damage and risk assessment, investigated only uncertainty in models of different scenarios such as land use (Te Linde, Bubeck, Dekkers, De Moel, & Aerts, 2011), hydraulic simulation (Bales & Wagner, 2009), or damage estimation (Koivumaki, et al., 2010) Relatively fewer and more recent publications addressed the question of sensitivity along with uncertainty analysis. De Moel and co-authors (2012) proposed a new approach for flood inundation depth estimation incorporated with an uncertainty analysis (de Moel, Asselman, & Aerts, 2012). They also discussed the source of uncertainty related to the damage estimation and pointed as the most influential parameter as depth-damage curves in damage calculation. Another application on flood risk management with sensitivity analysis was conducted by Saint-Geours (2012). In this study, uncertainties in flood damage modeling and cost-benefit analysis of flood risk management plans were investigated by applying variance-based global sensitivity analysis to NOE model which is a model for computing expected annual flood damages at the scale of land use and water depth maps (Saint-Geours, 2012). Finally, Baroni and Tarantola (2014) illustrate a general framework for uncertainty and sensitivity analysis for deterministic models considering the scalar, non-scalar or correlated inputs. They used the first- order sensitivity indices to improve and simplify the model and applied the developed model to a 1D hydrological model (Baroni & Tarantola, 2014).

This research integrates the spatial and statistical analysis methods for flood damage assessment to explore the uncertainty in input factors on damage estimation model output. The model used in the study has been provided by Carinthia municipality, which uses the damage estimation model to assess the flood risk analysis at building level. In this research, the concept damage estimation extended through uncertainty and sensitivity analysis of model output due to input factors. The results are expected to help to prioritize the input parameters and understand the relative importance for the model output.

3. Problem Definition and Research Questions

The goal of this research is to explore the methods to flood damage assessment by investigating the relationship between the input and output in damage estimation model. Since flood damage assessment is depend on several factors, the dependability of those factors and their effect on the result is definitely important for policy making. Specifically, in this research, we address two principle questions:

1. Which factors are more sensitive to the model output in damage estimation model used in flood damage assessment in Carinthia region?

2. What would be the necessary steps to improve the applicability of GSA to flood damage assessment?

Thus, initially, this research evaluates the input/output relation for existing damage estimation model used for flood damage assessment in Carinthia region by applying iUSA framework at building level. Then, the research investigates the approaches which may improve the coupling of GSA to flood damage assessment.

4. Methodology

4.1 Overview

In this research, the spatially-explicit iUSA framework (Ligmann-Zielinska & Jankowski, 2014) has been used to investigate the relationship between model input and output for flood damage assessment. The existing script implementing iUSA framework, written in Python, is extended by adding the damage estimation model provided by the Department for Water Resource Management of the regional government of Carinthia. This model is based on a guideline for cost-benefit assessment for structural flood mitigation published by the Austrian Federal Ministry of Agriculture, Forestry, Environment and Water Management (BMLFUW 2009).

The implementation consists of three steps. In the first step, a sample set for each input factor is created. Next, for the uncertainty analysis, the multiple outputs are calculated through MC simulations and they are summarized intro average damage estimation and uncertainty maps. For the last step, variance-based decomposition GSA is performed. As the result of variance-based decomposition method, the variability of the output is apportioned to each input factor and the results are mapped in the form of S and ST sensitivity index maps.

4.2 Conceptual Model

The conceptual model for the iUSA for damage assessment model has been illustrated in Figure 1.

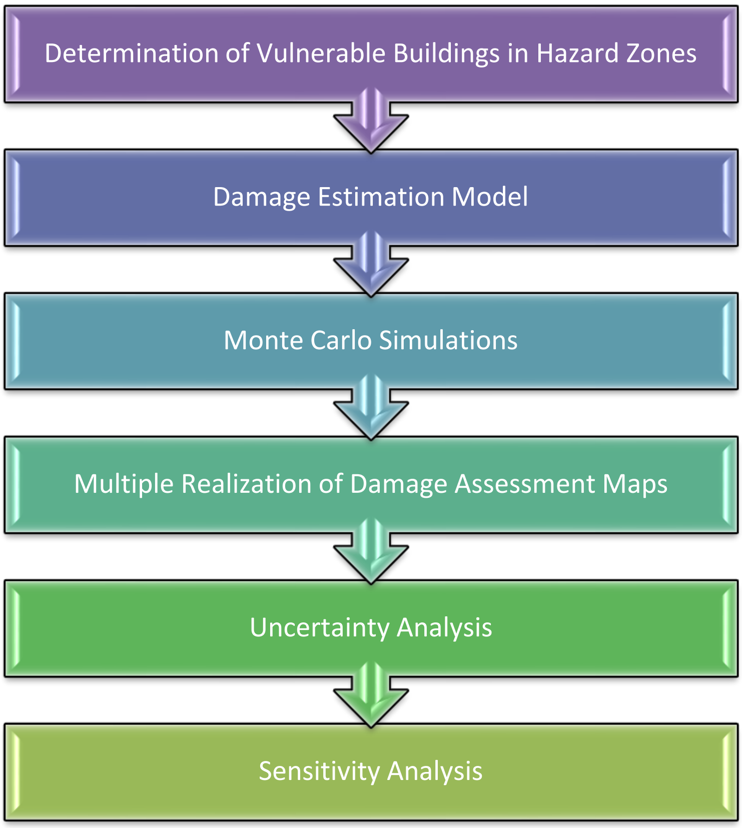

Figure 1 Conceptual Framework for iUSA for Damage Estimation Model

The hazard zones play a paramount importance in the hazard damage assessment. These zones are representation of the water depth which is used in estimation of damage in flood prone zones. This is a fundamental concept in flood damage assessments since it is tightly coupled to the flood inundation and damage caused to building. Therefore, first and most important step in a flood damage assessment is the determination of hazard zones by considering the water depth for the flood zone. Since in this study, damage estimations are done in building level, buildings in hazard zones are determined prior to damage estimation model.

Although water depth has strong evidence in the variability in flood damage, there are also other tangible factors which should be considered in damage assessment such as economic consideration or the type of the building in use. Therefore, to be able to estimate the damage caused by flood, addition to water depth information, damage estimation function for buildings also consider the type of the building in use, and some constant minimum damage values for different floor levels. This minimum value is referred as S_{min} and varies with the building type, independent from water depth. (Prettenthaler, Amrusch, & Habsburg-Lothringen, 2010). During damage estimation, a use-specific factor (symbolled as B in the equation 4.1) is also taken into account which represents the relation of amount of damage occurring at a specific depth without considering an initial damage. These factor values might have a wide range and they are adapted according to the specific characteristics of the project site. In general, B values has a negative relation with presence of older or smaller buildings, low construction and furnishing quality, long time ahead warning, short flood period or existing protective actions. According to guidelines for cost-benefit studies in the protection of hydraulic engineering (BMLFUW, 2009), it is expected to have higher B values in case of:

- New and/or larger buildings compared to statistical mean
- Higher construction/furnishing compared to statistical mean,
- No or very short time ahead warning
- Fast water level rise
- Long flood duration
- Dynamic forces present due to high water flow velocities/erosion/material transport
- Flood with high material component like mud, contamination
- Flood only during winter time

In general, these parameters affecting the damage caused by flood has some pre –defined ranges determined by experts. These ranges are also coupled with a certain building type are embedded into a look-up table for conventional damage estimation (Table 1). Depending on the parameters on Table 1, for each different building type, damage is calculated based on damage estimation function as follows:

$$Damage = \left(S_{\min Basement} + B_{Basement} * 1000 * \sqrt{waterdepth}\right) + \left(S_{\min First\ Floor} + B_{First\ Floor} * 1000 * \sqrt{waterdepth}\right) \quad \text{(Eq. 4.1)}$$

Table 1 Damage Estimation Look-up Table for Buildings

Building Type	**S_{min} Basement**	**S_{min} First Floor**	**B Basement**	**B First Floor**	**Waterdepth (depending on zone)**
Industrial or Commercial Buildings	12000	30000	21.3	168.8	0.77/0.15
Public Buildings	12000	30000	21.3	168.8	0.77/0.15
Building with one flat	3250	13360	11	30	0.77/0.15
Building with two or more flats	2800	11800	11	29	0.77/0.15
Tourism	10000	20000	20	62.5	0.77/0.15
Other buildings	1000	7000	8	20	0.77/0.15
Buildings for	1000	8000	5	25	0.77/0.15

communities					

One important distinction for input parameter water depth is that although the rest of the input factors depend on the type of the building, water depth is related with hazard zone severity. For example, if a building is in Hazard Zone 1 (Red) which is regarded as highly risk area, water depth value for that building is taken as 0.77 m in damage estimation. For moderate and low severity hazard zones, water depth is selected as 0.15 m for the same calculation. These values are decided by expert knowledge and originally coming from damage curves. Flood damage curves are the graphical representations of depth of flood versus monetary values, considering the land-use classification such as residential, commercial, industrial or public services (Nascimento et al., 2006). Direct damages are largely estimated through damage curves which show the difference between flood inundation level and floor level therefore any error or uncertainty attached to this information will be carried through the damage estimation (Messner et al., 2007).

Following, in MC simulation, a sample set of N is generated for each input in the damage estimation model by using corresponding probability distribution functions. MC simulations can use different sampling methods to generate uncertainty surfaces. Simple random, quasi-random, and stratified (Latin Hypercube Sampling (LHS)) are among the commonly used sampling methods in MC simulations.

The basic MC method is based on random number generation, however, this technique is not preferred since the generated random numbers do not necessarily cover the sample region. Clusters or gap regions can occur in random sampling generation. Samples obtained in stratified sampling or LHS are more evenly distributed in the sample space. Stratified sampling can be achieved by using partitions (strata) and producing at least one sample from each interval in this partition.

Especially for monotonic and nonmonotonic functions, with strong nonlinear relationships, the stability of LHS is noticeable when compared to random sampling. However, LHS fails to provide good uniformity properties in an n-dimensional unit hypercube (Kucherenko et al., 2013). Although it performs superior to random sampling, sample exploration may still be improved. Moreover, there is a possibility of correlation between variables.

In each sample generation algorithm, a deviation of sample point from the ideal uniform distribution occurs. This quantitative measure is defined as discrepancy and the amount of discrepancy is related with the effectiveness of MC simulations. Quasi-random sampling, sometimes called as low discrepancy sequences, has the ability to both act as a random variable and ability to show a uniform distribution. Quasi random sequences produce random numbers but these points know the positions of previously sampled points therefore do not form clusters or gaps in the sample space. For this reason they are called quasi-random and their discrepancy from original input are low. This characteristic of quasi-random sequence is an important advantage in MC simulation. Considering these advantages, for this model, quasi-random sampling method is selected for sample generation for MC simulation. The quasi-random sampling by using Sobol's experimental design implemented in a software called Simlab, which is developed by Joint Research Center (The software can be freely accessed from simlab.jrc.ec.europa.edu) (Sobol, 2001; Lilburne & Tarantola, 2009; Saltelli, et al., 2010). Output of Simlab software is a .sam file and this file is read through one part of the code to be used for MC simulation embedded in the main code.

The input factors which are considered to be affected by significant uncertainties will be randomly derived from *n* distributions. The type of the distribution should be given in advance depending on the range of preferences, empirical observations and priory expert knowledge or opinion. The selection of specific probability density functions (pdfs) or wider intervals for the input factors has the possibility of affecting the conclusions therefore, whenever there is a possibility of calibration or detailed observations to acquire more precise representations for distributions, the pdf selection can be reconsidered and updated with posterior information (Tarantola, Giglioli, Jesinghaus, & Saltelli, 2002).

For the sensitivity analysis, as explained in detail in section 2, variance-based GSA has been selected. To illustrate variance-based GSA, a model can be represented in the form of $\mathrm{Y} = \mathrm{f}(\mathrm{X}_1, \mathrm{X}_2, \cdots, \mathrm{X}_\mathrm{k})$ where Y is a scalar value corresponds to output and X_i is the generic input factor. As given in Saltelli and his coworkers' study, the sensitivity measure can be expressed by first order sensitivity coefficient which can be shown as below equation (Saltelli, et al., 2010):

$$S_i = \frac{V_{X_i}\left(E_{X_{\sim i}}(Y|X_i)\right)}{V(Y)} \qquad \text{Eq. (4.2)}$$

For the numerator inner operator, the mean of Y is calculated for all factors except X_i when X_i kept fixed. The outer operator takes the variance of all possible values of X_i. This is divided by the total variance so that the first order effect can be calculated for *i*th input factor. The total effect (S_{T_i}), is a measure of variance of all higher order effects for factor X_i and can be calculated as follows:

$$S_T = \frac{E_{X_{\sim i}}\left(V_{X_i}(Y|X_{\sim i})\right)}{V(Y)} = 1 - \frac{V_{X_{\sim i}}\left(E_{X_i}(Y|X_{\sim i})\right)}{V(Y)} \qquad \text{Eq.(4.3)}$$

By calculating these indices, the influence of the input parameters in the damage estimation variability can be expressed mathematically.

5. Study Area

For the implementation of iUSA for flood damage estimation model, for this case study, conducted in twelve different municipalities along the river Drau in Upper Carinthia has been selected. Flood risk zones are determined by hydraulic modeling and after an expert fieldwork campaign has been conducted in the study area. Hazard zone map is the combination of the four outputs from four fieldwork projects and shown in Figure 2.

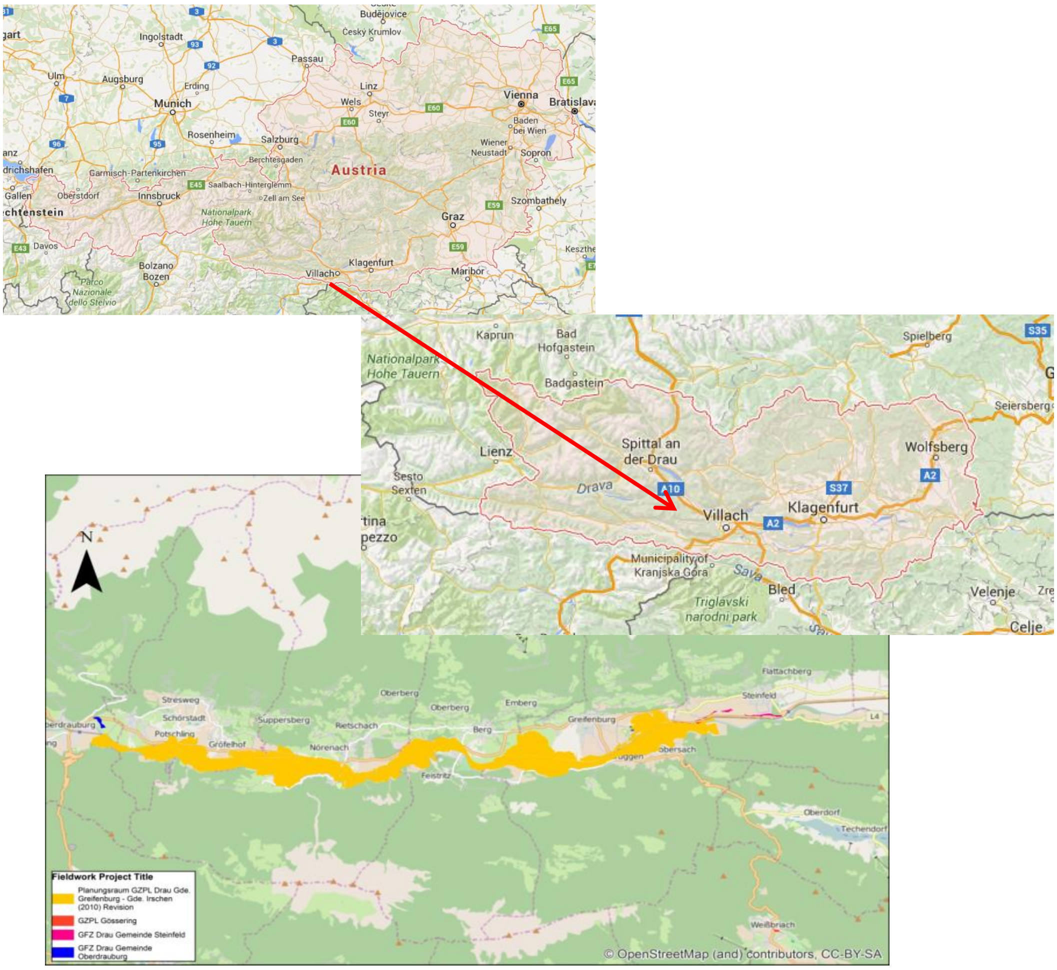

Figure 2 Fieldwork Project Boundaries in the Upper Drau Valley, Carinthia, Austria

Depending on the fieldwork outputs for the study region, hazard zones are defined as red, yellow, and moderate, which is a scale used for expressing the severity of hazard in a particular zone (Figure 3). In this scale the red zone is representing the highest intensity for a flooding event following by yellow and moderate flood hazard zone.

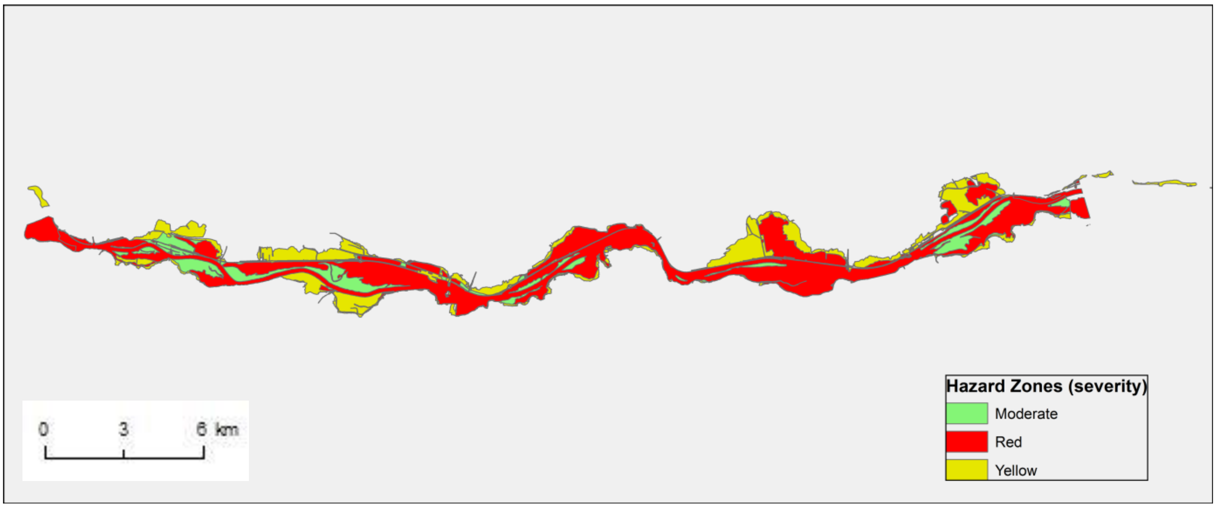

Figure 3 Flood Hazard Zones coming from Fieldwork Study

6. Implementation

6.1 Data Preparation

For the iUSA , first building in the hazard zones are extracted by zonal statistics. A hazard zone surface with 1 m cell resolution was used to define hazard zone boundaries for different severity levels (Figure 3). Buildings in these zones were determined by using Zonal Statistics as Table in ArcMap 10.1 software. In zonal statistics analysis, within the boundaries of the selected building, the most occurring hazard zone value of the cells is selected and assigned for each building object. According to the output tables, the number of the buildings in the hazard zones vary depending on the hazard zone scale. With the highest resolution (1 m cell resolution), 114 buildings are in the hazard zone where in the case of 30 cell size, only 36 buildings are considered in the hazard zone. To have more spatial variability, dataset is prepared from 1m hazard zone data, resulting in 114 buildings with three different level of hazard severity.

For the damage estimation model, since every distinct building type has different ranges for each parameter, a look-up table is formed in the code so that for each and every single execution, the parameters are selected for each building depending on the building type. This information is bridged over the identification number key (IDNK) which has been created in the database for former applications.

6.2 Quasi Random Sample Generation and MC Simulation for Uncertainty Analysis

Since there isn't sufficient prior information about the range or distribution characteristics of input parameters, their perturbation is considered to follow a uniform distribution with an equal chance of being selected from the allowable ranges determined by expert knowledge (Table 2). For example, for water depth, a +/- 10% change in the red (0.77) and yellow zone (0.15) water depth values are considered as the upper and lower limits for the uniform pdf. By using quasi-random sampling method proposed by Sobol, input samples are generated for each input.

For each factor, S_{min}, $S_{min\ first\ floor}$, $B_{basement}$, $B_{min\ first\ floor}$ and *water depth* parameters, (k=5) and 6656 samples (N=6656), the damage estimation model was run 46592 times (N*(k+2)) for each buildings in the hazard zone.

For the spatially explicit uncertainty analysis, multiple realizations of the damage estimation are computed from all input values generated by quasi-random sampling. These estimations are summarized with minimum (MIN), maximum (MAX), average (AVG) and standard deviation (STD) maps. The two extreme value maps (MAX and MIN) help to understand the repeating high and low damage estimation buildings whereas AVG and STD maps are the key surfaces to explain the distribution and the accompanying uncertainty.

Table 2 . Allowable Minimum and Maximum Value Ranges for Input Factors

Inputs	Minimum Allowable Value	Maximum Allowable Value
Smin	10000	30000
Smin First Floor	25000	35000
B Basement	20	22
B First Floor	150	170
Water depth (Red Zone)	0.693	0.847
Water depth (Yellow Zone)	0.135	0.165

6.3 Variance-Based Sensitivity Analysis

For each input factor in Table 2, by using the equations 4.2 and 4.3, both first order and total order sensitivity indices are calculated and those values are added as attribute values for the buildings in the hazard zone. Namely, 46592 model output coming from MC simulations are evaluated and summarized into sensitivity index values for input factors for damage estimation equations.

The overall flowchart of the whole implementation is summarized in Figure 4.

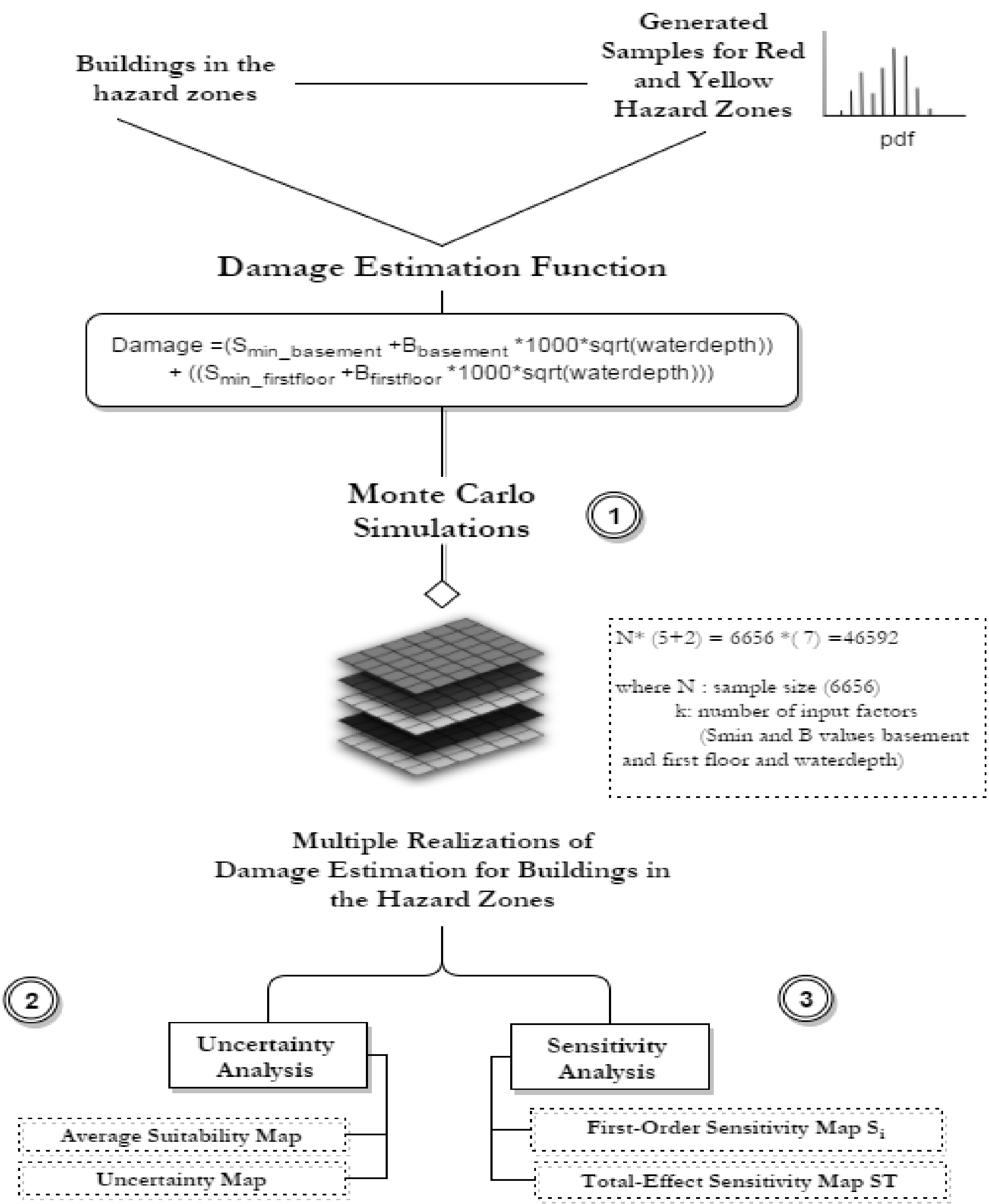

Figure 4 Flowchart of the iUSA Framework for Flood Damage Assessment Model

7. Results and Discussion

7.1 UA Results for Flood Damage Assessment

The results of MC simulations were summarized as average (AVG) damage estimation map (Figure 5) and standard deviation of average suitability (STD) maps (Figure 6). By examining the results of AVG map, buildings with higher damage estimations can be obtained. However, the level of confidence for these buildings can be only ascertained by comparing the AVG map with the STD map since higher uncertainty is expected with high standard deviation. Therefore, in order to select and observe priority buildings depending on the uncertainty associated with input factors, AVG map values should be examined together with STD map values.

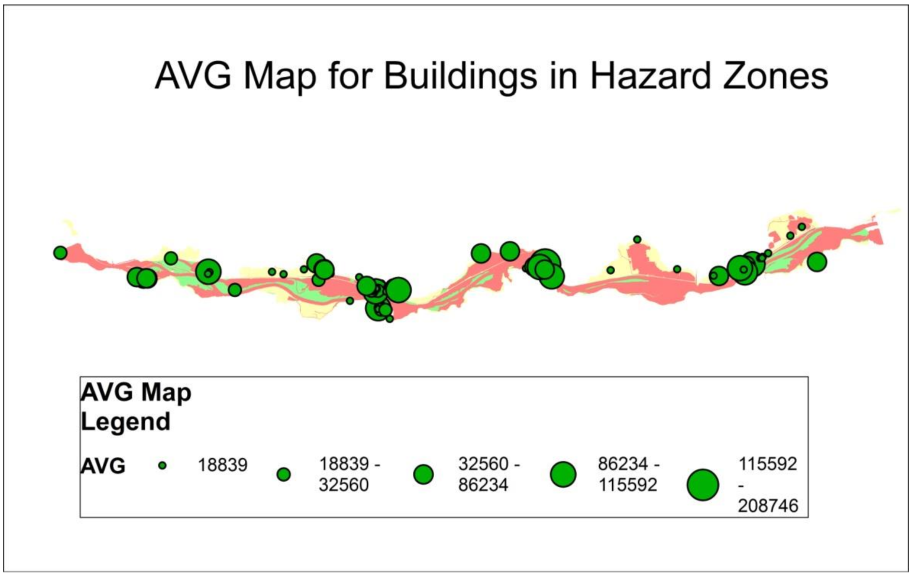

Figure 5 AVG Map for Building Damage Estimates in Damage Estimation Model

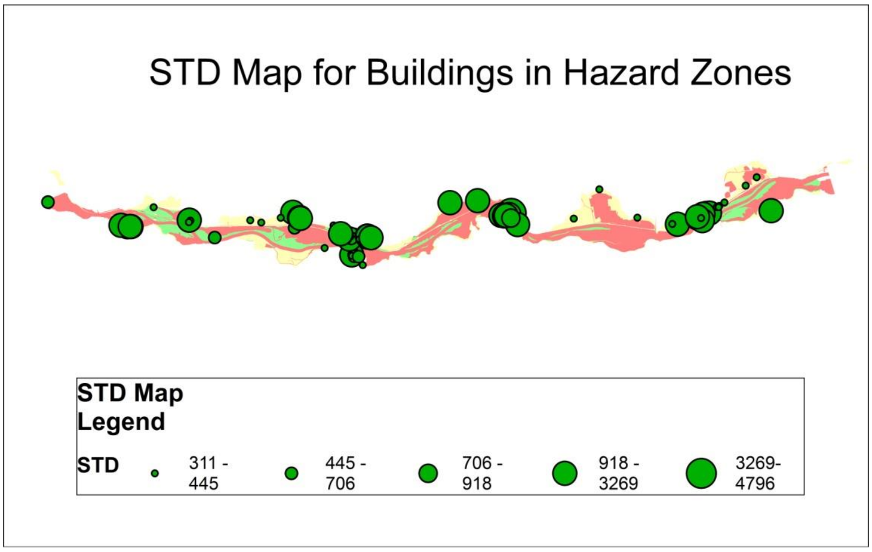

Figure 6 STD Map for Building Damage Estimates in Damage Estimation Model

However, since it is visually hard to inspect and compare the high and low vulnerability buildings due to dispersed polygons over the study area, the buildings were further grouped into four categories, which are High AVG- High STD, High AVG- Low STD, Low AVG – High STD, and Low AVG – Low STD.

The value threshold for high average damage estimation is estimated as 100,000 Euros and high standard deviation (uncertainty) is estimated as 1000 Euros by comparing the histograms of AVG (Figure 7) and STD values (Figure 8). According to these threshold values, buildings in High-High (Table 3) values are selected as below:

Table 3 Buildings with High AVG-High STD Damage Estimation

OBJECTID *	building_category	NAME	IDFNK	Zone_1	AVG	STD
82	Tourism	GREIFENBURG	4	1	102364.909082	2081.431313
2	Industrial_or_Commercial	GITSCHTAL	5	3	115592.720418	2117.107903
3	Industrial_or_Commercial	GITSCHTAL	5	3	115592.720418	2117.107903
6	Industrial_or_Commercial	GITSCHTAL	5	3	115592.720418	2117.107903
8	Industrial_or_Commercial	GITSCHTAL	5	3	115592.720418	2117.107903
11	Industrial_or_Commercial	DELLACH IM DRAUTAL	5	3	115592.720418	2117.107903
12	Industrial_or_Commercial	IRSCHEN	5	3	115592.720418	2117.107903
38	Industrial_or_Commercial	DELLACH IM DRAUTAL	5	3	115592.720418	2117.107903
61	Public	GREIFENBURG	7	3	115592.720418	2117.107903
80	Industrial_or_Commercial	BERG IM DRAUTAL	5	3	115592.720418	2117.107903
83	Industrial_or_Commercial	GREIFENBURG	5	3	115592.720418	2117.107903
109	Industrial_or_Commercial	DELLACH IM DRAUTAL	5	3	115592.720418	2117.107903
111	Industrial_or_Commercial	BERG IM DRAUTAL	5	3	115592.720418	2117.107903
114	Industrial_or_Commercial	STEINFELD	5	3	115592.720418	2117.107903
22	Industrial_or_Commercial	BERG IM DRAUTAL	5	1	208746.293484	4796.122353

As can be seen from Table 3, there are repetitive average estimates for damage for multiple buildings which is expected since those matching values correspond to the same building type within same hazard zone. Following the damage equation (Eq.4.1), building type and water depth are the key factors determining the amount of damage expected. Therefore, with the small variations in those parameters, perturbations in the output can be visible. However, to better explain the reasons behind the observed differences, a GSA should be applied to understand which input factors have more effect on the output.

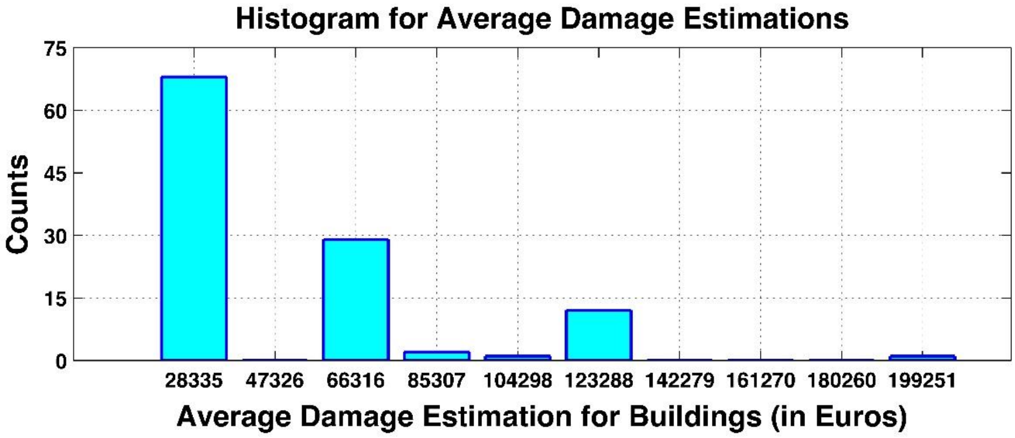

Figure 7 Histogram for Average Damage Estimations

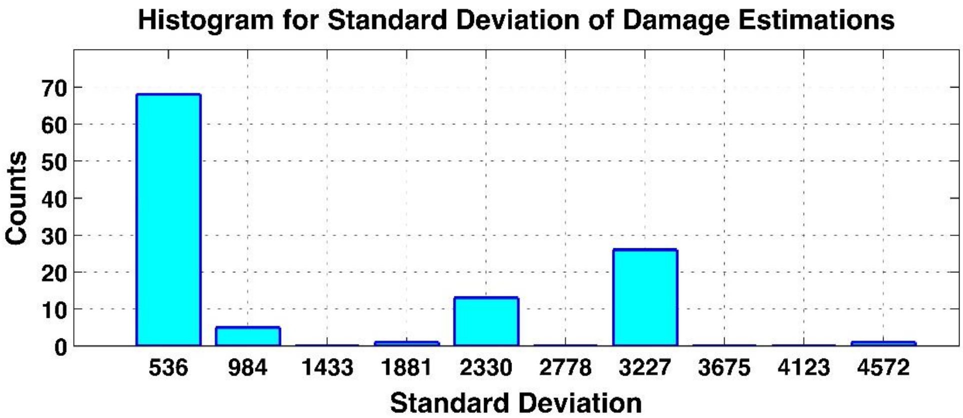

Figure 8 Histogram for STD Damage Estimations

7.2 SA Results for Flood Damage Assessment

Similar to the average damage estimation case, there are repeating values for first and total order sensitivity indices as well. The first order sensitivity index for an input factor gives us the relationship between that input and output and if it is zero than it can be interpreted as non-influential, meaning that the changes in the input factor do not influence the result. Conversely, if the first order index value equals to 1.0 then that could be interpreted as the observed variability at given location is due to the input factor under investigation. However, in some cases, the first order index may exceed 1.0 which makes interpretation difficult. According to Saltelli and his co-authors (2000), very small sample sizes (small N) are likely to produce values exceeding 1.0 for first order indices (Saltelli, Chan, & Scott, 2000). Another possible reason of the failure to get unexpected ranges for index values could be result of the poor judgment of pdf for input factors. Last, spatial variability in the input factors also affects the range of first order sensitivity indices. Considering these factors, index values different from zero is selected for each input factor.

As a result, the Table 4 shows which factors affect which buildings at the first order level. The most frequent building type affected by the most of the input factors is single flat building. This may be a predictable result considering the flooding event and its nature. Another result that be gleaned from Table 4 is that the damage estimation is more sensitive to the 10% variations in the some of the input factors (Smin and Smin first floor) when compared to rest (B basement and B first floor). This could be a guide for possible calibration or detailed observation for more precise distribution selection for those input factors.

Table 4 Comparison Table for First order Sensitivity Index Results

	Smin	*Smin First Floor*	*B basement*	*B First Floor*	*Water Depth*
Count of buildings	26	26	2	None	12
Majority Type	Single Flat	Single Flat	Single Flat	None	Other
S_i ***min***	0	0	0	0	0
S_i ***max***	0.13	0.91	0.01	0	Greater than 1 (>>1)

For the ease of visualization of dispersed buildings, the study area was divided into four sub parts (Figure 9). The buildings which have greater values than zero for every input are: 30 and 41. Higher first order index values are common in 21 buildings (Table 5) for Smin and Smin first floor factors are all single flat buildings (Figure 10).

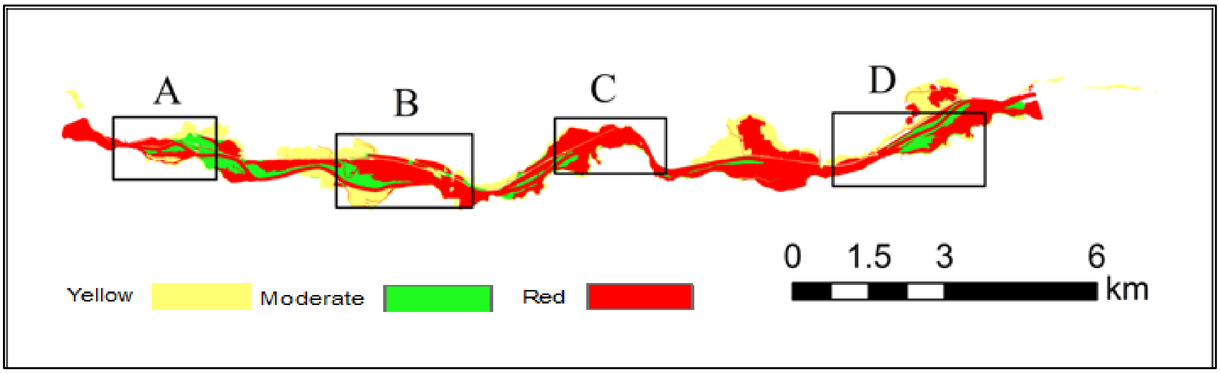

Figure 9 Sub parts in the study Area

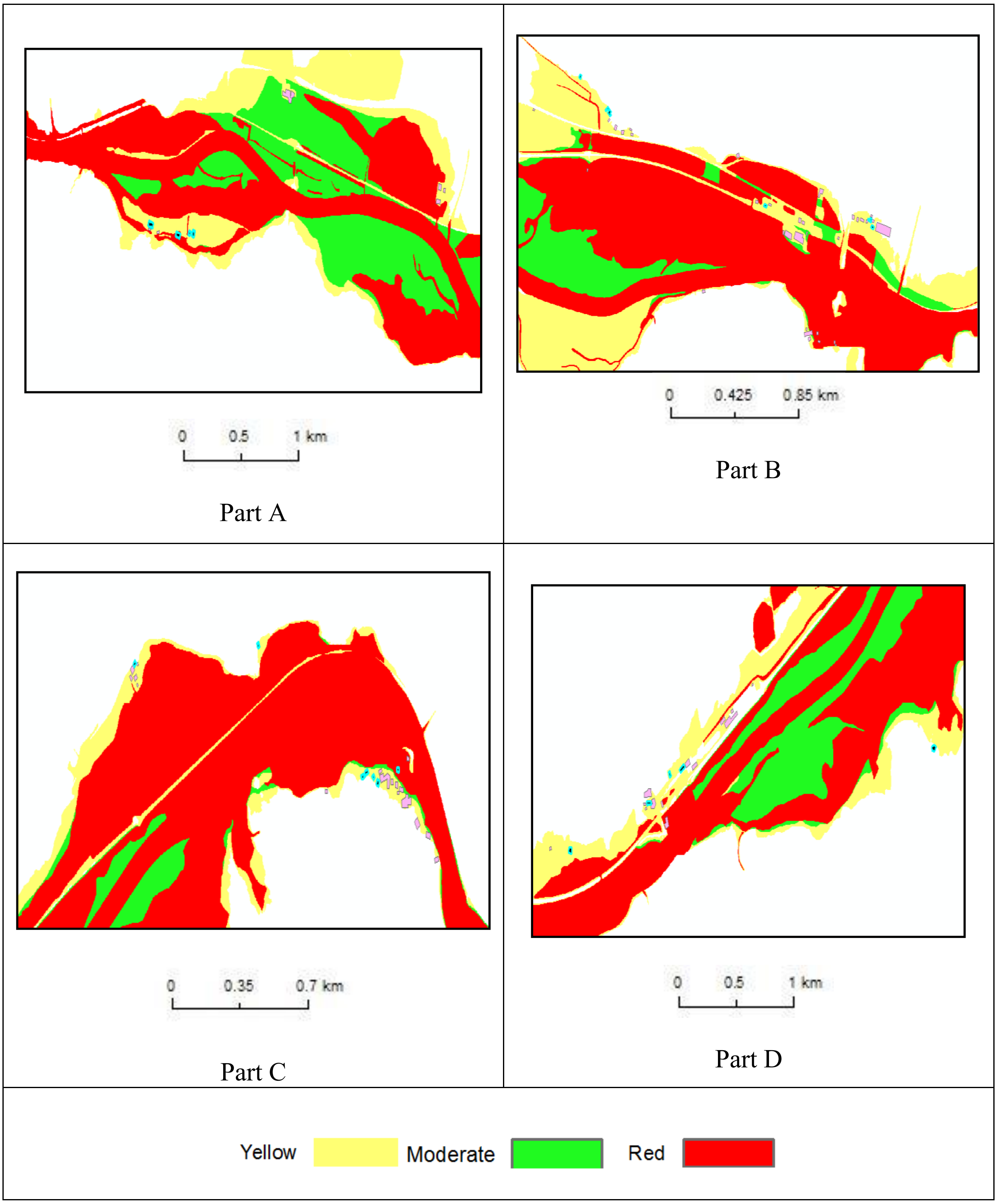

Figure 10 Spatial Locations of Buildings with Relatively high first order index values for Smin and Smin first floor (selected buildings are blue colored)

Table 5 Common buildings with high first order index values for Smin and Smin first floor

OBJECTID *	building_category
30	Single_Flat
41	Single_Flat
46	Single_Flat
48	Single_Flat
50	Single_Flat
54	Single_Flat
55	Single_Flat
56	Single_Flat
57	Single_Flat
59	Single_Flat
66	Single_Flat
68	Single_Flat
70	Single_Flat
74	Single_Flat
78	Single_Flat
81	Single_Flat
88	Single_Flat
97	Single_Flat
106	Single_Flat
110	Single_Flat
112	Single_Flat

Although S_{T_i} indices do not fully explain the uncertainty of model output, it is more reliable to investigate the overall (S_{T_i}) effect in concert with single factors than individual (S) effects alone. Therefore, S_{T_i} indices also compared in a table for each factor (Table 6).

Table 6 Comparison Table for First order Sensitivity Index Results

	Smin	*Smin First Floor*	*B basement*	*B First Floor*	*Water Depth*
Count of buildings	26	26	26	None	12
Majority Type	Single Flat	Single Flat	Single Flat	None	Other
$\boldsymbol{S_{T_i}min}$	0	0	0	0	0
$\boldsymbol{S_{T_i}max}$	0.08	0.89	0.01	0	1.03

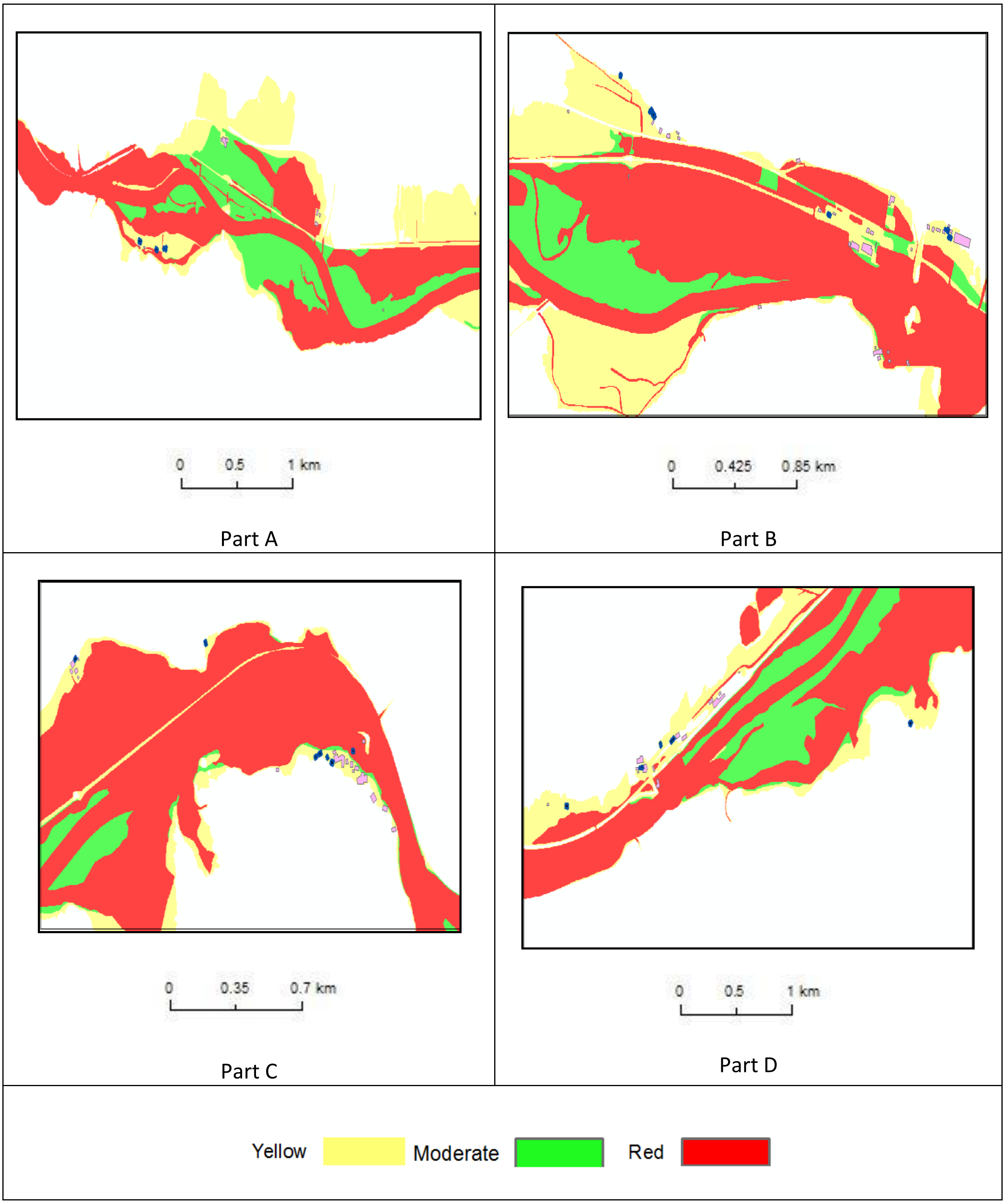

Figure 11 Locations of Buildings with Relatively high first order index values for Smin and Smin first floor (selected buildings are blue colored)

Like in the first order representation, study area was divided into four sub parts for S_{T_i} indices as well. Similarly to the single factor results, the buildings which have greater values than zero for every input are: 30 and 41. Higher first order index values are common in 26 buildings for Smin and Smin first floor factors are all single flat buildings (Figure 11). Differently from selected buildings for Table 5, $S_{T_i}$are high for buildings 4, 5, 15, 21 and 27 which are again single flat buildings

As pointed out for both first and total order results for sensitivity analysis, buildings 30 and 41 are the most influenced buildings to small variations in the input factors, specifically S_{min} and S_{min} first floor. When these buildings are investigated at larger scale in Figures 12 and 13, the building 30 is located in the transition zone between red(high) to yellow(low) and 41 is located in the red (high severity). They are both regarded as high risk zone buildings in the zonal statistics different from rest of the buildings in the output. The reason behind the highly dependence on perturbations on S_{min} values can be related with Single Flat building type since these variable is independent from water depth. For the other buildings in the Table 5, an argument can be made depending on Messner and his co-authors' discussion. They comment on the relationship between the estimated error in damage assessment and water depths as follows:

"..The effect of error coming from estimated difference between flood level and floor level are greatest for shallow depths of flooding because flood damages at 0.1 meters of flooding for the UK average house is estimated to be 23% higher than those for 0.05 meters (and considerably higher for 0.05 as opposed to 0 meters)" (page 16) Flood Damage Guidelines, (Messner et al, 2007)

Following this argument, we can expect higher sensitivity index values for lower water depths, which corresponds yellow zone in our study. The majority of the buildings with higher sensitivity indices are in low hazard zones, which can be interpreted as the water depth or related hazard zone information is much more vulnerable to uncertainties in the input values.

One last comment can be made on the comparison of outcomes of uncertainty and sensitivity analysis. As shown in Tables 3 and 5, selected buildings from the sensitivity analysis do not overlap with high average and high standard deviation buildings. The sensitivity of the output in those buildings can be misleading however; the validity of this statement can only be possible after retesting the whole model with the improved pdf distributions and reconsidering the damage estimation methodology. Since the flood damage curves are also affected by the land-use classification, the model can be re-run accordingly.

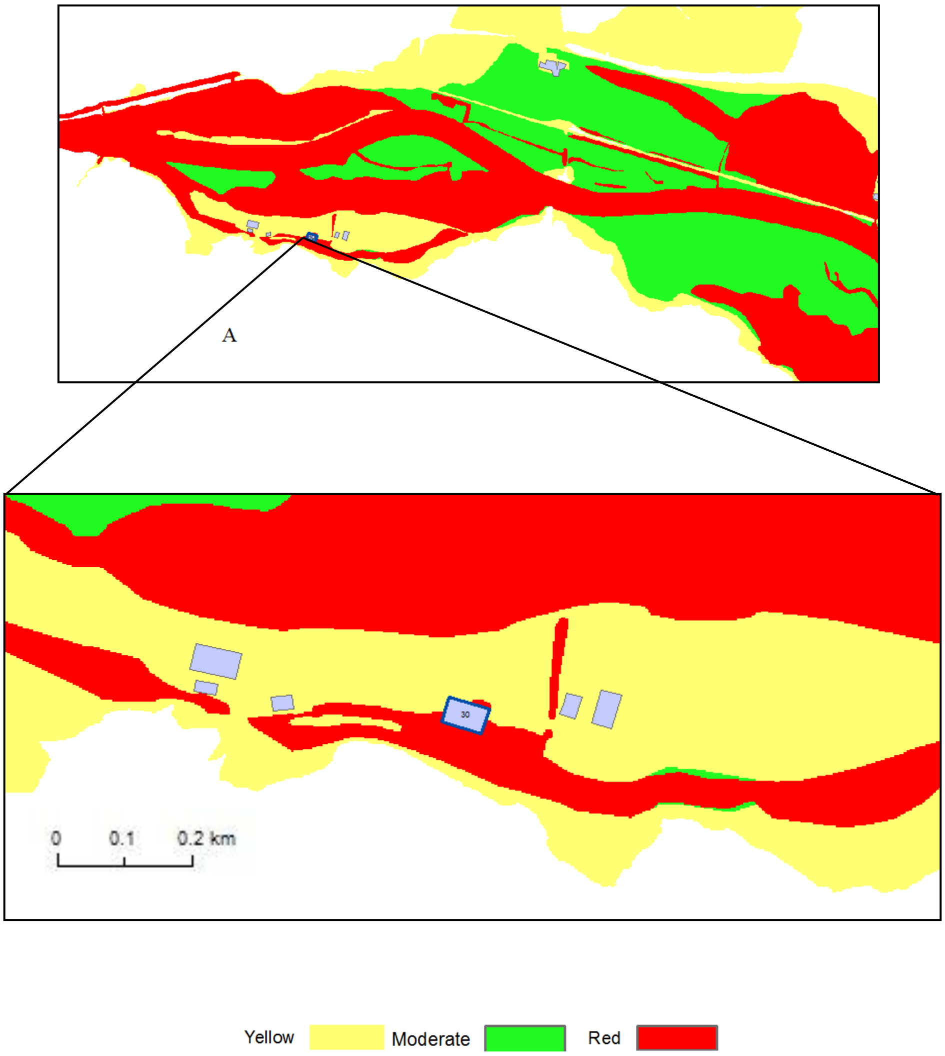

Figure 12 Building 30 in detailed Zoom Level

We need SA for understanding the quality of the results in the absence of any information regarding the errors and this is established by imposing variations on the inputs. Therefore, SA helps us to point out critical values in the output. In this analysis, with the help of multiple simulations and extensive statistical calculations, we can visualize the effect of some input factors, which are much more influential to others. Therefore, the necessary steps to improve the applicability of GSA for flood assessment should include improving the prior information coming from fieldwork and provide more empirical observations, expert knowledge, and expert opinion in the selection of proper probability distribution for input factors. These steps will help to calibrate the model and acquire more precise representations in sensitivity analysis. Consequently, more reliable conclusions can be drawn from output maps.

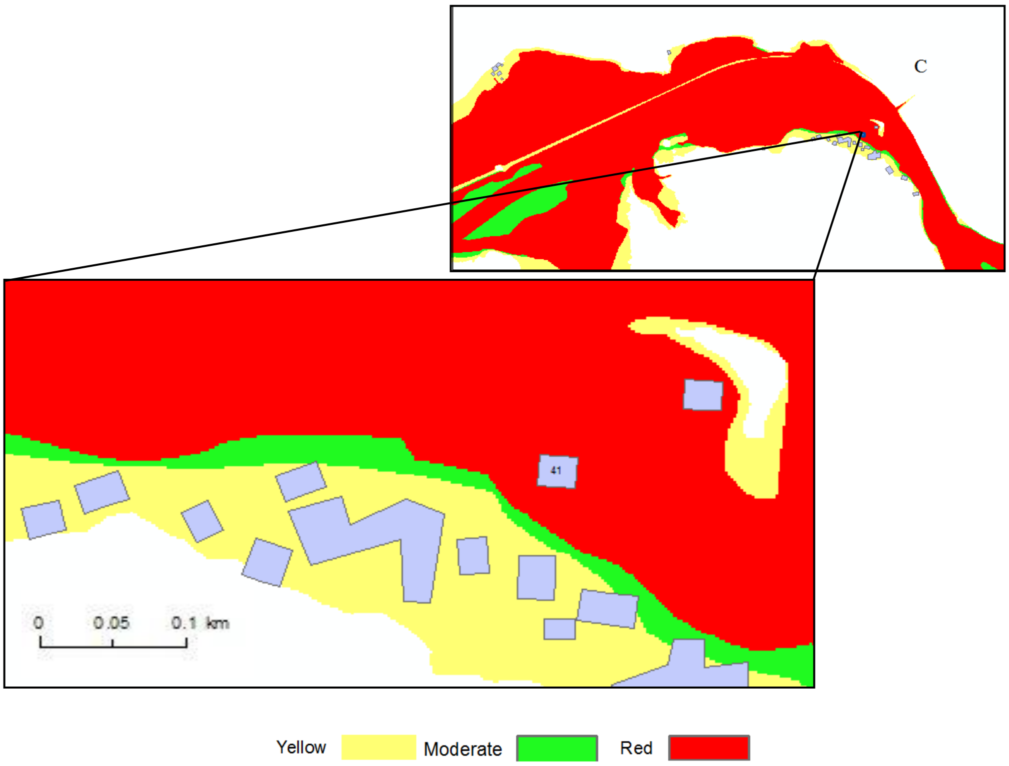

Figure 13 Building 40 in Detailed Zoom Level

8. Limitations and Future Works

As discussed in the methodology section, the spatially explicit iUSA is based on simulating many model solutions in response to variability in model parameter values, which puts high demand on computational resources. In this research, with the selected 114 buildings in the hazard zone and 46592 model runs including 5 inputs, the execution time was 8h 49min. However, this number will drastically increase when the scale of the study increases from Carinthia to whole Austria. Even including other infrastructures such as roads or bridges will increase the execution time for simulations.

Potential solutions to this problem could involve employing high performance architecture in the simulation (Zhang & You, 2012). High-performance architectures can be achieved by multi-central processing unit (CPU), multi-core graphical processing unit (GPU), clustered computing using network of workstations, cloud & grid computing or general-purpose computing. All of these methods have promising performance advantages. However, GPU when compared to closed computing architecture counterparts (supercomputers or other parallel computing resources) has advantages of higher operating performance, higher main memory (off-chip) bandwidth, and efficiency of cost, energy and physical size (Zecena, Burtscher, Jin, & Zong, 2013). These advantages make high performance architectures attractive for spatially complex decision making. Especially, as stated in recent studies in the literature, some examples of cyberinfrastructure-enabled GPU parallel computing seem promising for spatiotemporal uncertainty and sensitivity analysis (Tang & Jia, 2013).

9. Conclusion

Floods have caused severe economic and social loses due to growing population density and urbanized areas encroaching on natural hazard zones (Yalcin and Akyurek, 2004). In the context of the European Flood Directive, each member state of the European Union must perform a flood risk assessment for its river basins. Over the last years such flood risk assessment studies have also been performed by the water resource department of the Regional Government of Carinthia. For this purpose a GIS-based flood damage assessment model has been developed and applied in several case studies in Carinthia.

Flooding damage assessment is usually conducted based on prior information and estimates obtained from using interpolated real damage data from historic flood events. However, dependability of a model is closely related with the confidence in the model output as well as model itself. The uncertainty coming from different sources (lack of knowledge about phenomena, measurement errors, model assumptions, etc.) can be investigated through uncertainty analysis, which gives an idea about the confidence in the output by representing confidence intervals. In addition, how these uncertainties can be apportioned to the input variables can be answered by sensitivity analysis followed by uncertainty analysis. Therefore, to increase the robustness of a model and investigate the level of confidence in the results, the uncertainty and sensitivity analysis becomes crucial for spatially explicit models. In this sense, uncertainty analysis aims to uncover the multiple sources of uncertainty and their relative magnitudes. However, uncertainty analysis is not quite useful without translating its findings into decision or policy making.

Flood damage evaluation is an essential part of flood risk analysis, however, it is not only related to monetary damages but also to some intangible terms such as loss of life, health effects, and loss of ecological value. As stated in the “Directive on the assessment and management of floods proposal of EU Flood Directive, more concrete forms of analysis and practices are now expected to elaborate under EU Water Framework Directive. To be able to consider flood risk analysis as a comprehensive approach, it is necessary to include intangible terms is inevitable. This aim may be achieved with multi-criteria evaluation approach by considering the all intangible effects and their weights in the analysis.

Acknowledgement

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Appendix

Snippets of Source Code for Damage Estimation Model

```
def buildingDamage(OBJECTID,IDFNK,damage_LUT,waterdepth,samples):
    for i in range(0,len(damage_LUT)):
        if  IDFNK == damage_LUT[i][0]:

            if IDFNK == 1:

                smin_basement = samples[0]
                smin_1st=samples[1]
                b_basement = samples[2]
                s_1st_floor=samples[3]

            else:
                smin_basement =damage_LUT[i][1]
                smin_1st=damage_LUT[i][2]
                b_basement = damage_LUT[i][3]

            s_1st_floor=damage_LUT[i][4]

            damage = smin_basement+(b_basement*1000*npy.sqrt(float(waterdepth)))+\
            smin_1st+s_1st_floor*1000*npy.sqrt(float(waterdepth))
            damage =float("{0:.3f}".format(damage))


    return (damage)
```

```
def DamageEstimation(buildings,damage_LUT,samples):

    samples = [float(sample) for sample in samples]
    damageestimate=[]
    damageNew =[]
    outputtable=[]
    output=[]

    for i in range(0,len(buildings)):
        ZoneNumber =buildings[i][3]
        IDFNK = buildings[i][2]
        OBJECTID = buildings[i][0]

        if ZoneNumber == 0:

            damageNew = 0
        if ZoneNumber == 1:
            ZoneRed = samples[4]

            damageNew = buildingDamage(OBJECTID,IDFNK,damage_LUT,ZoneRed,samples)

            damageestimate.append(damageNew)
            output= [OBJECTID,damageNew]
            outputtable.append(output)
        elif ZoneNumber == 2:
            ZoneRed = samples[4]
            damageNew = buildingDamage(OBJECTID,IDFNK,damage_LUT,ZoneRed,samples)
            damageestimate.append(damageNew)
            output= [OBJECTID,damageNew]
            outputtable.append(output)

        elif ZoneNumber == 3:
            ZoneYellow = samples[5]
            damageNew = buildingDamage(OBJECTID,IDFNK,damage_LUT,ZoneYellow,samples)
            damageestimate.append(damageNew)
            output= [OBJECTID,damageNew]
            outputtable.append(output)

    return (damageestimate)
#     return (outputtable)
```

```
def damage_radial(N,buildings,damage_LUT,radial_block_samples):
#    """ in: number of base runs (N: int), radial samples (list of radial weight blocks), list of fea
#        out [generator]: radial Ideal Point maps - numpy 1D arrays [mapA,mapB,k*mapsAb]
#    """
    n = 0
    try:
        while n < N:
            completed = round(float(n)/N*100.0,2)
            one_sample_block = radial_block_samples[n]
            IPmaps = [DamageEstimation(buildings,damage_LUT,sample) for sample in one_sample_block]
            yield IPmaps # one radial set of 1D array maps [mapA,mapB,k*mapsAb]
            n += 1
#            print "n GOES ON >>>>>>"+str(n)
            dont_print_me = completed%10
            if not dont_print_me:
                if completed >= 10:
                    print "completed",completed,"%"
#
    except GeneratorExit:
        print("Only made it to %d out of %d" % (n,N))
#
```

```
for fcs in listFeatures:
    if fcs =='buildings':
        cellsize = raw_input("Select a cell size : ")
        cellsize = int(cellsize)
        Zone = "Zone_"+str(cellsize)
#        getFieldNames(fcs)
        buildings= arcpy.da.TableToNumPyArray(fcs,('OBJECTID', 'building_category', 'IDFNK',Zone))



for table in listTables:
    if table == 'damage_LUT':
        damage_LUT=arcpy.da.TableToNumPyArray(table,('IDFNK','SminBaseme','Smin_First','B_Basement','B_First_Fl'))

```

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