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Seamless Estimation of Hydrometeorological Risk Across Spatial Scales

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Key Points:
- The proposed method resolves differences between risk assessments at different spatial scales
- Resulting probability distributions capture uncertainties associated with hazard, exposure, and vulnerability at all scales
- The object-based method performs as well as or better than state-of-the-art land use-based models

Supporting Information:
- Supporting Information S1
- Figure S1
- Figure S2

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Abstract Hydrometeorological hazards caused losses of approximately 110 billion U.S. Dollars in 2016 worldwide. Current damage estimations do not consider the uncertainties in a comprehensive way, and they are not consistent between spatial scales. Aggregated land use data are used at larger spatial scales, although detailed exposure data at the object level, such as openstreetmap.org, is becoming increasingly available across the globe. We present a probabilistic approach for object-based damage estimation which represents uncertainties and is fully scalable in space. The approach is applied and validated to company damage from the flood of 2013 in Germany. Damage estimates are more accurate compared to damage models using land use data, and the estimation works reliably at all spatial scales. Therefore, it can as well be used for pre-event analysis and risk assessments. This method takes hydrometeorological damage estimation and risk assessments to the next level, making damage estimates and their uncertainties fully scalable in space, from object to country level, and enabling the exploitation of new exposure data.

1. Introduction

Hydrometeorological events cause high damage; for instance, in 2016, they generated more than 60% of the overall losses due to natural hazards (MunichRE, 2017). The attribution of these hazards to climate change is still fuzzy and under debate (James et al., 2014), yet the risk associated with hydrometeorological hazards will most likely increase in the future (IPCC, 2012). Hence, the hazardous consequences of potential future events require adaptation in all parts of society (IPCC, 2012; Moss et al., 2012).

Adaptation measures can take place at different spatial scales (Adger et al., 2005). These scales range from the local scale comprising single objects, for example, buildings or infrastructure elements, to larger scales including whole cities, countries, or even transnational regions (de Moel et al., 2015). At the local scale, adaptation measures include flood proofing of buildings or adapted use of flood-prone stories. At the regional scale, for instance, flood protection can be implemented. In this way different risk management measures can be undertaken at different spatial scales. However, informed decisions regarding natural hazard management are still heavily influenced by biases and uncertainty associated with damage estimates and therefore risk assessments (Kreibich et al., 2014).

Risk can be defined as the likelihood over a period of time that a certain hazard negatively affects parts of the society, which are exposed to this hazard (IPCC, 2012). Consequently, risk can be described as product of a hazard, the exposed objects, and their vulnerability toward the hazard (Kron, 2005). All of these components are affected by uncertainties.

Uncertainties regarding the description of the hazard influence the assessment of the damage and risk. This applies to past events, for example, in terms of estimating the event intensity through metrics like wind speed, inundation depth, or extent, as well as to future scenarios, for example, in terms of unknown return periods. Exposure uncertainty is related, for instance, to the number of exposed objects or their characteristics and asset values. Vulnerability uncertainty originates from an inappropriate description of the damage processes at the affected objects due to a lack of data and understanding (Meyer et al., 2013). These uncertainties occur at any spatial scale. Yet current approaches miss to represent these uncertainties sufficiently within the damage model results (Ward et al., 2015).

Consequently, hazard impact estimations and the associated uncertainties should be represented consistently across spatial scales. This spatial consistency remains challenging for hydrometeorological events (de Moel et al., 2015; Prahl et al., 2016) due to the use of different exposure data. Land use data, aggregated across (many) objects, are used for the large scale, whereas small-scale assessments are based on data at the object level (Jongman et al., 2012; Schwierz et al., 2010). Recently, however, exposure data sets at the object level have benefited from rapid technological improvements and an increase in data quantity and quality (Pittore et al., 2017). Publicly available data sets, such as from openstreetmap.org, can provide specific information such as the occupancy or height of buildings at the object level (Figueiredo & Martina, 2016). This kind of information could be used to assess damage caused to individual buildings by means of, for example, engineering-based hurricane damage models (Pita et al., 2013; Vickery et al., 2006) or multivariable flood damage models (Merz et al., 2013; Sieg et al., 2017; Wagenaar et al., 2017). So far, state-of-the-art damage models (Prahl et al., 2016; Sieg et al., 2017; Wagenaar et al., 2017) are not able to keep up with this development causing a gap between what is currently done and what improvements would theoretically be feasible. Consequently, the value of this data has not been exploited for large-scale hydrometeorological risk assessments.

Hence, there is a need for a methodology which enables a consistent estimation of hydrometeorological risk and damage across spatial scales, including a comprehensive uncertainty quantification.

2. The Method of Seamless Estimation

We present a method for the seamless estimation of hydrometeorological damage across spatial scales (Figure 1). Damage estimates, which are provided as probability distributions for individual objects (e.g., buildings), are accumulated for an unrestricted and consistent spatial scaling. As damage estimation is a fundamental part of any risk assessment, the proposed method can easily be integrated in risk assessments as well. The method provides a consistent pre- and post-event hazard impact analysis across spatial scales, including a comprehensive uncertainty quantification.

The method uses the definition of risk as a product of the three components, hazard, exposure, and vulnerability (Figures 1a–1c). Hazard is, in this method, described by variables like the water depth or wind speed, which can be based on observations for post-event analysis. For pre-event analysis, such variables can be derived for deterministic scenarios or modeled according to a chosen recurrence interval (Figure 1a). Exposure is described by the number, type, and characteristics of exposed objects, which can be identified, for instance, by an overlay of hazard maps with building maps (Figure 1b). Vulnerability is expressed by damage models describing the damaging processes affecting the individual objects. Any kind of hazard damage model (engineering or empirically based, single parameter or multiparameter, etc.) can be used to describe the vulnerability of an exposed object and to estimate the damage (Figure 1c).

Uncertainties are included by considering distributions instead of fixed values (Figures 1d and 1e). Depending on the hazard damage model, information concerning the asset values and the damage-influencing variables is required. This includes the characteristics of the exposed objects (e.g., building type) or the extent to which the objects are affected by the hazard (e.g., water level or wind speed). These input variables of the damage models are prone to uncertainties, for instance, due to limited information as to the number and characteristics of the affected objects and the local hazard intensities. In cases where observations of the input variables are available, uncertainty associated with these observations can be included, for example, by assuming a normal distributed error (Figure 1d). If direct observations are unavailable, as is often the case, these variables can be treated as random variables, with their distributions based on expert knowledge or proxy data, for example, official statistics, survey data, or hazard maps of comparable events (Figure 1d). In both cases, these distributions represent the uncertainty of the hazard and exposure data. Several (n) versions of exposed objects are then sampled from these distributions (Figure 1d).

For each sampled object, the damage is estimated by applying the chosen damage model. Most damage models provide point estimates that do not capture the uncertainties related to the damage process. For a consistent consideration of uncertainties, we suggest applying models that yield damage distributions instead (Figure 1e), as it is done in a few studies, for example, for the hazards of flooding (Egorova et al., 2008), wind storms (Prahl et al., 2015), or hurricanes (Wang et al., 2017).

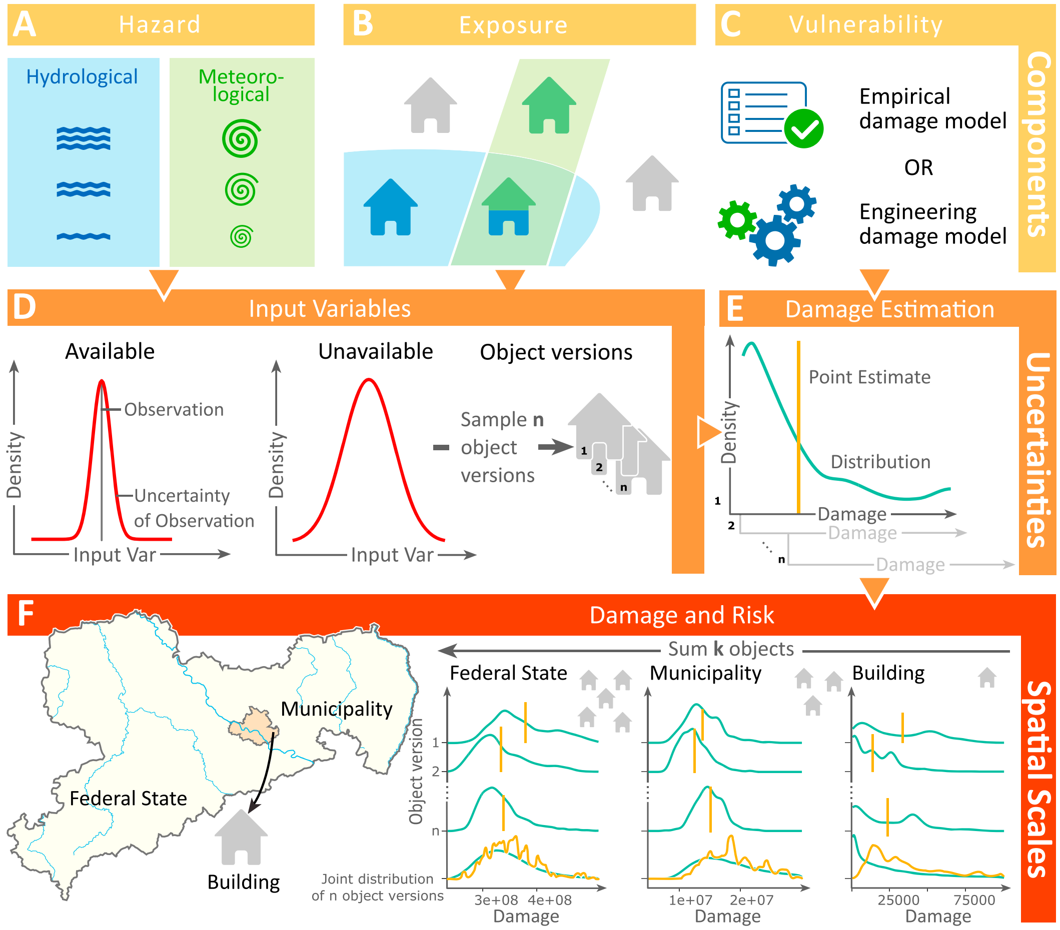

Figure 1. The method includes the three components of hydrometeorological risk: hazard (a), exposure (b), and vulnerability (c). The consideration of associated uncertainties of input variables describing hazard and exposure (d) and the uncertainty within the damage estimation (e) by distributions. Application of seamless spatial scaling of damage estimations by summing up *k*-affected objects (f).

The combination of k objects in a specific area within the same sampling step n forms an object set. Depending on the number of objects k within these object sets, they can represent single companies, cities, or regions. For $k = 1$, the object set represents a single company. Yet the object set can also represent larger scales, such as cities ($k > 1$) or regions ($k >> 1$). Summing up the damage estimates of (k) individual objects within this object set enables seamless spatial scaling (Figure 1f). Object sets can also be formed (and damage estimates summed up) according to other characteristics, for example, objects that belong to a certain economic sector. Thus, the proposed method allows not only for consistent spatial scaling but also for a detailed thematic grouping. Finally, the aggregation of n sampled object versions results in a probability distribution describing the possible damage under consideration of the uncertainties associated with the hazard, exposure, and, depending on which damage model is used, the vulnerability.

3. Results and Discussion

As a proof of concept, we apply the method to the flood event occurring in central Europe in the year 2013 (Schröter et al., 2015). The regional focus of the application is the federal state of Saxony, Germany. We simulated 300 object versions (Figure 1d; $n = 300$) based on survey data and official statistical data from the German Federal Statistical Office (see supporting information Text S1 and Tables S1 and S2 for further details about the data sets). For the estimation of flood damage (Figure 1e), we used Stage-Damage Functions, Random Forests giving point estimates (RF point), and distributions (RF distribution) trained on survey data (see Text S2 for further details about the application of the methods). Damage estimates were computed at the municipality level (Figure 1f) and validated with reported damage values from the Saxony Relief Bank.

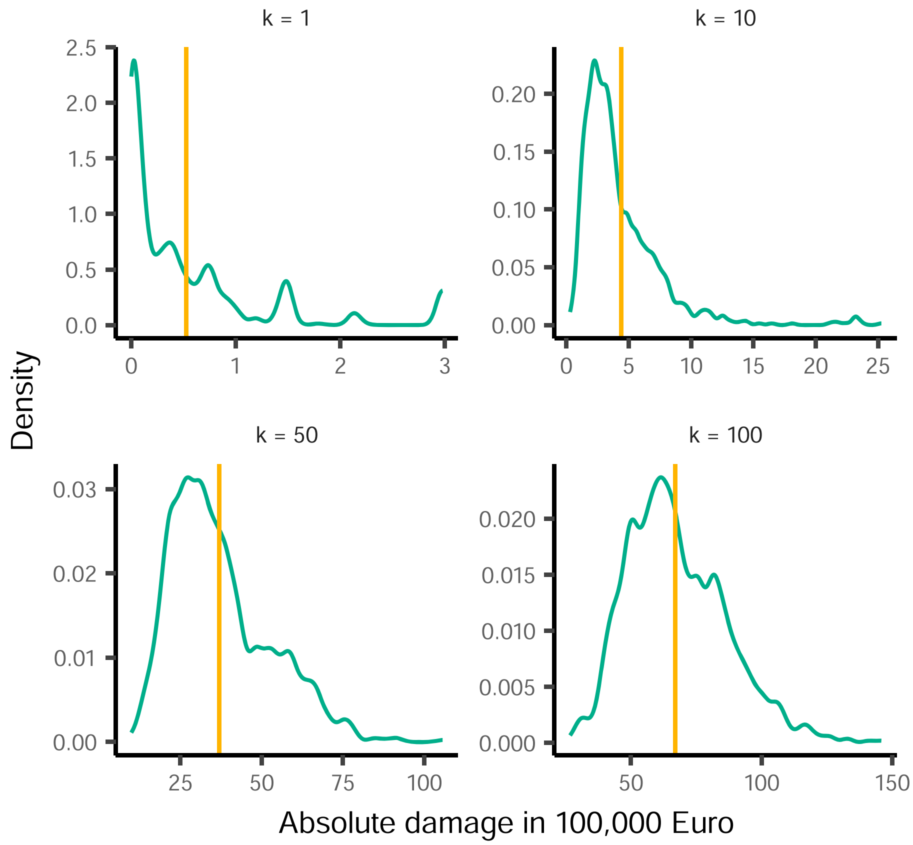

Figure 2. Damage estimation for k manufacturing companies with (green; Random Forests distribution) and without (yellow; Random Forests point) consideration of vulnerability uncertainty. Note that the k manufacturing companies all originate from the same object set; hence, the hazard and exposure uncertainty is not considered here ($n = 1$).

3.1. The Role of Vulnerability Uncertainty

In the first step, we compared the results from damage models providing point estimates (RF point) and models with probability distributions (RF distribution; see Figure 1e). To single out the effect of vulnerability uncertainty, we ignored the uncertainties originating from hazard and exposure (Figure 1d; $n = 1$). The comparison shows how the damage estimation benefited from using damage model probability distributions (Figure 2).

The vulnerability uncertainty represents the lack of knowledge about the damage process at the object level by showing a probability distribution of all the possible damage values for a specific object. Considering only one object, it can be seen that the point estimate, that is, the mean, is a rather unlikely value within the skewed damage distribution (Figure 2, $k = 1$, and Figure S1). In most cases, the point estimate for single objects will overestimate or underestimate the flood damage, which results in large errors as observed in Seifert et al. (2010), Sieg et al. (2017), and Wagenaar et al. (2017). The higher the number of objects, by summing up their damage estimates, the better the empirical distribution fits to a normal distribution (Central Limit Theorem). Hence, the larger the spatial scale (Figure 1f; $k > 1$) for which the damage is estimated, the more the mean corresponds to the most likely value, but also the range of possible damage values gets proportionally wider as well (Figure 2).

Despite the progress in damage estimation in recent years (Figueiredo et al., 2018; Kreibich et al., 2016; Schröter et al., 2014; Sieg et al., 2017; Wagenaar et al., 2017), the available damage models are not able to describe the damage process reliably, and the process is stochastic to a substantial extent. Therefore, as implemented in this approach, the distribution of the damage estimate should be assessed at every spatial scale in order to report the lack of knowledge about the damage estimates.

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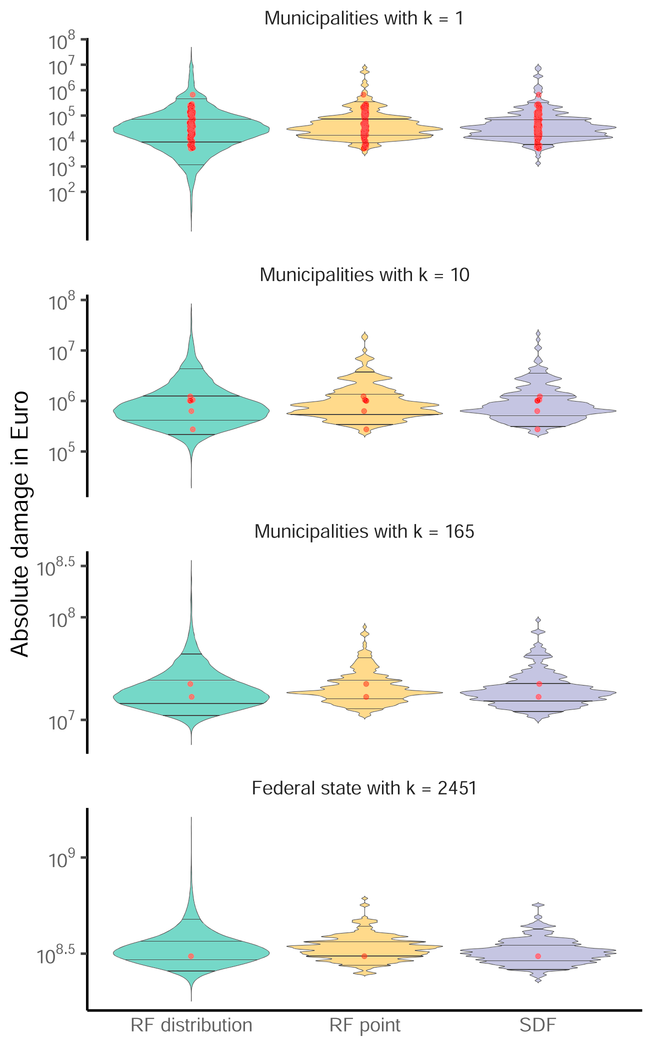

Figure 3. Distribution of damage estimates with different flood damage models for municipalities with *k*-affected objects. The red dots represent reported damages to the respective municipalities and federal states. The lines within the distributions show the 90% and 50% intervals, respectively. Note that the amount of absolute damage in Euro increases in orders of magnitude with the increasing number of affected objects. RF = Random Forests; SDF = Stage-Damage Function.

3.2. Hazard and Exposure Uncertainty and Validation

The additional inclusion of uncertainties associated with hazard and exposure and the spatial scaling of damage estimations to municipalities in Saxony results in a good agreement of damage estimations with reported damage values (Figure 3).

The estimated damage ranges are quite reliable (Figure 3). Depending on the flood damage model used, 90% to 97% of the reported damage lies within the 90% interval of the distributions, and 57% to 61% lies within the 50% interval (Figure S2). Hence, the approach does not overestimate the uncertainties. On the contrary, it captures the diversity of reported damage values (Figure 3, top). In addition, the distribution of damage estimates for larger scales, for example, cities or federal states, covers the observed damage well (Figure 3, center and bottom). Note that the damage models and input data type are the same for the estimation at any spatial scale, ensuring consistency without any jumps between scales. The inconsistencies in land use data and the application of the same models to different kinds of exposure data are currently weaknesses of state-of-the-art models (de Moel et al., 2015; Jongman et al., 2012; Prahl et al., 2016; Schwierz et al., 2010).

3.3. Comparison of Land Use-Based and Object-Based Models

A comparison of land use-based and object-based models shows the potential of the proposed method to improve damage estimates across various spatial scales (Figure 4).

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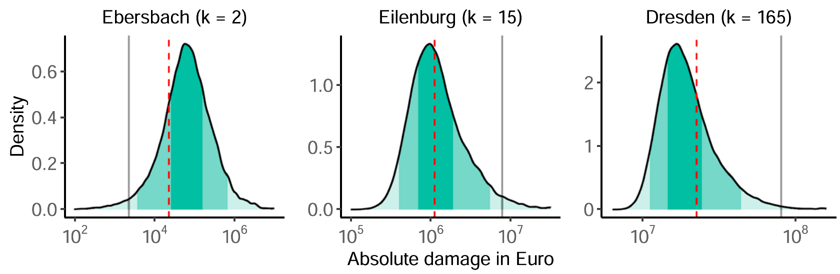

Figure 4. Estimated damage distributions for the 2013 flood event for municipalities with ($k =$) 2, 15, and 165 affected companies (different greens indicate the 50% and 90% intervals). Reported values for flood damage to companies (red dashed lines) for selected municipalities and the hypothetical overestimation or underestimation by a factor corresponding to the estimation bias of the model FLEMOcs (Seifert et al., 2010) for the flood event in the year 2002 in the same municipality (black lines).

Previous studies report an overestimation or underestimation of absolute flood damage at any spatial scale (Alfieri et al., 2016; Kreibich et al., 2016; Seifert et al., 2010; Ward et al., 2013; Winsemius et al., 2013). At large scales, such as the global or European scale, overestimations by a factor of up to 2 are observed (Alfieri et al., 2016; Ward et al., 2013), while at smaller spatial scales, such as municipalities or cities, even higher deviations of up to a factor of 40 are observed (Kreibich et al., 2016; Seifert et al., 2010).

The land use-based, multivariable flood damage model FLEMOcs overestimated the reported flood damage to companies in Dresden during the flood event of 2002 by the factor 3.6 (Seifert et al., 2010). Considering the damage distribution for affected companies in Dresden in 2013 derived with the approach presented here, the reported damage is located in the center of the distribution, whereby a hypothetical overestimation by the factor 3.6 is located in the tail (Figure 4, right; see also Figure 3, $k = 165$, green). The same effect can be observed for smaller or less affected municipalities in cases of underestimation (Figure 4, left) and overestimation (Figure 4, center), respectively. Hence, the use of an object-based modeling approach including uncertainties results not only in a more complete picture of possible flood damage, but our results also suggest that it is more accurate compared to the widespread approach of land use-based modeling. In addition, statements about the probabilities associated with certain damage ranges can be made, which is important information for decision making (Pappenberger & Beven, 2006).

4. Conclusions

The presented method exploits new exposure data sets (e.g., openstreetmap.org), which become increasingly available due to rapid technological progress, and thus takes hydrometeorological damage assessment to the next level. It offers a consistent damage estimation across spatial scales by using object-based data at all spatial extents. The coherent use of the same detailed input data and modeling approaches, independent of the spatial scale, prevents the introduction of uncertainties through coarse exposure data sets at mesoscale and the inconsistent use of damage models across spatial scales. Furthermore, the object-based approach dissolves differences between risk assessments at different spatial scales.

Point estimators (e.g., mean) are not able to represent the highly variable damage processes at individual objects, since the damage values are not normally distributed. Methods which give probability distributions of possible damage should be preferred instead, especially at the object level. Mean estimators have their justification at larger spatial scales, where the damage distribution approximates a normal distribution and therefore the performance of point estimators improves. However, point estimators have the disadvantage of a lacking uncertainty quantification of vulnerability at all spatial scales.

The proposed method has proven to be precise and accurate in post-event analysis and can therefore also be used for the analysis of future risks, even more so because of the probabilistic nature of the method and the possibility of including any kind of uncertainty. Uncertainty originating from missing data or assumptions can be reflected in the results, which is of the utmost importance for future projections of risk and in data-scarce situations. Consequently, the proposed method facilitates informed risk management and decision making under consideration of uncertainties consistently at all spatial scales.

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