We thank the reviewers and editor for taking the time to analyse our manuscript. Below we list the comments (C) and our responses (R). After this response, the marked-up version of the manuscript is included.

Reviewer 1

C: I agree that 'the problem of accurately identifying buildings and occupancy, especially with open data, is outside the scope of this paper'. However, it remains unclear how residential buildings were eventually defined in this study. This needs to be clearly stated for the sake of reproducibility. Apparently, two OSM layers (buildings and land use) were downloaded (On a sidenote: a date indicating the day of the download would be nice to reference the status/version of the data set used). Was information obtained from the buildings layer enhanced or modified based on the land use? If so, how?

R: Firstly, we downloaded two Map Features ("Buildings" and "Landuse") for the 30 study areas and the example application study from section 3.3. For the analysis, residential buildings were objects from "Buildings" layer which (1) had tags "residential", "apartments", "house", "detached" or "terrace", and (2) had tags "yes" (indicating that a building exists, but the function is not defined) and were located within an object from "Landuse" layer which had a tag "residential". OSM is updated continuously, and the data used here were downloaded between 22 and 25 January 2019. Data for the example application was downloaded from OSM on 18 July 2019. We added this information to p.4, l.90-96.

C: Seven potentially important variables were initially defined. Three of these variables were included in the final model. Even though it can be guessed how these variables were selected (p.4, l.113), the variable selection process is not clearly described.

R: The variables first variable (POP) was chosen as it had the highest unconditional rank correlation with H (Table S1). The second variable (B) had the highest conditional rank correlation with H among the remaining six variables, and then IMD had the highest conditional rank correlation with H among the remaining five variables. Further variables had very low (<0.1) correlation with H only, therefore only three variables were used to explain H. Remaining arc between POP and IMD was added due to high correlation between the two. All arcs further have a theoretical explanation, as we now clarify in the explanation in p.5, l.121-126.

C: I think that the use of a 2% sample is somewhat critical, since a lot of information is dropped. Why were so many instances dropped, how was this number (2%) chosen, and how can the authors guarantee that this is a representative sample? The full data set should include roughly 2,373,300 records (2% correspond to 47,466 records). A data frame with 2 million rows and maybe 10 columns is definitely still manageable on local machines.

R: The principle reason for using a sample of the OSM buildings for all cities was reducing the time of data processing with GIS to arrive with table of data. Then, the efficiency of a non-parametric Bayesian Network calculation (or a Random Forest computation) drops significantly with large numbers of data points, which would make it less suitable for a possible operational pan-European application. Those aspects notwithstanding, the buildings of 30 capital regions are not the complete population of the European residential buildings, but a small fraction of them, and using all data would still mean using a sample of European buildings. We went back to the full dataset and extracted a larger share of the data, so that the influence of using different dataset size can be presented. The whole population of usable data (i.e. no data missing for any variable at a given location) results in a correlation matrix almost identical correlation matrix, differing by a rank correlation of 0.007 at most. This matrix (N = 2,375,058) is used in revised Table S1.

C: In addition, the 2% sample was only used once. Results were then tested once on a 1% sample. This approach is not very robust. Proper k-fold cross-validation using the full data set would be desirable.

R: We made a new extraction of the data from the full dataset, containing 10% of the data. This sample was used for a 10-fold cross-validation, and the revision of other results. We have revised Tables 2 and 3 (as Tables 3 and 4), and revised section 3.1 accordingly.

C: What was the reason to use a BN for predicting exposure? Was the BN the only model that was tested, or was it contrasted to other approaches? Once the full data set is created, model comparison is comparatively less time-consuming than data preparation. Since Bayesian approaches are often computationally demanding, a classical regression approach or simple machine learning model (e.g. random forest) might be worth trying. This would also allow to investigate more complex interactions between variables as well as non-linear effects.

R: There are several advantages of the class of BNs used here, compared with other approaches: (1) they are probabilistic, providing uncertainty bounds, (2) they can be applied when some of the input data is missing (which Random Forests can't), as e.g. the imperviousness dataset is not gap-free for Europe, which makes it more useful for applications, (3) the whole model can be presented graphically (in Random Forests, only singular trees out of the forest could be presented), (4) accuracy depends only on the configuration of nodes and arcs, and not on model parameters such as number of splits, leaves, trees etc. We applied Random Forests to our data (using Matlab functions 'TreeBagger' and 'predict'), with a 10-fold cross-validation on the basis of the 10% of the data – the same set-up as for the BN. The number of trees was set to 100, maximum number of leaves to 50, in-bag fraction to 1/3, and splits to two. The resulting R^2 is slightly lower, RMSE higher, MBE strongly negative and only MAE is slightly lower than when using the BN. Overall, the performance is quite similar, though still worse. The comparative results are now discussed in section 4.1.1 and presented in Table S10.

C: The authors assume that there are no country-specific differences in H, apart from those that are implicitly modelled by including POP, IMD and B. The authors claim that they provide a 'universal method for estimating exposure of residential assets' (p.1, l.3f) across whole Europe. Since the method was only validated with data from Poland, Germany and the Netherlands, I am not sure if this statement is fully justified. Since the characteristics might be different in different countries, using a variable specifying geographical location (e.g. country or even broader geographical region) might be helpful to tackle unobserved heterogeneity.

R: The datasets for Poland, Germany and the Netherlands were the only independent datasets with information on floor space or number of floors for individual buildings that we were able to collect. If the reviewer knows other datasets like those for other countries, we would add them to the analysis. Regarding the heterogeneity, individual models for each country could be made, and they would improve performance at each, but this would still give only a good prediction for the capital city region of a given country, leaving uncertainty how well such a model would perform in other parts of the country. We have moved results for individual cities from the Supplement to the main text (Table 2) to make the variation in the model's quality more visible to the reader. We also note that we discovered and corrected an error related to the dataset German flood-affected households. In the original submission, only those households affected by fluvial floods were included, and not those affected by pluvial floods as suggested by the years provided in revised Table 3. We have added those missing households, increasing the number of records from 2330 to 2868, though the validation results didn't change much.

C: I found the explanation for the empirical relationship given in Eq. (1) a little bit difficult to understand, since the numbers are scattered throughout the paragraph below the formula. I suggest to streamline this explanation.

R: We have rewritten the paragraph to clarify the explanation (p.5, l.136-147).

C: Also, I realized that within Eq. (1), B is used (1.) to derive H, and (2.) to compute F, which is based on H. I don't think that this is a problem, but I noticed that this puts quite a lot of weight on B.

R: The conditional correlation between B and H was considerable, therefore it had to be included in predicting H, and it is indispensable in calculating F, which strongly depends on both B and H.

C: I suggest to include a supplementary table to show which formula for deriving St was used for each country.

R: A supplementary table was added (Table S5).

C: Generally speaking, the coefficient of determination denotes the share of explained variance in the dependent variable that is predictable using independent variable. Note that R2 == r 2 holds only in special cases such as simple linear regression if an intercept is included. While this is the case in the assessment of predicted vs observed values presented in the paper, where the coefficient of determination equals the square of the correlation coefficient, the authors may want to clarify this.

R: The linear regression of revised Fig. 1 is approximately 1.02x – 0.3 (varies slightly within the 10-fold cross-validation).

C: Being a very common error metric, root mean squared error could be included as well, since it provides more information content with respect to outliers.

R: RMSE was added to the results in Tables 2 and 3.

C: The first two sentences of Section 2.4.2 are unclear to me. The collective out-of-sample validation was done using an unseen 1% sample across all cities. How was the individual validation performed? By using stratified 1% samples of each city? The second sentence starting with 'Then' suggests that the procedure is different and that the samples are not the same. If the same stratified sample is used, validation results can be assessed both city-specific and at an aggregated European level.

R: We replaced the existing results with a 10-fold cross-validation, and corrected the text in the methods and results sections accordingly, and revised Tables 2-4.

C: An overall R2 of 0.36 is moderate, indeed. This means that only a third of the observed variance in building height can be explained using modelled building height (given that observed vs. predicted regression was used). The confusion matrix (Table 3) showing around 25% (and an increasingly lower amount as the number of floors increases) correctly classified outcomes for buildings with more than 2 floors is also slightly puzzling. Again, this might be a hint to try (1.) using more data and (2.) comparing different modelling approaches. Good results for average height are of rather limited explanatory power in terms of model quality assessment, since I would naturally assume that the differences in means are not too large when using any reasonable model. The problem of low variance might also be tackled by (1.) and (2.) mentioned in the previous sentence. That the model does not perform satisfactory at all for cities like Nicosia and Reykjavik might indicate that there are country-specific differences. All cities that exhibit good performance are located in Central Europe (Vienna, Berlin, Amsterdam, Luxembourg, Warsaw, Zagreb).

R: We added more data (10% instead 2%), but this had only marginal effect on the data, as one might expect from a randomized sample of a very large dataset. Several cities have rather poor performance, but it is also partly due to variation in the quality of height data (which routinely shows errors of 1–3 m, according to the validation information contained in the dataset) and OSM buildings (which is particularly poor for Nicosia, for instance, using visual inspection). Some of the cities with good results are not located in Central, but Western and Northern Europe (Amsterdam, Berlin, Luxembourg, Stockholm, Vienna). We revisited the dataset using Random Forests, as described in a previous comment, which didn't lead to improvement. However, we tested the model for different urban-rural typologies using "Degrees of Urbanisation 2014" dataset from Eurostat. This allows classifying our data points according to whether they were located in "cities", "towns and suburbs" or "rural areas" (defined at the level of local administrative units - LAUs). The results are now presented in the supplement (Table

S9) and show that the R^2 is lower for towns and rural areas than for cities, though this stems from the much lower variation in building height; MAE is lower in those cases, and in all three types of LAUs MAE has almost the exact same proportion to average height.

C: In the abstract, a validation with (1) buildings in Poland and (2) a sample of Dutch and German houses is mentioned. In the paper, (1) can be found in section 3.3, and (2) is described in the last paragraph of 3.1. I think the title of subsection 3.3 should be reworked, as 'Example application' is rather generic. Maybe a dedicated validation subsection for these new data sources could be helpful?

R: The example in section 3.3 is not based on the validation dataset for Poland. The Polish dataset is from a government-run national database (BDOT) and is used for validation in 3.1 as shown in Tables 2 and 3. The example in 3.3 uses an extraction of OSM data, as the BDOT dataset is not openly available in contrast to OSM. The example is meant to present how the methods from the paper can be used in practice. We now highlight this better in the text.

C: In fact, there does seem to be a slight systematic bias in the results. Figure 2 shows overestimation for low building heights and underestimation of high building heights, with accurate results around 12 m. The regression line likely has a negative intercept and a slope larger than 1.

R: The linear regression of revised Fig. 1 is approximately 1.02x – 0.3 (varies slightly within the 10-fold cross-validation). We note that the model underestimates the height of tall buildings, but this is partly because few buildings are very tall.

C: The structure of the discussion is generally well thought through. However, the authors again solely focus on the BN model. Maybe the use of other models might lead to better results on the same data set? Limitations of the BN model itself and implications of using a comparatively small sample size (given available data) are not discussed.

R: We added more information about the uncertainty related to the data analysis (section 4.1.1), and we add results generated with Random Forests (section 4.1.1 and Supplementary Table S10).

C: Figure 1: The histogram plots do not have any axis labels and units, which is a major limitation (in terms of information content) of this figure, since the histograms are essentially incomplete. Also - for the sake of consistency: the unit for population density is missing in the caption.

R: The graph and caption were corrected.

C: Figure 2: Please use the same spacing for axis ticks (either steps of 5 or 10).

R: The ticks were corrected.

C: Figure 3: I suggest to use points instead of bars. The information that needs to be transported is the value at the end of the bar, not the area of bar itself. Therefore, information density is higher when using points. Also, the two colors of the bars are different (orange indicating building value in a and yellowish indicating household contents value in b), but the legend matches only the color in b.

R: The legend was corrected and the graphs were reworked, so that points are used instead of bars.

C: Figures 4 & 5: I think it should be mentioned in the caption that values for each country are based on the respective capitals, since this is important when interpreting the results.

R: The values for each are not based on capitals, but on the economic statistics at national level (section 2.2).

C: Figure 7: Legend for a is missing, only legend for b is provided. Again, I suggest to consider using points instead of bars. If points overlap, you may slightly jitter them along the x axis or use some transparency.

R: The legend was corrected and the graphs were reworked, so that points are used instead of bars.

C: Figure 8: It seems that this figure is not referenced in the text. If this is the case (I might have overlooked it), please add a reference in the text. Also, it reveals a substantial difference when compared to the JRC values, this could be explored/discussed further. Again, I suggest to consider using points instead of bars.

R: Fig. 8 (in the revised manuscript, it is Fig. 9) is now correctly mentioned in line 464. The graph was reworked, so that points are used instead of bars. The large difference between JRC and our estimates could be caused by the assumption of a single ratio between building and contents loss (which we show is far from uniform), transposition of this value from an American flood damage model, and possible differences in definition (JRC estimate including more items). This aspect bis now described better (p.14, l. 437-440).

C: Figure 9: It seems that this figure is not referenced in the text. If this is the case (I might have overlooked it), please add a reference in the text.

R: Fig. 9 (in the revised manuscript: Fig. 10) is now correctly mentioned in lines 467 and 574.

C: Table 1: I am wondering why two different sources for 'Population per area' were used. If both are based on the 2011 census, why not using the one with higher resolution if the model is fitted at a building level?

R: the 1 km data are, in most cases, an aggregation of georeferenced records of all enumerated population during the 2011 censuses, therefore represent very accurately the spatial distribution of population. The 100 m dataset is a disaggregated version constructed in the cited study using land cover/use and soil sealing data, therefore introducing modelling error. The 1 km dataset also represents neighbourhood/urban district population, and the 100 m the population of a group of buildings, and the first proved more relevant to represent the dominant type of buildings in an area.

C: Table 3: '% of correctly predicted floors' is confusing. Only the diagonal values indicates the percentage of correctly predicted floors, all other number are simply the percentage of predicted floors?

R: The text in the table (in the revised manuscript: Table 4) was changed to "% of predicted floors within observed floor class"

C: p.7: Lmean should read Lmean, or simply $\bar{L}$.

R: This was corrected to "L_{mean}".

C: Please check consistency regarding capitalization (e.g.: 'Eq.' vs 'eq.'). NHESS manuscript preparation instructions suggest 'Eq.'.

R: We have corrected the capitalization throughout the manuscript.

C: Please format the supplement according to the journal's standards.

R: The supplement was reformatted according to the NHESS Word template.

Reviewer 2

C: One of my main concerns is the rather unorganized structure of the manuscript. It deals with different scales, e.g. nationally aggregated data, data from 30 major cities, different validation samples, and a local case study. Moreover, the manuscript has also different time scales. It lists different states of the datasets and includes timeseries of the temporal development of the economic values. This is on the one side a benefit in terms of the broad scope but hampers the readability for the reader on the other side. I urge the authors to elaborate a more thorough structure of the manuscript to help reader's orientation.

R: We prepared a new graphic with the workflow of the paper (Figure 1), with references to all sections, figures and tables, which is now included at the beginning of the methodology section. We also reorganized sections 2 and 4, so that the two major components of the study are clearly separated.

C: Another concern is the transferability of the model from an urban context to a rural context. This needs to be validated. For instance, Roethlisberger et al (2018) in the same journal state that a difference in the values per square meter between Centre areas (urban areas) and Residential areas of 60%. An alternative is to restrict the title of the manuscript towards urban context of Europe. The conclusion in the abstract "The study shows that the resulting standardized residential exposure values provide much better coverage and consistency compared to previous studies" is not supported by the results.

R: The referenced paper shows a 60% difference in the insured values per square meter of landuse, not of replacement values per usable floor space as in our paper (Table 2 of Roethlisberger et al. 2018). The other authors' findings are not surprising given the higher density of construction in the city/town centers (to which "Centre" class refers) that in other residential areas. Table 3 of Roethlisberger et al. (2018) actually shows lower average insured values per building volume for "Centre" zones (861 CHF per M^3) than in "Residential" areas (897). However, we agree that there are differences between asset values in urban and rural areas, as exemplified by the cited Portuguese data. We have highlighted this aspect better in the discussion (p.18, l.557-560), but at the moment the availability of both regional economic data and local validation data is very limited, and therefore we didn't attempt (yet) to calculate sub-national asset values per m^2.

C: In the Introduction section, the authors state that the developed procedure is "applicable in any location". This proof is not provided (discussion about urban-rural context). Another main criticism is that the identification of residential buildings is not described. There is an explicit subsection on this topic (section "2.1 Identification of residential buildings"). However, how this identification has been done is described within brackets in section "2.2 Building size estimation" in line 109 ("(identified either through the buildings or the land use layers of OSM)") while in section 2.1 is stated that the identification of buildings and their occupancy (i.e., residential use?) is outside the scope of this paper.

R: We added information on the selection of OSM buildings. Firstly, we downloaded two Map Features ("Buildings" and "Landuse") for the 30 study areas and the example application study from section 3.3. For the analysis, residential buildings were objects from "Buildings" layer which (1) had tags "residential", "apartments", "house", "detached" or "terrace", and (2) had tags "yes" (indicating that a building exists, but the function is not defined) and were located within an object from "Landuse" layer which had a tag "residential". We added this information to p.4, l.90-96.

Editor

C: please put particular attention to the overall structure so it will be accessible to the readers of the target journal.

R: We have reorganized sections 2 and 4 and provided Figure 1 as a guide to the different components of the paper.

C: As given in the guidelines of NHESS; I kindly ask you for inclusion of a competing interests statement as follows: "Heidi Kreibich and Kai Schröter are members of the Editorial Board of NHESS" or something similar, please see: https://www.natural-hazards-and-earth-system-sciences.net/about/competing_interests_policy.html (examples section).

R: We added the suggested competing interests statement to the paper.

Estimating exposure of residential assets to natural hazards in Europe using open data

Dominik Paprotny[1], Heidi Kreibich[1], Oswaldo Morales-Nápoles[2], Paweł Terefenko[3], and Kai Schröter[1]

[1]Section Hydrology, Helmholtz Centre Potsdam, GFZ German Research Centre for Geosciences, Telegrafenberg, 14473 Potsdam, Germany

[2]Department of Hydraulic Engineering, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, 2628CN Delft, The Netherlands

[3]Institute of Marine and Environmental Sciences, University of Szczecin, Adama Mickiewicza 16, 70-383 Szczecin, Poland

Correspondence: Dominik Paprotny (paprotny@gfz-potsdam.de)

Abstract. Natural hazards affect many types of tangible assets, the most valuable of which are often residential assets, comprising buildings and household contents. Yet, information necessary to derive exposure in terms of monetary value at the level of individual houses is often not available. This includes building type, size, quality or age. In this study, we provide a universal method for estimating exposure of residential assets using only publicly-available or open data. Using building footprints (polygons) from OpenStreetMap as a starting point, we utilized high-resolution elevation models of 30 European capitals and a set of pan-European raster dataset to construct a Bayesian Network-based model that is able to predict building height. The model was then validated with a dataset of: (1) buildings in Poland endangered by sea level rise, for which the number of floors is known, and (2) a sample of Dutch and German houses affected in the past by fluvial and pluvial floods, for which usable floor space area is known. Floor space of buildings is an important basis for approximating their economic value, including household contents. Here, we provide average national-level gross replacement costs of the stock of residential assets in 30 European countries, in nominal and real prices, covering years 2000–2017. We relied either on existing estimates of the total stock of assets or made new calculations using the Perpetual Inventory Method, which were then translated into exposure per m^2 of floor space using data on countries' dwelling stocks. The study shows that the resulting standardized residential exposure values provide much better coverage and consistency compared to previous studies.

1 Introduction

Residential assets are typically the most valuable components of national wealth (Piketty and Zucman, 2014). In Europe, dwellings contain 46 % of the gross value of tangible fixed assets (Eurostat, 2019a). Apart from dwellings, residential assets are composed of consumer durables, often referred to as household contents (Kreibich et al., 2017). These are durable goods used by households for final consumption (Eurostat, 2013). Altogether, residential buildings and their contents tend to constitute the largest share of damages induced by natural hazards. For example, 60 % of flood damages and 59 % of windstorm damages (based on the value of insurance claims) caused by hurricane Xynthia in France in 2010 were related to damages to households. This fraction is significantly larger than damages to businesses (32 % and 37 %, respectively) or automobiles (FFSA/GEMA, 2011). During the 2007 summer floods in the United Kingdom households suffered an estimated 38 % of the total value of direct and indirect damages, while companies represented 23 % and public infrastructure with critical services 22 % (Chatterton et al., 2010).

Modelling damages to residential buildings requires quantifying their exposure in terms of monetary value. This is particularly important as exposure was found to be the primary driver of long-term changes in damages due to natural hazards in Europe and other continents (Paprotny et al., 2018b; Pielke and Downton, 2000; Weinkle et al., 2018; McAneney et al., 2019). Exposure represents the value of assets at risk of flooding and is analysed with a variety of methods. More than half of flood damage models identified by (Gerl et al., 2016) operated at the level of land-use classes and the remainder at the level of individual buildings. Most commonly, also the value of assets is expressed per unit of area of a given land-use class, typically urban fabric in context of residential buildings, obtained usually by disaggregating the stock of assets in a given country or its subdivisions per land use units (Kleist et al., 2006; Paprotny et al., 2018a). At the level of individual residential buildings, two distinct challenges appear: (1) obtaining building characteristics that are relevant for estimating their replacement cost and (2) calculating the total value of a residential building and its contents.

Information on building characteristics, including floor space area, is not uniformly available. Many studies rely on national or local administrative spatial databases such as cadastres which record multiple characteristics of buildings such as occupancy, usable floor space or number of floors (Elmer et al., 2010; Fuchs et al., 2015; Paprotny and Terefenko, 2017; Wagenaar et al., 2017). 3D city models can also provide the dimensions of buildings to support estimating exposure, but only in the few locations that have such models (Schröter et al., 2018). Crowd-sourced databases such as OpenStreetMap could be an alternative, though their utility is limited by frequently missing information on occupancy and size of buildings. Attempts have been made to combine building footprints with other pan-European datasets such a population or land use to improve exposure estimation (Figueiredo and Martina, 2016), but they lack scalability as they still require some locally-collected data.

Values of residential buildings are typically compiled per particular case study. A typical source of this information are local insurance industry practices (Thieken et al., 2005; Totschnig et al., 2011). Approaches vary from assigning uniform value per building to regression models considering building size, type and quality (Röthlisberger et al., 2018). Frequently, exposure is computed by multiplying the building's useful floor space area by a fixed value per unit area, which in turn is taken from national statistical institutes, government regulations, surveys of construction costs or disaggregation of the national stock of buildings, using either gross or net values (Paprotny and Terefenko, 2017; Huizinga et al., 2017; Röthlisberger et al., 2018; Silva et al., 2015). European-wide information on the subject is scarce. Huizinga (2007) compiled existing national estimates of building values and filled missing data for most countries using gross domestic product (GDP) per capita. This approach was extensively used for e.g. pan-European flood risk studies (Feyen et al., 2012; Alfieri et al., 2016) and later extended to the whole world (Huizinga et al., 2017). Additionally, Huizinga et al. (2017) reported values of residential buildings for many countries based on surveys by two construction companies. Ozcebe et al. (2014) also provided building replacement values for a single reference year based on construction cost manuals and reported stock of different building types in European countries. Finally, almost no information at all is available regarding the value of household contents. Huizinga et al. (2017) suggested, following literature analysis, to assume that the content is worth 50 % as much as the building. For application to flood damage modelling in Germany, Thieken et al. (2005) used household insurance reference values as a basis of estimating the value of household contents. Yet, no pan-European dataset on the topic has been created so far.

In this paper we develop a universal method of estimating exposure of residential assets at the level of individual buildings. It covers both building structure and household contents for application, at the very least, to the European Union (EU) member states. We focus on the approach that considers the total value of buildings and contents as a product of usable floor space area of a building and the average gross replacement cost of buildings and contents per m^2 in a given territory. Additionally, we use only publicly available datasets to achieve the task. The methodology is applicable to any location within the 30 countries covered by this study. Building size estimation routine is validated on a set of natural hazards-related case studies. Our estimates of the current gross replacement costs of building and household contents are provided at national level from 2000 to 2017 to facilitate their use in assessments of past natural disasters.

2 Materials and methods

The workflow of the paper is presented in Fig. 1. It highlights the two different spatial scales on which the building size and economic valuation are done, with separate input data and methods applied, but coming together in an example application for specific case study. This section firstly describes how residential buildings were identified using open data, then how this information is used to derive the size of the buildings and finally how average values of building and household contents are obtained utilizing national accounts and demographic data. ~~Finally, datasets~~ Datasets and measures used to validate the building size predictions and to compare the values of residential assets with previously published estimates are then described. Unless otherwise noted, all references to values of residential assets in this paper pertain to the gross stock (without loss of value due to depreciation) at current replacement costs.

2.1 ~~Identification of residential buildings~~Building-level useful floor space estimation

2.1.1 Identification of residential buildings

Applying a building-level damage model requires information on the analysed objects such as size and value. Before those quantities could be calculated, residential buildings have to be identified in the area of interest. Variety of cartographic sources could be used depending on local availability, from governmental databases to topographic maps and remote sensing. The problem of accurately identifying buildings and occupancy, especially with open data, is outside the scope of this paper as this issue is still subject to intense research (Schorlemmer, 2017). Here, we use OpenStreetMap (OSM), which is an openly available, crowd-sourced online database of objects constituting the natural and artificial environment of the Earth's surface (OpenStreetMap, 2019). Though created primarily by volunteers, it also contains spatial data imported from governmental GIS databases for some cities, regions or even whole countries (e.g. resulting in exceptionally comprehensive data on buildings in the Netherlands). In the context of this study the data of interests are buildings represented in a vector layer of building footprints. Occupation of buildings (residential and other) is not always indicated, but can be further identified using land use information also contained in OSM.

We obtained the OSM building and land use layers to develop the building size estimation method~~as well as the validation case studies~~. The download was carried out during 22–25 January 2019 through Overpass API, a system that allows obtaining custom selections of OSM data (OpenStreetMap Wiki, 2019). The data obtained included two Map Features (*buildings* and *landuse*). For the purpose of this analysis, residential buildings were objects from the *buildings* layer which (1) had tags "residential", "apartments", "house", "detached" or "terrace", and (2) had tags "yes" (which indicates that a building exists, but its function is not defined) and were located within an object from the *landuse* layer which was tagged as "residential". Data retrieval and processing into other GIS formats was done with open-source solutions, namely Python with GDAL/OGR tools.

2.2 ~~Building size estimation~~

2.1.1 Building size estimation

Once residential buildings, i.e. their footprints are obtained, their size in terms of usable floor space area needs to be derived. The usable (also called useful) floor area of a dwelling is the total area of the rooms, kitchen, foyers, bathrooms, and all other spaces within the dwelling's outer walls. Cellars, non-habitable attics and, in multi-dwelling houses, common areas are excluded (OECD, 2019; Statistics Poland, 2019). This information is not directly available; it can be indirectly estimated from building height or the number of floors. Yet, those variables are very rarely recorded in OSM and typically not accessible from other sources either. A method of estimating building height and consequently the number of floors of a building from publicly available datasets was therefore devised here, so that the floor space area could be computed as a product of building footprint area and the number of floors. A predictive model was created by building a Bayesian Network (BN) correlating the variable of interest – building height – with seven candidate variables obtained from OSM and pan-European spatial datasets (Table 1).

A Bayesian Network is a graphical, probabilistic model which allows multivariate dependency analysis, provides uncertainty distributions of the predictions made with it. BNs are directed acyclic graphs consisting of nodes (representing random variables) and arcs indicating the dependency structure (Hanea et al., 2006). Here, we use a class of BNs known as non-parametric Bayesian Network which are quantified with empirical margins and normal (Gaussian) copulas as a dependency model. The copulas are parametrized using Spearman's (conditional) rank correlation coefficient. This class of BNs is for continuous variables only. For the purpose of this study, we use our own implementation of non-parametric Bayesian Networks as a Matlab code, the mathematics of which are described in Hanea et al. (2015).

Building height was derived from a high-resolution digital surface model "Building Height 2012" by Copernicus Land Monitoring Service (2019), which is available for 30 European cities (all European Union members' capitals plus Oslo and Reykjavik). Residential buildings (~~identified either through the buildings or the land use layers of OSM~~as defined in section 2.1.1) for each location were extracted~~and a random~~ , totalling 2,375,058 records. For higher efficiency of the statistical analysis, a random 10 % sample was drawn to reduce to size of the dataset~~and ensure an even spatial distribution of samples within the~~

~~city limits. The final sample has 47,466 records~~. The sample contains 237,361 records, with the number of data points ranging from 123 for Valetta to 25,526 for Berlin. Variables for the model were chosen first based on the unconditional rank correlation matrix (Supplementary Table S1) and then analysing the (conditional) rank correlations between variables.

The final model is presented in Fig. 2. Building height (~~H~~H) has the highest rank correlation (0.47) with population density per 1 km grid (~~POP). Only two variableshave conditional rank correlations with building height larger than 0.1, namely building~~ P). Among the remaining six variables, the the highest conditional rank correlation with H was recorded for building footprint area (~~B)and soil~~ B). Soil sealing (or imperviousness) per 100 m grid cell (~~IMD) . Additionally, soil sealing was highly correlated with population density, but not with building footprint.~~ S) had the highest conditional rank correlation with H among the remaining five variables. Further variables had only very low (r<0.05) conditional correlation with H, therefore only three variables were used to explain H. Remaining arc between P and S was added due to high correlation between the two. B and S were not correlated (r=-0.02).

The dependencies defined in the model can be explained theoretically as follows. Firstly, high population density was highly correlated with height, as one might expect the presence of tall residential buildings (high-rises, tower blocks) in densely-populated cities. High buildings also typically have a large footprint compared to single-family houses. Finally, the height of buildings is correlated with soil sealing, as urban districts with apartment blocks are largely covered by artificial surfaces proving supporting services to the buildings, such as roads, sidewalks, parking lots etc. Such surfaces reduce the perviousness of the soil. On the other hand, small single-family houses are rather found in less-densely build-up and populated suburban zones.

The accuracy of the model is analysed in section 3.1. Predicted building height was transformed into floor space area ~~F~~ F using the following empirical formula:

$$F = \cancel{0.7}c\left(\left\lfloor \cancel{\frac{H-3.3}{2.4}}\frac{H-b}{a}\right\rfloor + 1\right)B \qquad (1)$$

where H is the building height in metres and B is the building footprint area (m^2), a, b and c are empirical coefficients. The $\lfloor\rfloor$ function indicates rounding down the value in brackets to the nearest integer. ~~It is assumed~~ The empirical parameters were set to a=2.4 m, b=3.3 m and c=30 %. This indicates that the average height of floors ~~is~~ was assumed to be 2.4 m, except the first floor ~~which is assumed 3.3 m including floor~~ (b). This value was firstly based on Figueiredo and Martina (2016), who analysed building sizes in Italy, and then adjusted using the comparison between observed and predicted (using methodology described herein) number of floors in the validation case study of houses in the Polish coastal zone. The lowest storey includes the flood elevation above ground, which was found to be 90 cm on average for German households affected by floods between 2002 and ~~2014 (see section ??)~~2014. Consequently, b=a+0.9 m. Eq. 1 further includes an allowance for the fact that not all floor space of a building is useful, as it can contain common spaces or other non-habitable spaces. Such non-usable spaces are assumed to be 30 % of total floor space. ~~The values of 2.4 m and 30 % were based on Figueiredo and Martina (2016), who analysed building sizes in Italy, and~~ This values was based on the comparison between observed and predicted (using methodology described herein) ~~number of floors and~~ usable floor space of validation case studies of flood-affected houses in ~~Poland,~~ Germany and the Netherlands (~~sections ??~~ see sections 2.1.1 and 3.1).

The described routine can be applied to any location in Europe for which ~~any of the three explanatory variable is available.~~ at least the building footprint area is known. The Bayesian Network model can be used when data for any variable is missing, though building footprint is required for Eq. 1. In fact, all data should be available at least for the European Union countries: building footprint from OSM or other databases and soil sealing/gridded population from pan-European datasets. An example application of the model to exposure computation is shown in section 3.3.

2.2 ~~Valuation of buildings and household contents~~

2.1.1 Validation of the method

Predictions of building height, number of floors, and floor space area are compared with observations using several error metrics (Moriasi et al., 2007; Wagenaar et al., 2018):

- Pearson's coefficient of determination (R^2) was used to measure the degree of collinearity between predicted and observed values, with higher R^2 indicating stronger correlation.
- Mean absolute error (MAE) was used to measure the average absolute difference between predicted and observed values, with higher MAE indicating higher error.
- Mean bias error (MBE) was used to measure the average difference between predicted and observed values, with positive MBE indicating overprediction and negative MBE indicating underprediction.
- Symmetric mean absolute percentage error (SMAPE) normalizes MAE by considering the absolute values of predictions and observations, with value close to 0 indicating small error compared to the variability of the phenomena in question.
- Root mean square error (RMSE) was used to measure the difference between predicted and observed values, with higher RMSE indicating higher error.

Equations for the listed measures are shown in Supplementary Table S2. For validation purposes, we use the predictions as mean (expected) values of the uncertainty distribution of the variables of interest per each data point (building). We also analyse the uncertainty of the height prediction model and perform an out-of-sample validation.

An out-of-sample validation of building heights was done individually for each of the 30 capital cities contained in the sample quantifying the BN. Validation for all cities collectively was done using 10-fold cross-validation. Predictions of building heights transformed into the number of floors were validated using a large (N = 62,580) sample of residential buildings that were identified as potentially endangered by coastal floods and sea level rise in Poland according to a study by Paprotny and Terefenko (2017). The dataset contains building polygons with the number of floors and constitutes part of the Topographical Objects Database (BDOT) maintained by the office of surveyor-general in Poland. It was created through combination of remote sensing, field surveys and administrative registers and is accurate as of year 2013. The quality of the data should correspond to a 1:10,000 scale map and the quantitative information contained in the dataset should nominally deviate from real values by no more than 20 %. For each building, the footprint area, population and soil sealing were derived to run the BN-based model and converted into number of floors using Eq. 1.

Validation of floor space area predictions was carried out using results of post-disaster household surveys covering six river floods and three flash floods that affected Germany between 2002 and 2014 and a river flood along river Meuse in the Netherlands in 1993 (Thieken et al., 2005, 2017; Rözer et al., 2016; Spekkers et al., 2017; Wagenaar et al., 2017, 2018). In the German surveys, conducted mostly in the south and east of the country, respondents were asked to provide information on the floor spaces of their households. The floor space area of multi-family buildings was extrapolated using the total number of flats in the building multiplied by the floor space of the surveyed household. In the Dutch survey, the information on the floor space area was taken from the national cadastre. For each survey data point an OSM building polygon was downloaded and other statistics necessary to run the BN model were extracted. However, both survey datasets include considerable uncertainty related to the location of individual buildings. Therefore, the analysis was done only for buildings for which there was good confidence that corresponding OpenStreetMap buildings were correctly identified, based on the building footprint area recorded in the survey datasets. Also, the analysis for Dutch data was done only for single-family houses, as the floor space data for apartment buildings only referred to particular households, not the whole buildings. As this was also occasionally the case in the German sample, instances of floor space being less than half of building footprint were excluded. This threshold also helps excluding residential buildings with large non-residential parts (e.g. agricultural or commercial), as was done by Fuchs et al. (2015).

2.2 Country-level valuation of buildings and household contents

When the floor space of a building is known, it is multiplied by the average replacement cost of dwellings and household contents per m^2. The total floor space of dwellings in a country is available for European countries due to recording of this information in population and housing censuses, sometimes also in household surveys (Eurostat, 2019a). This data has to be gathered from national statistical institutes, as it is not collected by Eurostat. Some countries only disseminate floor space information at census dates (e.g. Italy, Portugal, Spain), while others from surveys carried out less frequently than annually (e.g. France) or only as part of the EU Survey of Income and Living Conditions (e.g. Norway, Sweden). There are also countries that calculate continuous balances of housing stock or extract data from housing registers, thus providing annual time series of floor space area in the country (e.g. Denmark, Germany, the Netherlands, Poland, Romania). Finally, for some countries only household floor space data from the 2012 edition of the EU Survey of Income and Living Conditions were available (e.g. Belgium, Norway, Sweden). Information on the data collected on dwelling stock is provided in ~~Table S2~~Supplementary Table S3.

2.2.1 Residential buildings

Statistical institutes in most European countries are recording the stock of fixed assets, including dwellings, for purposes of national accounting (Eurostat, 2013). Annual time series of the gross stock of dwellings is available for 22 EU countries from

Eurostat, though the data for two countries – Latvia and Poland – couldn't be used due to major methodological differences which are discussed in Table S3. The value of dwellings is provided from the aforementioned resource in nominal and previous year's prices. A deflator to obtain real (2015) prices was constructed based on the two timeseries. Finally, the value of all dwellings was divided by the total floor space area in a country to obtain average value per m^2. The method does not consider building types or quality, but this information is scarcely available from open datasets on buildings. Information on specific data sources on dwelling values is provided in ~~Table S2~~Supplementary Table S3.

The remaining EU countries and three other Western European nations (Iceland, Norway, Switzerland) required more data collection efforts. According to the European System of Accounts (ESA) 2010 manual (Eurostat, 2013), the Perpetual Inventory Method (PIM) should be applied whenever direct information on the stock of fixed assets is missing. In practice, most countries use PIM to arrive at the stock estimates that are published through Eurostat (Eurostat and OECD, 2014). PIM accumulates past investments over time to indirectly estimate the value of the stock (U.S. Department of Commerce. Bureau of Economic Analysis, 2003). The general formula for PIM to obtain the gross stock is as follows (National Bank of Belgium, 2014):

$$S_t = \sum_{j=0}^{L} (I_{t-j} G_j) \tag{2}$$

where:

S denotes stock of an asset;

t is the calendar year;

j is an annual increment;

I is investment in year $t - j$;

L is the maximum service life of an asset in years;

G is the proportion of an asset purchased in $t - j$ and still in use in t.

Three quantities are needed to obtain the stock of dwellings S: investment in housing, an estimate of the dwellings' service life and the fraction of dwellings of the same vintage that are retired every year. Investment (gross fixed capital formation for asset type 'dwellings') is available from Eurostat, national statistical institutes or country-specific research estimates. However, sufficiently long investment series were only identified for Sweden, while for other countries had to be extrapolated using total investment or gross domestic product (GDP), a method which is also applied by national statistical institutes when necessary (Eurostat and OECD, 2014; Rudolf and Zurlinden, 2009).

Parameters L and G are assumptions that usually stem from estimates of average service life of assets. Most national statistical institutes derive G by assuming certain probability distributions known as retirement patterns or survival functions. This means that a different proportion of dwellings is retired each year, with the highest proportion around the average service life. However, this requires assuming a certain probability distribution, and national methodologies indicate a large variety of those (normal, lognormal, Gamma, Weibull, Winfrey etc.). Further assumptions have to be made regarding the distribution's dispersion and maximum service life (OECD, 2009). It also vastly increases the length of investment time series necessary to apply PIM, which would require collecting investment series going back even to the early 19th century. In effect, some countries with short data series apply no survival function (Eurostat and OECD, 2014). This approach is known as “simultaneous exit” and assumes that all assets are only retired when reaching a given service life. Eq. 2 is therefore simplified to:

$$S_t = \sum_{j=0}^{L_{mean}} I_{t-j} \tag{3}$$

which now only requires assuming an average service life of dwellings ~~L_mean~~L_{mean}. As a sensitivity check, we applied a lognormally and normally-distributed retirement pattern to the Swedish investment series, the longest we have collected. We assumed a dispersion factor from 2 to 4 (i.e. ratio of mean and standard deviation of service life) and maximum service life equal to twice of the average, as suggested by the National Bank of Belgium (2014). The calculation yielded a gross stock of dwellings in Sweden in 2017 lower by 5–15 % compared to an estimate derived with no survival function. Consequently, we relied on the simplified method to apply PIM for six countries (Iceland, Malta, Norway, Spain, Sweden and Switzerland). L_mean for each country was taken from national methodologies collected in a survey by Eurostat and OECD (2014), except for Switzerland, which was taken from Bundesamt für Statistik (2006).

For further four countries, where data on investment is limited, but the balances of the number of buildings and their floor space is available, a modified PIM was applied. In those cases, we computed an initial estimate of the stock of dwellings (Bulgaria in 1999, Latvia in 2000, Poland and Romania in 1995) based on national construction costs in the base year and then used annual data on investments in, and retirement of, dwellings in the country to arrive to a timeseries of the gross stock. In this case ~~eq~~Eq. 2 becomes:

$$S_t = S_{t-1}(1 - G_t) + I_t \tag{4}$$

here G_t is the fraction of the stock retired during year t. In this way, service life assumption and long data series are not needed, with the drawback of assuming uniformity of the existing stock of dwellings and that all investment goes into building new dwellings rather than also into renovation of dwellings. We also tested the method from ~~eq~~Eq. 4 using extrapolated investment series, but it yielded far lower estimates of building asset values which were also much lower than for neighbouring Central European countries. With a modified PIM, the exposure estimates were more closely aligned to countries at a similar level of development. Calculation for the remaining country, Croatia, was not possible due to the lack of even basic data needed for the computation. Data sources and assumptions for individual countries are provided in ~~Table S2~~Supplementary Tables S3 and S4, while the overall reference to methods used is given in Supplementary Table S5.

2.2.2 Household contents

Data availability for the stock of household contents is much lower than for dwellings. This item is termed in national accounting as ‘consumer durables’ and assumed to be consumed within the accounting period, rather than accumulated, as those durables are not relevant from the perspective of economic production processes. As such, they are considered memorandum items in ESA 2010 (Eurostat, 2013) and consequently few European countries have published national estimates of the stock of consumer durables, namely Estonia, Germany, Italy and the Netherlands (OECD, 2019). Yet, even those few available datasets include personal vehicles in the stock. Cars and motorcycles are typically located outside the residential buildings, hence including them in estimates disaggregated by m^2 of floor space would not be suitable. Further, they are insured separately from houses and their contents, therefore not included e.g. in reported flood damages from post-disaster household surveys (Thieken et al., 2005; Carisi et al., 2018; Wagenaar et al., 2018). Given all those constraints, we calculate our own estimates of the stock of household contents (durables) for all countries included in the study.

In order to estimate the stock of household contents, the PIM method is applied again. However, the contents consist of various durables of different service lives, therefore ~~eq~~Eq. 3 has to be rewritten as:

$$S_t = \sum_{a=1}^{A} \sum_{j=0}^{L_a} I_{t,a-j} \tag{5}$$

where the stock of household contents equals the sum of stocks for items $a = (1,...,A)$, each with service life L_a. No retirement pattern was assumed, hence all items are included in the stock until reaching their average service life. The data on annual investment was gathered from final consumption expenditure of households split according to the Classification of Individual Consumption by Purpose (COICOP). The relevant durables are a set of twelve items at COICOP 4-digit level, i.e. all durables less items under code 07.1 “Purchase of vehicles”. However, only Sweden publishes annual data with such level of detail; data disaggregated at COICOP 3-digit level are disseminated for 28 countries, at COICOP 2-digit level for Switzerland and no data are available for Croatia. We therefore computed the average share of spending on durables within COICOP 3-digit categories using 5-yearly household survey data from Eurostat on detailed consumption expenditure patterns per country. The same approach was previously applied by Jalava and Kavonius (2009) to estimate the stock of durables in Europe. It allowed us to estimate spending on durables from COICOP 3-digit data. Assumptions about service life of durable items (aggregated to COICOP 3-digit items) were calculated from German estimates presented by Schmalwasser et al. (2011). We averaged 1991 and 2009 estimates of service lives from that study and weighted the COICOP 4-digit items according to their share in spending. The service life of appliances for personal care (COICOP code 12.1.2) was not provided in the aforementioned resource, hence it was taken from Jalava and Kavonius (2009). A list of durable items, assumptions on their service life and the share of spending on durables per COICOP 3-digit items are shown in ~~Tables S4 and S5~~Supplementary Tables S6 and S7. For Iceland detailed consumption expenditure surveys are not available, hence average share in 15 EU members states was used instead.

Final consumption expenditure data were collected from Eurostat, OECD and national statistical institutes. Due to the very long estimated service life of durables in the ‘personal effects’ (COICOP code 12.3.1) category (45 years), the spending on those items had to be extrapolated using data on total private consumption expenditure, or GDP. This should have, however, limited influence on the results for recent years given the rather small share of spending on durable personal effects. For France, which has detailed expenditure going back to 1959, truncating the data to 1995 (the minimum availability for the countries considered except Malta) and extrapolating it with total private consumption resulted in a 2–5 % lower estimate of the stock of household contents, depending on the year. The uncertainty increases when moving back in time. Detailed sources of data are shown in ~~Table S6~~Supplementary Table S8. The calculation in ~~eq~~Eq. 5 was carried out with expenditure time series in real (2015) prices, and then converted to nominal prices using country- and item-specific deflators. Additionally, country-specific deflators of household contents were devised from the time series of the stock of consumer durables in real and nominal prices. Those deflators can be used to estimate the value of damages to household contents in real prices. Lastly, the stock of consumer durables was divided by the total floor space area in a country to obtain average value per m^2, as for residential buildings. However, for several countries, due to a large number of unoccupied dwellings (as identified in data from Eurostat (2019a)), only the floor space area of occupied dwellings or the number of households was used in this calculation. Instances of using different floor space area estimates to obtain average building and contents values are indicated in ~~Table S2~~Supplementary Table S3.

2.3 ~~Validation of the exposure model~~

2.2.1 Validation of the method

2.2.2 ~~Validation measures~~

~~Predictions of building height, number of floors, and floor space area are compared with observations using several error metrics (Moriasi et al., 2007; Wagenaar et al., 2018):~~

- ~~Pearson's coefficient of determination (R^2) was used to measure the degree of collinearity between predicted and observed values, with higher R^2 indicating stronger correlation.~~
- ~~Mean absolute error (MAE) was used to measure the average absolute difference between predicted and observed values, with higher MAE indicating higher error.~~
- ~~Mean bias error (MBE) was used to measure the average difference between predicted and observed values, with positive MBE indicating overprediction and negative MBE indicating underprediction.~~
- ~~Symmetric mean absolute percentage error (SMAPE) normalizes MAE by considering the absolute values of predictions and observations, with value close to 0 indicating small error compared to the variability of the phenomena in question.~~

~~Equations for the listed measures are shown in Table S7. For validation purposes, we use the predictions as mean (expected) values of the uncertainty distribution of the variables of interest per each data point (building). We also analyse the uncertainty of the height prediction model and perform an out-of-sample validation.~~

2.2.2 ~~Datasets for validation and comparison~~

~~The out-of-sample validation of building heights was done individually for the 30 capital cities contained in the sample quantifying the BN. Then, a collective out-of-sample validation was done using a new 1 % sample of the buildings in those~~

~~cities, which does not overlap with the sample used to quantify the BN. Predictions of building heights transformed into number of floors were validated using a large (N = 62,580) sample of residential buildings that were identified as potentially endangered by coastal floods and sea level rise in Poland according to a study by Paprotny and Terefenko (2017). The dataset contains building polygons with the number of floors and constitutes part of the Topographical Objects Database maintained by the office of surveyor-general in Poland. It was created through combination of remote sensing, field surveys and administrative registers and is accurate as of year 2013. The quality of the data should correspond to a 1:10,000 scale map and the quantitative information contained in the dataset should nominally deviate from real values by no more than 20 %. For each building, the footprint area, population and soil sealing were derived to run the BN-based model and converted into number of floors using eq. 1.~~

~~Validation of floor space area predictions was carried out using results of post-disaster household surveys covering six river floods and three flash floods that affected Germany between 2002 and 2014 and a river flood along river Meuse in the Netherlands in 1993 (Thieken et al., 2005, 2017; Rözer et al., 2016; Spekkers et al., 2017; Wagenaar et al., 2017, 2018). In the German surveys, conducted mostly in the south and east of the country, respondents were asked to provide information on the floor spaces of their households. The floor space area of multi-family buildings was extrapolated using the total number of flats in the building multiplied by the floor space of the surveyed household. In the Dutch survey, the information on the floor space area was taken from the national cadastre. For each survey data point an OSM building polygon was downloaded and other statistics necessary to run the BN model were extracted. However, both survey datasets include considerable uncertainty related to the location of individual buildings. Therefore, the analysis was done only for buildings for which there was good confidence that corresponding OpenStreetMap buildings were correctly identified, based on the building footprint area recorded in the survey datasets. Also, the analysis for Dutch data was done only for single-family houses, as the floor space data for apartment buildings only referred to particular households, not the whole buildings. As this was also occasionally the case in the German sample, instances of floor space being less than half of building footprint were excluded. This threshold also helps excluding residential buildings with large non-residential parts (e.g. agricultural or commercial), as was done by Fuchs et al. (2015).~~

Estimates of building and contents value cannot be directly validated due to the lack of information on this subject at the level of individual objects. We can only compare our results with other published results, which is done in section 4.2.1. Those published results include two pan-European studies: (1) a flood risk assessment for the European Commission – Joint Research Centre (JRC) by Huizinga et al. (2017) and (2) seismic risk assessment for the “Network of European Research Infrastructures for Earthquake Risk Assessment and Mitigation” (NERA) project by Ozcebe et al. (2014). Both studies used construction cost surveys and manuals as well as regression analyses with socio-economic factors. Additionally, we compare estimates calculated in this study with values used in available local or national risk assessments.

3 Results

3.1 Validation of building height and floor space predictions

The exposure estimation procedure was first validated by comparing observed and modelled residential building height. This analysis was done through ~~an out-of-sample validation in which we use the original sample of 2~~a 10-fold cross-validation using a 10 % ~~of~~ sample of residential buildings in 30 European capitals (section 2.1.1)~~to predict another sample of 1 % of the buildings, with no overlaps between the two datasets. Figure 2~~. Fig. 3 displays a comparison between observed and modelled heights. The coefficient of determination (R^2) is a moderate ~~0.36~~0.35. Still, the model predicts correctly the average height (~~9.65~~9.69 m versus ~~9.57~~9.60 m observed), but underestimates the variation, as the modelled sample has a standard deviation of 3.30 m versus 5.89 m found in observations. In effect, despite the negligible bias of the model in general, height of tall buildings (more than 20 m high) is mostly underestimated. Mean absolute error is ~~3.24~~3.25 m, which is 34 % of the mean height (Table 2).

An out-of-sample was also carried out for each city in the dataset, where only the capital in question was excluded from the data quantifying the dependency structure of the BN model ~~. The full results are provided in Table S8~~(Table 2). Lowest R^2 were computed for Nicosia ~~(0.02)~~ and Reykjavik (~~0.04~~0.05), though the latter has lowest average building height among the cities considered here. On the other end of the scale are Vienna (~~0.55~~0.50) and Berlin (~~0.50~~0.49). Relatively low errors and bias was found for e.g. Amsterdam, Luxembourg, Stockholm, Vienna, Warsaw and Zagreb. The largest MAE and negative MBE was identified for Bratislava (~~7.28~~6.81 m and ~~-5.38~~-4.61 m, respectively), while the highest MBE was recorded for London (+~~2.69~~2.65 m).

The second step in obtaining floor space – the number of floors – was tested against a large number of Polish residential buildings located in the coastal zone, obtained from the national database BDOT. Results in Table 3 show that average error is slightly less than a third of the average number of floors. R^2 for particular building types is low, but better overall, as the method has clearly ability to distinguish small single-family house from multi-family buildings. Overall, ~~47.1~~45.0 % of the buildings had the number of floors predicted correctly (Table ~~3~~4). The number of floor is rather underestimated than overestimated, especially for higher buildings. The error does not exceed one floor for 4–6 floor buildings in ~~around~~ almost 70 % of cases. For buildings of 7 floors or more, underestimation is mostly by two floors.

Finally, predictions of the floor space area were tested against Dutch and German households (Table 3). The average error was equal to about a third of average building height of the Dutch buildings. For the German buildings, average error was almost half the average height. The size of Dutch buildings is on average slightly underestimated (-11 %), but the opposite happens for German houses (+15 %). Nonetheless, the model clearly can distinguish between single-family (detached) and multi-family houses. Larger variation in heights of apartment buildings also results in higher R^2 and lower SMAPE compared to detached houses which are typically quite similar in the number of floors. Mean absolute error (MAE) is still larger for multi-family houses, but bias is lower than for the other two types of buildings in the German sample.

3.2 Pan-European estimates of building and household contents value

As described in section 2.3, statistical data on buildings and household expenditure were collected for a study area of 30 countries (Iceland, Norway, Switzerland and the European Union less Croatia). The dataset reveals a considerable stock of residential assets in place. Based on those statistical data alone, we estimate that there were 259 million dwellings in the study area at the end of 2017, some 12 % of which are vacant or occupied seasonally. Those dwellings had a collective useful floor space area of almost 24 billion m^2 and were worth 36.7 trillion euro in gross replacement costs. At country level, the value of assets per m^2 of floor space varies substantially (Fig. 4 and 5). Iceland had the highest estimated value of dwellings per m^2 (2284 euro), followed closely by Germany and Finland. Differences in dwelling sizes, vacancy rates and average number of persons per household result in average home replacement costs varying even more. Icelandic dwellings, typically larger than European average, are the most expensive in Europe, though in per capita terms costs are higher in Denmark (Fig. 4a). On the other side of the spectrum, Romanian dwellings are the smallest (in terms of average floor space) and cheapest to reconstruct (412 euro per m^2). Higher values are recorded in Bulgaria, Lithuania and other Central European states. Southern European and Benelux nations fall in the middle of the distribution (Fig. 5a). The stock of dwelling and their prices have grown rapidly since year 2000 (Fig. 6a). Almost 5 billion m^2 of floor space was added and the average dwelling size has increased as well. In nominal prices, the average replacement cost of residential buildings per m^2 of floor space has grown at least by 14 % (Greece) and as much as six-fold in Romania; the growth in average European dwellings costs was 53 %. In constant prices, the average replacement cost of the existing dwelling stock has declined in four countries (Denmark, France, Luxembourg, Slovenia). The highest growth of 79 % was recorded in Slovakia. Average European replacement costs per m^2 has gone up by a modest 7 %. Changes of dwelling value in constant prices should be interpreted as change in the characteristics of the stock of residential buildings: its average quality, material, size and type (single- and multi-family houses, dwellings for permanent or seasonal use, etc.). There appears to be no clear pattern of the distribution of those changes, but southern countries had rather lower rates of cost growth than the northern states. The country with the highest replacement costs per m^2 changed multiple times in the 17-year timeframe, alternating between Germany, Ireland, Sweden, Switzerland and finally Iceland.

Household contents in Europe is diversified collection of durable items, which we estimated were worth 6.6 trillion euro at the end of 2017. Furniture, furnishings and floor coverings constituted 39 % of the gross stock of household contents, followed by jewellery, clocks and watches (25 %); audio-visual, photographic and information processing equipment (11 %); major household appliances (10 %) and various other tools, equipment and appliances (16 %). Variation between countries is higher than for dwellings (Fig. 5b), albeit mainly due to exceptionally large stock of consumer durables in Switzerland (666 euro per m^2 as of 2017). Nordic countries are less prominently featured in the top of the ranking compared to building values (Fig. 6b). The highest values are recorded, apart from Switzerland, in Austria, the United Kingdom, Norway and Germany. Switzerland also comes first in the value of contents per household and per person. Lowest stocks of durables per m^2 were estimated for Hungary (84 euro), Bulgaria and Cyprus, though the latter's value is a result of large sizes of dwellings, hence an average Cypriot household has more assets than homes in other Central European countries. In nominal terms, the growth in household contents was smaller than for dwellings in nominal terms: 30 % for the growth in average European value per m^2, varying from decline in Ireland to an almost four-fold increase in Slovakia and Romania. Yet, many household items have seen their prices grow slowly or decline, especially for electronic equipment. In effect, an average household in Europe had 19 % more consumer durables per m^2 in 2017 than in 2000, even if growth was lowered by the increase in average floor space available to households. Three countries (Italy, Luxembourg, Spain) recorded a decline (Fig. 6b), while more than tripling of contents value was recorded in Latvia and Slovakia. Growth was clearly higher in Northern and Central Europe than in Southern Europe, as consumer spending on durables is very sensitive to the countries' economic performance. Switzerland had the highest values of contents per m^2 throughout 2000–2017, while the lowest values were first estimated for Latvia, later Bulgaria and finally Hungary.

3.3 Example application

To illustrate an application of the two components of the study – building-level height predictions and country-level valuations of residential assets – we downloaded current (as of 18 July 2019) OSM building data for Szczecin, Poland. A city of slightly more than 400,000 people is endangered in its low-lying parts by floods and sea level rise (Paprotny and Terefenko, 2017). OSM data indicated 27,971 residential buildings within the city limits. After calculating the footprint area of each building, corresponding population density and gridded soil sealing at 100 m resolution was extracted from pan-European datasets, as in section 2.1.1. The BN model predicted building height for each building, which was then transformed into number of floors and consequently useful floor space area (~~eq~~Eq. 1). The average building was found to have a floor space of 467 m^2 (uncertainty range 453–482 m^2). The number of residential buildings and their average size slightly larger than the values for 2017 recorded in the national statistics – 27,068 and 419 m^2, respectively (Statistics Poland, 2019). The floor space of each building was multiplied by the average replacement costs of buildings and household contents in Poland in 2017, which is 683 and 109 euro per m^2, respectively (Tables ~~S2 and S6~~ S3 and S7 in Supplementary Information 2). The total value of residential assets per building in a fragment of the city is presented in Fig. 7.

Combining our exposure estimates with flood maps for extreme sea levels (Paprotny and Terefenko, 2017), we can identify 209 residential buildings in the city that exist within the 100-year flood hazard zone. Their aggregate value amounts to 19.3 million euro. Then, a flood vulnerability model can be applied to estimate damages in case of the event, e.g. pan-European JRC depth-damage function for residential assets (Huizinga, 2007). This vulnerability model applied to water depths computed by Paprotny and Terefenko (2017) produces an estimate of damages from a 100-year flood event amounting to 6.1 million euro.

4 Discussion

4.1 ~~Comparison with alternative estimates of residential assets value~~Building-level useful floor space estimation

4.1.1 Uncertainties and limitations

Predictions of floor space area involve several uncertainties along the chain of computations. Firstly, the Bayesian Network (BN) for predicting buildings was quantified based on a set of capital cities. Those cities vary enormously in size, cover 30 countries and include at least to some extent the surrounding metropolitan area, but they don't include area of more rural character. Incorporation of those areas could improve predictions for single-family houses. At the moment, the R^2 is lower for buildings located in local administrative units with a suburban or rural character, as identified by intersecting the available height data with "Degrees of Urbanisation 2014" dataset by Eurostat (2019a). Yet, the mean absolute error is smaller, and almost exactly proportional to the average building height at all three urbanisation levels (Supplementary Table S9).

Bias in predictions for high-rise buidlings is observed, which largely can be a consequence of relatively small number of those, even within large cities. Some errors originate in the source elevation model, which has a resolution of 10 m, therefore the height of buildings with small footprint areas could be less accurately assigned to OpenStreetMap polygons. Also, the validation information provided by Copernicus Land Monitoring Service (2019) show variation in the accuracy of the elevation data between cities. Differences of 2-3 m are fairly common when compared with an alternative elevation model.

The OSM dataset is also not homogenous. Sometimes, individual buildings are not distinguished within a city block, creating an artificially large building, leading to overestimation of height in the BN model. The quality of building and landuse is uneven also within the cities themselves, resulting in relatively few useful data points e.g. for Nicosia, Rome or Madrid. In the second step of obtaining floor space of building, i.e. calculating the number of floors, a constant height of each floor was assumed, though they tend to vary to some degree (Figueiredo and Martina, 2016). Also, a more diversified set of evidence could the improve the calculation, similarly for the last step of deriving useful floor space, which depends on the assumption what percentage of the area of a building is actually used for living purposes. This is particularly problematic with building of mixed use, as first floors of residential buildings are often utilized by shops and other services.

The method used for data analysis, a non-parametric BN, is a model configured primarily using expert knowledge. The dependency structure modelled with a Gaussian copula is the main assumption in the model that could affect the results. Due to the moderate accuracy of the height model's predictions, we also tested an automated data-mining method, Random Forests (RF). It utilizes ensembles of regression trees, which split continuous variables into subsets in order to approximate nonlinear regression structures (Merz et al., 2013). We used the 10 % sample of the available data of building height and seven explanatory variables, the same as for the BN model, and made a RF model with a 10-fold cross-validation. At each validation step, 100 trees were generated with a maximum of 50 leaves. For each split, 1/3 of the training data was used. The RF model produced slightly lower R^2, higher RMSE, strongly negative MBE and slightly lower MAE than the BN model. Still, the performance was not far from the BN model (Supplementary Table S10).

4.1.2 Future outlook

Improving building height predictions for the purpose of exposure estimation would involve incorporating new sources information. For building heights, lidar scanning results from smaller cities and rural areas should be incorporated to increase the diversity of the sample for a Bayesian Network model. The model itself could also be built separately based on data of different typology (urban, suburban, rural) or for different parts of Europe. More diversified resources are needed as well to analyse the relationship between building height and the number of floors and further with the usable floor space of the building, which can differ between countries and building types. As a more immediate step, the code used in this study is expected to become publicly available to facilitate its application and further testing.

4.2 Country-level asset valuation

4.2.1 Comparison with alternative estimates

Estimates of residential building replacement cost per m^2 from two external sources, by the JRC (Huizinga et al., 2017) and NERA project (Ozcebe et al., 2014) are gathered in ~~Table S9~~ Supplementary Table S11 and compared with our estimates in Fig. 8. In a few cases, two different estimates are provided by the JRC, as two construction surveys were used as source of information. Many of the JRC dwelling values for year 2010 are similar to our calculation for the same year. In most cases, JRC provides higher estimates, which can be the result of using information on the construction costs of modern dwellings, rather than the replacement value of actually existing stock of housing. It is noticeable that the two alternative estimates by JRC differ substantially between themselves, especially for Germany and Poland, with our calculation falling in the middle in those two divergent cases. NERA project estimates (for year 2011) show much less variation between countries and almost uniformly show lower replacement costs for Western European dwellings and higher for Central European houses. This is a result of using a set of “reference” countries and a regression based on GDP per capita. The latter was developed for global application, in effect compressing the variation in building costs: they vary only by a factor of 2 in the NERA estimates, despite GDP per capita in the countries in question changing by a factor of 15 as of year 2011.

Household contents was not directly estimated by JRC in the study by Huizinga et al. (2017), but rather recommended taking half of the dwelling value. We therefore take 50 % of JRC’s building value estimates for comparison with our estimates (Fig. ~~8~~9). In all cases, the resulting household contents value are much higher than our estimates. This could be partially a result of including more items in the contents, e.g. vehicles and semi-durables, though the extent of the term was not stated in the cited study. The 50 % also originate from HAZUS model developed for the United States. In our study, a ratio close to 2:1 for buildings and contents was found only in Malta (1.86), while for other countries it is at least 3:~~1.~~ 1 (Fig. 10a). The average ratio is almost 5.7, therefore the resulting contents value estimates are almost three times lower than based on JRC buidling value estimates and a single building-to-contents ratio based on an American model.

Some other literature estimated could be compared with our results. Studies based on German post-disaster surveys computed exposure based on a insurance sector guideline for residential building values deflated to a particular year with the construction price index (Thieken et al., 2005). Household contents was computed using a regression analysis of average insurance sums and local purchasing power. Average replacement costs of buildings affected by riverine floods between 2002 and 2013 was, on average, 2594 euro per m^2 in 2013 prices. The corresponding value for household contents was 545 euro, a ratio of 4.76:1. A weighted average of our estimates would be 1944 and 377 euro at price level of 2013. While both estimates are lower, the ratio of 5.16:1 is close to the value used in the German surveys. In a study of coastal floods and sea level rise in Poland (Paprotny and Terefenko, 2017), the authors used the average construction costs of new multi-family dwellings from the national statistical institute. Household contents was estimated on the basis of average share of consumer durables in GDP identified for some developed countries by (Piketty and Zucman, 2014) and total floor space of dwellings in the country. Their estimates of 936 and 147 euro for year 2011 are higher than 717 and 94 euro for dwellings and contents per m^2, respectively, computed in this study. However, the first value is based on new dwellings rather than replacement costs of existing stock, while the second value includes the cost of personal vehicles, which would add about half to our estimate of household contents (see section ~~??~~4.2.1), thus matching the other calculation. Silva et al. (2015) used residential building replacement costs from a governmental decree, updated annually, for their seismic risk assessment. As of 2013, the values per m^2 separately for major cities, other urban areas and rural areas were 793, 693 and 628 euro, respectively. Given the distribution of population by regional typology (Eurostat, 2019a), that amounts to around 700 euro on average of the country, only slightly more than 671 euro calculated here.

4.3 ~~Uncertainties and limitations~~

4.2.1 Uncertainties and limitations

~~Predictions of floor space area involve several uncertainties along the chain of computations. Firstly, the Bayesian Network for predicting buildings was quantified based on a set of capital cities. Those cities vary enormously in size, cover 30 countries and include at least to some extent the surrounding metropolitan area, but they don't include area of more rural character. Incorporation of those areas could improve predictions for single-family houses. Also, the source elevation model has a resolution of 10 m, therefore the height of buildings with small footprint areas could be less accurately assigned to OpenStreetMap polygons. In the second step, obtaining the number of floors, a constant height of each floor was assumed, though they tend to vary to some degree (Figueiredo and Martina, 2016). Also, a more diversified set of evidence could the improve the calculation, similarly for the last step of deriving useful floor space, which depends on the assumption what percentage of the area of a building is actually used for living purposes. This is particularly problematic with building of mixed use, as first floors of residential buildings are often utilized by shops and other services.~~

Uncertainties related to economic valuations are largely methodological or related to limitations in availability of some data for certain countries. Most of the gross stocks of dwellings are taken directly from national estimates, which are computed with a variety of assumptions related to service life and retirement patterns as well as investment data availability, coverage and detail. As noted in Supplementary Table S4, analysis of methods identified timeseries for two countries incomparable with others, but more datasets could be affected by local methodological specifics. The stock of household contents was computed with a uniform approach, but service life assumptions based on a German study might not be suitable for other countries. Also, the availability of historical data on consumption expenditure varies between countries and most detailed COICOP 4-digit data is not accessible on per annum basis, necessitating assumptions about share of durable spending in more aggregated data. Quality of the expenditure data could also be questioned given the very large differences between deflators for individual durable items between countries. This is most strongly visible in the data for Ireland, where prices of all items have dropped significantly since year 2000 according to national statistics, which is not in line with experience of other European economies. Consequently, the estimate of the stock of household contents for Ireland is likely too low and the strong upward trend overestimated. Further, availability of dwelling and household numbers and especially the floor space statistics is not uniform. For some countries, data on temporal changes in average floor space per dwelling or the total area are not published. Yet, housing statistics are typically better for Central European countries than Western European states, quite the opposite to economic data availability. This is likely a result of poorer living conditions in the new EU member states prioritizing gathering information on the subject compared to Western Europe, while their less-developed statistical systems usually generate lower detail and shorter time series of economic statistics.

The study presented only valuations of dwellings and household contents as gross stock, i.e. replacement cost without allowing for depreciation of assets. Merz et al. (2010) argued that for analysing damages to natural hazards net costs should be used instead, as the value actually lost is the remaining, depreciated value of assets. This is sensible in the perspective of national accounting, where changes to net stocks of assets are of main interest e.g. for calculating GDP using the income approach or indicators such as net disposable income of households or net savings. Still, an asset typically cannot be restored to a particular depreciated state, therefore from the perspective of those who would need to pay for repair or replacement of the damaged or destroyed assets the gross stock is a better indicator of the possible cost of post-disaster recovery. Depreciation of residential buildings varies to a large degree in Europe, not least due to very different assumptions on the patterns of depreciation. One method is called "straight-line", as it assumes an asset loses a given percentage of its gross value each year and also requires defining a retirement pattern as in the computation of gross stock. It is the default method in the ESA 2010 system and used e.g. in Belgium, France, Germany, Italy, Portugal and the United Kingdom (Eurostat, 2013; Eurostat and OECD, 2014). The other method, "geometric", assumes that an asset loses a given percentage of its remaining (net) value and is used in e.g. in Austria, Estonia, Norway and Sweden (Eurostat and OECD, 2014). The total stock of dwellings for the 22 countries available from Eurostat's database indicates a depreciation of 37 %, varying from 22 % in France to 55 % in Hungary (Eurostat, 2019a).

Consumer durables less personal vehicles are used here for household contents on the basis of what items are actually insured and compensated after natural hazards events. Overall damages to households could be yet higher. In the aftermath of the 2010 Xynthia storm, 8 % of flood-related insurance claims were related to cars on top of 5 % of windstorm-related claims (FFSA/GEMA, 2011). In the study area, annual consumer spending on purchase of vehicles amounts to some 300 billion euro per year, 92 % of which is on motor cars (Eurostat, 2019a), hence assuming 11–12 years of service life (Schmalwasser et al., 2011) the stock of vehicles owned by households would amount to about half of the value of other consumer durables. Households also stock semi-durables and perishables. They are generally excluded from any assessments on household wealth due to the limited information on the usage time of items in question and their rather low value (Goldsmith, 1985). Spending on semi-durables (e.g. clothing, footwear, books, toys, small appliances) in the study exceeded 750 billion euro in 2017, therefore it would add about 10 % to the estimated stock of durables for each year of assumed service life. Spending on perishables (e.g. food, fuel, medicines, newspapers) amounts to 2.5 trillion euro per annum in the countries considered here, but if households hold only a weekly stock of perishables, their total value is less than 1 % of the stock of durables.

4.3 ~~Future outlook~~

4.2.1 Future outlook

~~Improving building height predictions for the purpose of exposure estimation would involve incorporating new sources information. For building heights, lidar scanning results from smaller cities and rural areas should be incorporated to increase the diversity of the sample for a Bayesian Network model. The model itself could also be built separately based on data of different typology (urban, suburban, rural) or for different parts of Europe. More diversified resources are needed as well to analyse the relationship between building height and the number of floors and further with the usable floor space of the building, which can differ between countries and building types. As a more immediate step, the code used in this study is expected to become publicly available to facilitate its application and further testing.~~

Time series of building and contents value provided in this study (Supplementary Information 2) have several applications. The main use is providing economic valuation economic assets for natural hazard exposure and risk assessments carried out at the level of individual buildings (large-scale mapping). The time series could be used to correct past recorded damages from natural disasters both for changes in asset reconstruction costs (separately for dwellings and contents) over time, but also changes in average quality of residential buildings and incomes of households that translate into more expensive consumer durables kept at home. Finally, the data could be used to rescale absolute damage functions, which generate damage estimates based on intensity of the hazardous event not as percentage of assets lost, but as an absolute value for a given country in a specific year. In the field of flood risk, almost half of damage functions provide absolute values of damages instead of relative values (Gerl et al., 2016). With our data, for instance, flood damage curves for the United Kingdom at price levels of 2012 (Penning-Rowsell, 2013) could be applied to a German flood in 2002 by using the ratio of average replacement costs of residential assets in the UK and Germany in the respective years and currencies.

Further research on countries with good economic data would involve expanding the coverage in multiple aspects. Thematically, net (depreciated) value of residential assets could be added to the dataset, as most of the necessary data have already been collected here. Net stock of dwellings is directly available for four more countries than the gross stock (Norway, Spain, Sweden and Switzerland), while for others PIM method would be used (Eurostat, 2013; Eurostat and OECD, 2014). Net stock of consumer durables can be computed from the same data as gross stock (Jalava and Kavonius, 2009). Estimates of the stock of vehicles (gross and net) could be added, disaggregated on per household or per capita basis. Spatially, some developed non-European countries could be added which disseminate necessary data e.g. through OECD. It should be possible to add Croatia and EU candidate countries to the dataset once they start publishing detailed EU-mandated national accounts data. In the temporal dimension, the dataset could be extended in the past at least for certain countries with long data series (particularly France and the Nordic countries), so that it could be applicable natural hazard case studies that have occurred before year 2000. An analysis of the trends in the stock of residential assets and economic factors determining it could possibly also provide insights how could it change in the future, for the benefit of projections of natural hazard risk under climate change. ~~Furthermore, the~~

Furthermore, we provide valuations at national level, which neglects possible differences between urban and rural areas as well between regions of countries. This is exemplified by the example of Portuguese asset valuations for urban, intermediate and rural areas mentioned in section 4.2.1. The possibility of regionalization of asset values could be investigated to capture the possible differences between regions of a country and urban/rural areas. Some countries have disseminated building stock data at regional level (e.g. Germany, Poland, Spain), which could ~~lead to analysis what~~ be combined with regional economic data ~~could be used to predict inter-country variations, e.g.~~ such as GDP, gross fixed capital formation, compensation of employees in the construction sector, disposable income of households etc. ~~Combined with gridded population and land-use datasets~~A statistical analysis on such a dataset could reveal determinants of regional variation of asset values. Also, these estimates could result in detailed dasymetric exposure mapping in Europe if combined with gridded population and land-use datasets (Kleist et al., 2006; Thieken et al., 2006). Finally, incorporation of more detailed building characteristics, where available, could be applied to differentiate estimates of building value per m^2. Some countries distribute investment or stock data split by various types of buildings, which can be incorporated also in the PIM method. Several countries use different service life assumptions according to building type (Czechia, Estonia, Sweden), ownership (Latvia, Slovenia), age (Denmark, Germany) or material (some non-European countries), according to a survey by Eurostat and OECD (2014).

Still, most countries of the world do not disseminate so detailed housing, asset, investment or expenditure data as were used in this study. Simplified methods to indirectly estimate exposure will therefore be needed. GDP per capita was incorporated by the NERA study as such measure, but as the comparison in section 4.2.1 has shown, this is not necessarily a good indicator. Also, there are significant variations between value of residential assets per m^2 compared to GDP per capita and further differences between the composition of those assets. They vary by a factor of 4 and 6, respectively ~~.~~ (Fig. 10b). The lowest exposure relative to GDP per capita is recorded particularly in countries where GDP is far higher than actual income of their population, like Ireland and Luxemburg. Using e.g. final consumption expenditure of households per capita as a proxy gives better results, reducing the variation in total residential assets per m^2 between countries to a factor of 2.6. Estimates of this variable are available globally e.g. from the National Accounts Main Aggregates Database (United Nations, 2018). More detailed data is available approximately each five years from the International Comparison Programme, including household expenditure at COICOP 2-digit level. Developing such simplified approaches requires further analyses. Until then, we can propose the following rule of thumb based on the average asset values in the European countries, that the total residential assets per m^2 equal 6 % of GDP per capita, of which one-sixth are household contents.

5 Conclusions

In this study we have explored aspects related to estimating exposure of residential assets in Europe. Firstly, we proposed a methodology to estimate useful floor space area of buildings in situation when the only accessible quantitative measure about a house is its footprint area. This basic measure can be derived from various sources, from analogue topographic maps to crowd-sourced databases like OpenStreetMap (OSM). Building height or the number floors is only occasionally accessible, hence it has to be estimated based on other information. In our work, we have shown that a Bayesian Network quantified with a set of publicly available pan-European raster datasets and building footprints from OSM has the ability to differentiate between urban high-rises and suburban or rural single-family dwellings. Further, it can be applied to approximate building dimensions that can be the basis for assigning economic value to assets in question.

In the second part of the analysis, we harnessed publicly disseminated statistical data on housing stock and national economies to calculate time series of average value of residential assets—building structure and household contents—for 30 European countries. It can be applied whenever local exposure data are missing or no detailed characteristics of buildings are accessible. Additionally, it can improve analyses of past natural disasters by estimating exposure of assets in a particular year and country, as well as enable transferability of damage models that provide absolute rather than relative damages. More work is expected on expanding the thematic, spatial and temporal coverage and resolution of the dataset. It will be also applied as an important basis for constructing and validating a new generation of vulnerability models in natural hazards.

Code and data availability. This study relied entirely on publicly-available datasets, with the exception of validation datasets from Poland, Germany and the Netherlands in section 3.1 (see Acknowledgments). Data sources for the building height model are provided in Table 1. Detailed data sources for the economic computations are listed per country and variable in Supplementary Information 1. The full estimates of residential asset values are provided in Tables S1–S8 in Supplementary Information 2. Uninet software used to analyse and visualize the BN model is available from LightTwist Software for free for academic purposes (http://www.lighttwist.net/wp/). Implementation of the BN in Matlab is available from the authors upon request until it becomes publicly available.

Author contributions. DP conceived and designed the study, collected and analysed the data and wrote the first draft of the manuscript. HK and KS helped guide the research through technical discussions. OMN provided code for data analysis and was involved in technical discussions. PT provided, and supported processing of, some of the spatial datasets. All authors reviewed the draft manuscript and contributed to the final version.

Competing interests. Authors Heidi Kreibich and Kai Schröter are members of the Editorial Board of *Natural Hazards and Earth System Sciences*

Acknowledgements. This work was supported by Climate-KIC through project "SAFERPLACES – Improved assessment of pluvial, fluvial and coastal flood hazards and risks in European cities as a mean to build safer and resilient communities", Task ID TC2018_B4.7.3-SAFERPL_P430-1A KAVA2 4.7.3. Further funding was received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 730381. The authors would like to thank Dennis Wagenaar (Deltares) for kindly sharing the data from the 1993 Meuse flood, the office of the Polish surveyor-general for providing topographical data from the national cartographic repository, and colleagues at GFZ German Research Centre for Geosciences for their help with extracting the flood damage data contained in the HOWAS21 database (http://howas21.gfz-potsdam.de/howas21/). We also thank Danijel Schorlemmer (GFZ German Research Centre for Geosciences) for technical discussions.

References

Alfieri, L., Feyen, L., Salamon, P., Thielen, J., Bianchi, A., Dottori, F., and Burek, P.: Modelling the socio-economic impact of river floods in Europe, Natural Hazards and Earth System Sciences, 16, 1401–1411, https://doi.org/10.5194/nhess-16-1401-2016, 2016.

Bundesamt für Statistik: Nichtfinanzieller Kapitalstock: Methodenbericht, Technical Report 819-0600, Bundesamt für Statistik, Bern, Switzerland, https://www.bfs.admin.ch/bfsstatic/dam/assets/200442/master, 2006.

Carisi, F., Schröter, K., Domeneghetti, A., Kreibich, H., and Castellarin, A.: Development and assessment of uni- and multivariable flood loss models for Emilia-Romagna (Italy), Natural Hazards and Earth System Sciences, 18, 2057–2079, https://doi.org/10.5194/nhess-18-2057-2018, 2018.

Chatterton, J., Viavattene, C., Morris, J., Penning-Rowsell, E., and Tapsell, S.: The costs of the summer 2007 floods in England, Tech. rep., Environment Agency, Bristol, United Kingdom, https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/291190/scho1109brja-e-e.pdf, 2010.

Copernicus Land Monitoring Service: Pan-European, https://land.copernicus.eu/pan-european, 2019.

Elmer, F., Thieken, A. H., Pech, I., and Kreibich, H.: Influence of flood frequency on residential building losses, Natural Hazards and Earth System Sciences, 10, 2145–2159, https://doi.org/10.5194/nhess-10-2145-2010, 2010.

Eurostat: European system of accounts ESA 2010, Luxembourg, https://doi.org/10.2785/16644, 2013.

Eurostat: Database, http://ec.europa.eu/eurostat/data/database, 2019a.

Eurostat: GISCO: geographical information and maps, http://ec.europa.eu/eurostat/web/gisco/overview, 2019b.

Eurostat and OECD: Report on Survey of National Practices in Estimating Net Stocks of Structures, Tech. rep., Eurostat/OECD, https://ec.europa.eu/eurostat/documents/24987/4253483/Eurostat-OECD-survey-of-national-practices-estimating-net-stocks-structures.pdf, 2014.

Feyen, L., Dankers, R., Bódis, K., Salamon, P., and Barredo, J. I.: Fluvial flood risk in Europe in present and future climates, Climatic Change, 112, 47–62, https://doi.org/10.1007/s10584-011-0339-7, 2012.

FFSA/GEMA: La tempête Xynthia du 28 février 2010 – Bilan chiffré au 31 décembre 2010, https://www.mrn.asso.fr/wp-content/uploads/2018/01/2010-bilan-tempete-xynthia-2010-ffsa-gema.pdf, 2011.

Figueiredo, R. and Martina, M.: Using open building data in the development of exposure data sets for catastrophe risk modelling, Natural Hazards and Earth System Sciences, 16, 417–429, https://doi.org/10.5194/nhess-16-417-2016, 2016.

Fuchs, S., Keiler, M., and Zischg, A.: A spatiotemporal multi-hazard exposure assessment based on property data, Natural Hazards and Earth System Sciences, 15, 2127–2142, https://doi.org/10.5194/nhess-15-2127-2015, 2015.

Gerl, T., Kreibich, H., Franco, G., Marechal, D., and Schröter, K.: A Review of Flood Loss Models as Basis for Harmonization and Benchmarking, PLOS ONE, 11, e0159 791, https://doi.org/10.1371/journal.pone.0159791, 2016.

Goldsmith, R. W.: Comparative National Balance Sheets: A Study of Twenty Countries, 1688-1978, University of Chicago Press, Chicago, 1985.

Hanea, A., Morales Nápoles, O., and Dan Ababei, D.: Non-parametric Bayesian networks: Improving theory and reviewing applications, Reliability Engineering & System Safety, 144, 265–284, https://doi.org/10.1016/j.ress.2015.07.027, 2015.

Hanea, A. M., Kurowicka, D., and Cooke, R. M.: Hybrid Method for Quantifying and Analyzing Bayesian Belief Nets, Quality and Reliability Engineering International, 22, 709–729, https://doi.org/10.1002/qre.808, 2006.

Huizinga, J.: Flood damage functions for EU member states, Technical Report PR1278.10, HKV Consultants, 2007.

Huizinga, J., de Moel, H., and Szewczyk, W.: Global flood depth-damage functions. Methodology and the database with guidelines, Technical Report EUR 28552 EN, European Commission - Joint Research Centre, https://doi.org/10.2760/16510, 2017.

Jalava, J. and Kavonius, I. K.: Measuring the stock of consumer durables and its implications for euro area savings ratios, Review of Income and Wealth, 55, 43–56, https://doi.org/10.1111/j.1475-4991.2008.00304.x, 2009.

Kleist, L., Thieken, A. H., Köhler, P., Müller, M., Seifert, I., Borst, D., and Werner, U.: Estimation of the regional stock of residential buildings as a basis for a comparative risk assessment in Germany, Natural Hazards and Earth System Sciences, 6, 541–552, https://doi.org/10.5194/nhess-6-541-2006, 2006.

Kreibich, H., Botto, A., Merz, B., and Schröter, K.: Probabilistic, Multivariable Flood Loss Modeling on the Mesoscale with BT-FLEMO, Risk Analysis, 37, 774–787, https://doi.org/10.1111/risa.12650, 2017.

McAneney, J., Sandercock, B., Crompton, R., Mortlock, T., Musulin, R., Pielke, R., and Gissing, A.: Normalised insurance losses from Australian natural disasters: 1966–2017, Environmental Hazards, pp. 1–20, https://doi.org/10.1080/17477891.2019.1609406, 2019.

Merz, B., Kreibich, H., Schwarze, R., and Thieken, A.: Review article "Assessment of economic flood damage", Natural Hazards and Earth System Sciences, 10, 1697–1724, https://doi.org/10.5194/nhess-10-1697-2010, 2010.

Merz, B., Kreibich, H., and Lall, U.: Multi-variate flood damage assessment: a tree-based data-mining approach, Natural Hazards and Earth System Sciences, 13, 53–64, https://doi.org/10.5194/nhess-13-53-2013, 2013.

Moriasi, D., Arnold, J., van Liew, M., Binger, R., Harmel, R., and Veith, T.: Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, Transactions of the ASABE, 50, 885–900, https://swat.tamu.edu/media/1312/moriasimodeleval.pdf, 2007.

National Bank of Belgium: Computing capital stock in the Belgian national accounts according to the ESA 2010, https://www.nbb.be/doc/dq/e_method/m_sec2010d2_en.pdf, 2014.

OECD: Measuring Capital - OECD Manual 2009, OECD, Paris, second edn., 2009.

OECD: OECD Data, https://data.oecd.org/, 2019.

OpenStreetMap: OpenStreetMap, https://www.openstreetmap.org/, 2019.

OpenStreetMap Wiki: Overpass API, https://wiki.openstreetmap.org/wiki/Overpass_API, 2019.

Ozcebe, S., Crowley, H., Baker, H., Spence, R., and Foulser-Piggott, R.: D7.5: Census data collection and harmonisation for Europe, Deliverable 7.5, NERA Project, https://www.orfeus-eu.org/other/projects/nera/NERA_D7.5.pdf, 2014.

Paprotny, D. and Terefenko, P.: New estimates of potential impacts of sea level rise and coastal floods in Poland, Natural Hazards, 85, 1249–1277, https://doi.org/10.1007/s11069-016-2619-z, 2017.

Paprotny, D., Morales Nápoles, O., and Jonkman, S. N.: HANZE: a pan-European database of exposure to natural hazards and damaging historical floods since 1870, Earth System Science Data, 10, 565–581, https://doi.org/10.5194/essd-10-565-2018, 2018a.

Paprotny, D., Sebastian, A., Morales Nápoles, O., and Jonkman, S. N.: Trends in flood losses in Europe over the past 150 years, Nature Communications, 9, 1985, https://doi.org/10.1038/s41467-018-04253-1, 2018b.

Penning-Rowsell, E., P. S. P. D. M. J. T. S. V. C. C. J. O. D.: Flood and Coastal Erosion Risk Management: a Manual for Economic Appraisal, Routledge, London, 2013.

Pielke, R. A. and Downton, M. W.: Precipitation and Damaging Floods: Trends in the United States, 1932–97, Journal of Climate, 13, 3625–3637, https://doi.org/10.1175/1520-0442(2000)013<3625:padfti>2.0.co;2, 2000.

Piketty, T. and Zucman, G.: Capital is Back: Wealth-Income Ratios in Rich Countries 1700–2010, The Quarterly Journal of Economics, 129, 1255–1310, https://doi.org/10.1093/qje/qju018, 2014.

Röthlisberger, V., Zischg, A. P., and Keiler, M.: A comparison of building value models for flood risk analysis, Natural Hazards and Earth System Sciences, 18, 2431–2453, https://doi.org/10.5194/nhess-18-2431-2018, 2018.

Rudolf, B. and Zurlinden, M.: Measuring Capital Stocks and Capital Services in Switzerland, Swiss Journal of Economics and Statistics, 145, 61–105, https://doi.org/10.1007/bf03399275, 2009.

Rözer, V., Müller, M., Bubeck, P., Kienzler, S., Thieken, A., Pech, I., Schröter, K., Buchholz, O., and Kreibich, H.: Coping with Pluvial Floods by Private Households, Water, 8, 304, https://doi.org/10.3390/w8070304, 2016.

Schmalwasser, O., Müller, A., and Weber, N.: Gebrauchsvermögen privater Haushalte in Deutschland, Wirtschaft und Statistik, 2011, 565–578, 2011.

Schorlemmer, D., B. T. H. N. H. K. W. M. C. F. P. K.: Global Dynamic Exposure and the OpenBuildingMap - Communicating Risk and Involving Communities, Geophysical Research Abstracts, 19, 7060, 2017.

Schröter, K., Lüdtke, S., Redweik, R., Meier, J., Bochow, M., Ross, L., Nagel, C., and Kreibich, H.: Flood loss estimation using 3D city models and remote sensing data, Environmental Modelling & Software, 105, 118–131, https://doi.org/10.1016/j.envsoft.2018.03.032, 2018.

Silva, V., Crowley, H., Varum, H., and Pinho, R.: Seismic risk assessment for mainland Portugal, Bulletin of Earthquake Engineering, 13, 429–457, https://doi.org/10.1007/s10518-014-9630-0, 2015.

Spekkers, M., Rözer, V., Thieken, A., ten Veldhuis, M.-C., and Kreibich, H.: A comparative survey of the impacts of extreme rainfall in two international case studies, Natural Hazards and Earth System Sciences, 17, 1337–1355, https://doi.org/10.5194/nhess-17-1337-2017, 2017.

Statistics Poland: Statistics Poland, https://stat.gov.pl/, 2019.

Thieken, A., Kreibich, H., Müller, M., and Lamond, J.: Data Collection for a Better Understanding of What Causes Flood Damage-Experiences with Telephone Surveys, in: Flood damage survey and assessment: New insights from research and practice, edited by Molinari, D., Menoni, S., and Ballio, F., chap. 7, pp. 95–106, John Wiley & Sons, Inc., https://doi.org/10.1002/9781119217930.ch7, 2017.

Thieken, A. H., Müller, M., Kreibich, H., and Merz, B.: Flood damage and influencing factors: New insights from the August 2002 flood in Germany, Water Resources Research, 41, https://doi.org/10.1029/2005wr004177, 2005.

Thieken, A. H., Müller, M., Kleist, L., Seifert, I., Borst, D., and Werner, U.: Regionalisation of asset values for risk analyses, Natural Hazards and Earth System Sciences, 6, 167–178, https://doi.org/10.5194/nhess-6-167-2006, 2006.

Totschnig, R., Sedlacek, W., and Fuchs, S.: A quantitative vulnerability function for fluvial sediment transport, Natural Hazards, 58, 681–703, https://doi.org/10.1007/s11069-010-9623-5, 2011.

United Nations: National Accounts - Analysis of Main Aggregates, https://unstats.un.org/unsd/snaama/, 2018.

U.S. Department of Commerce. Bureau of Economic Analysis: Fixed Assets and Consumer Durable Goods in the United States, 1925–99, Tech. rep., U.S. Government Printing Office, Washington, DC, 2003.

Wagenaar, D., de Jong, J., and Bouwer, L. M.: Multi-variable flood damage modelling with limited data using supervised learning approaches, Natural Hazards and Earth System Sciences, 17, 1683–1696, https://doi.org/10.5194/nhess-17-1683-2017, 2017.

Wagenaar, D., Lüdtke, S., Schröter, K., Bouwer, L. M., and Kreibich, H.: Regional and Temporal Transferability of Multivariable Flood Damage Models, Water Resources Research, 54, 3688–3703, https://doi.org/10.1029/2017wr022233, 2018.

Weinkle, J., Landsea, C., Collins, D., Musulin, R., Crompton, R. P., Klotzbach, P. J., and Pielke, R.: Normalized hurricane damage in the continental United States 1900–2017, Nature Sustainability, 1, 808–813, https://doi.org/10.1038/s41893-018-0165-2, 2018.

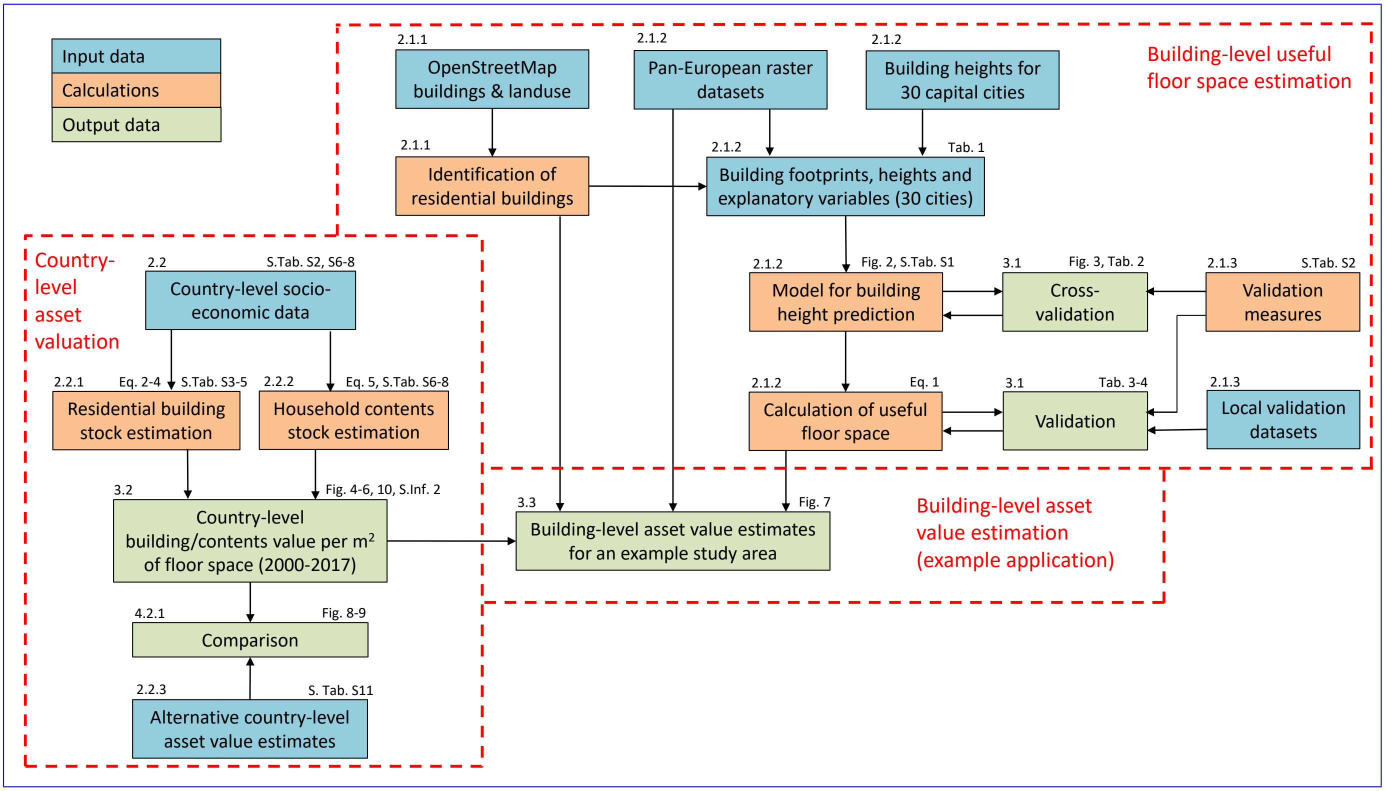

Figure 1. Workflow of the study. Boxes are coloured according to categories explained in the legend. In the top-left corners of the boxes are references to relevant sections of this paper. In the top-right corners of the boxes are references to figures, tables, supplementary tables (S.Tab.) in Supplementary Information 1, equations and Supplementary Information 2 (S.Inf. 2).

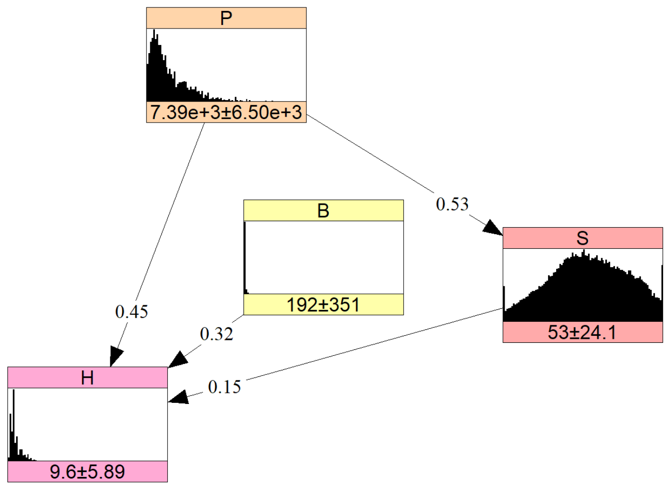

Figure 2. A Bayesian Network for predicting residential building height. Values on the arcs represent the (conditional) rank correlation; values under the histograms are the mean and standard deviation of the marginal distributions. ~~H~~ *H* – building height [m], ~~POP~~ *P* – population density [persons/km2], ~~IMD~~ *S* – soil sealing [%], ~~B~~ *B* – building footprint area [m2]. Graph generated using Uninet software (Hanea et al., 2015).

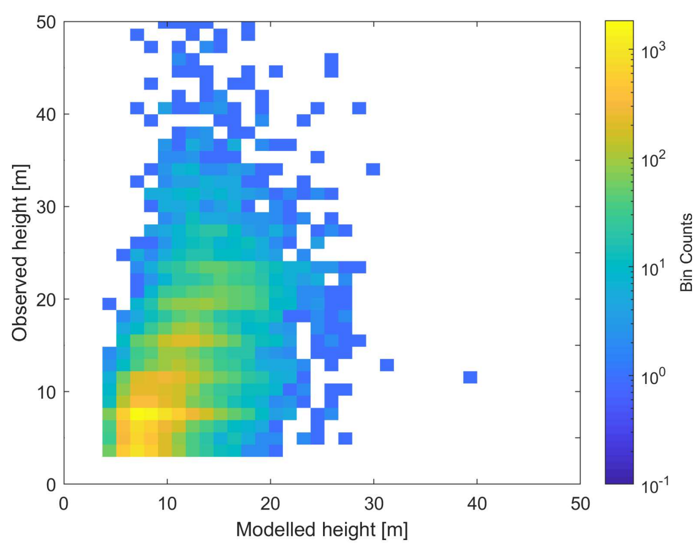

Figure 3. Binned scatter plot for observed and modelled heights of residential buildings for 30 European capitals, out-of-sample validation.

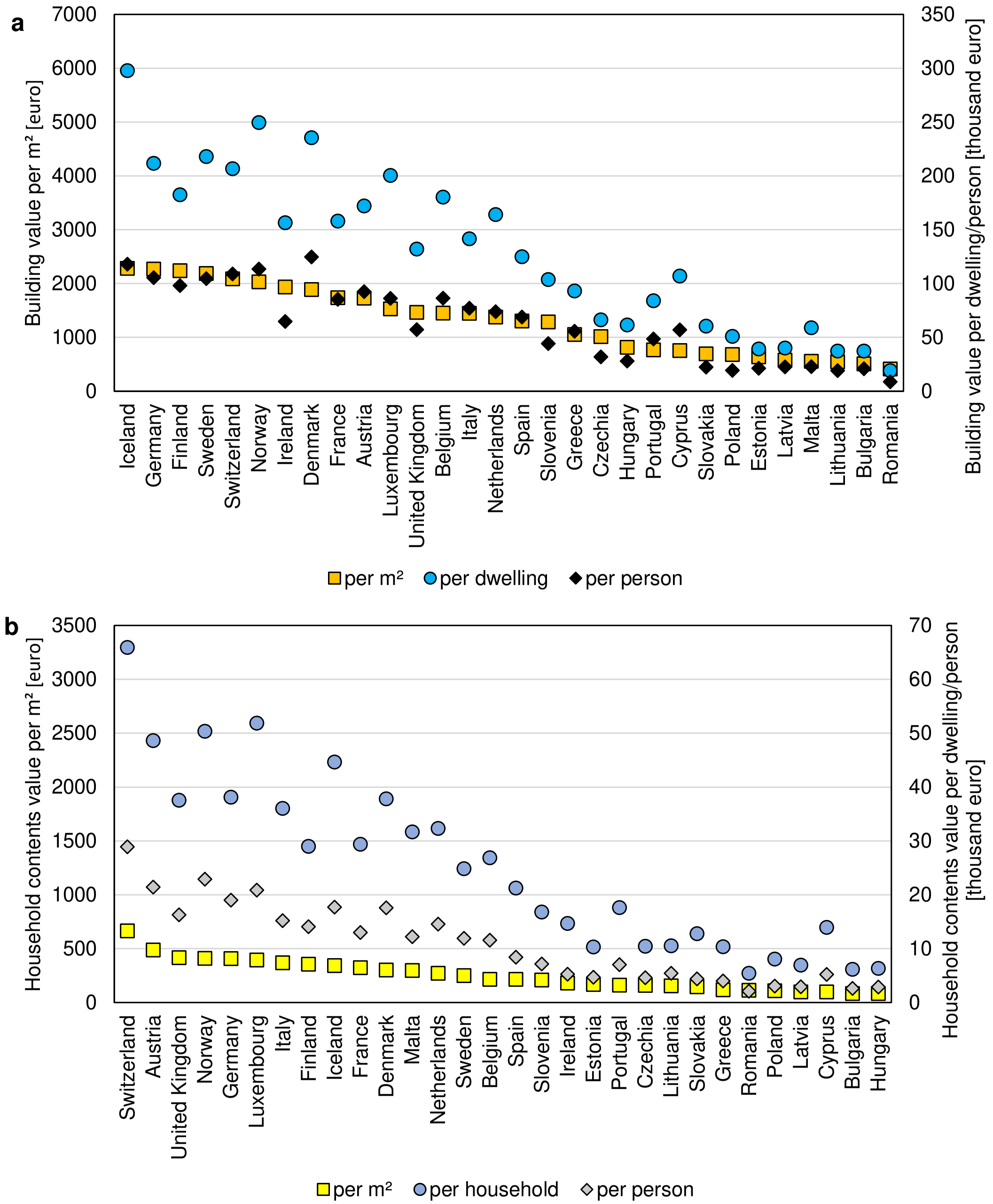

Figure 4. Value of (a) residential buildings and (b) household contents per m^2 of floor space, per dwelling/household and per person, ranked by values per m^2 of floor space, as of 2017.

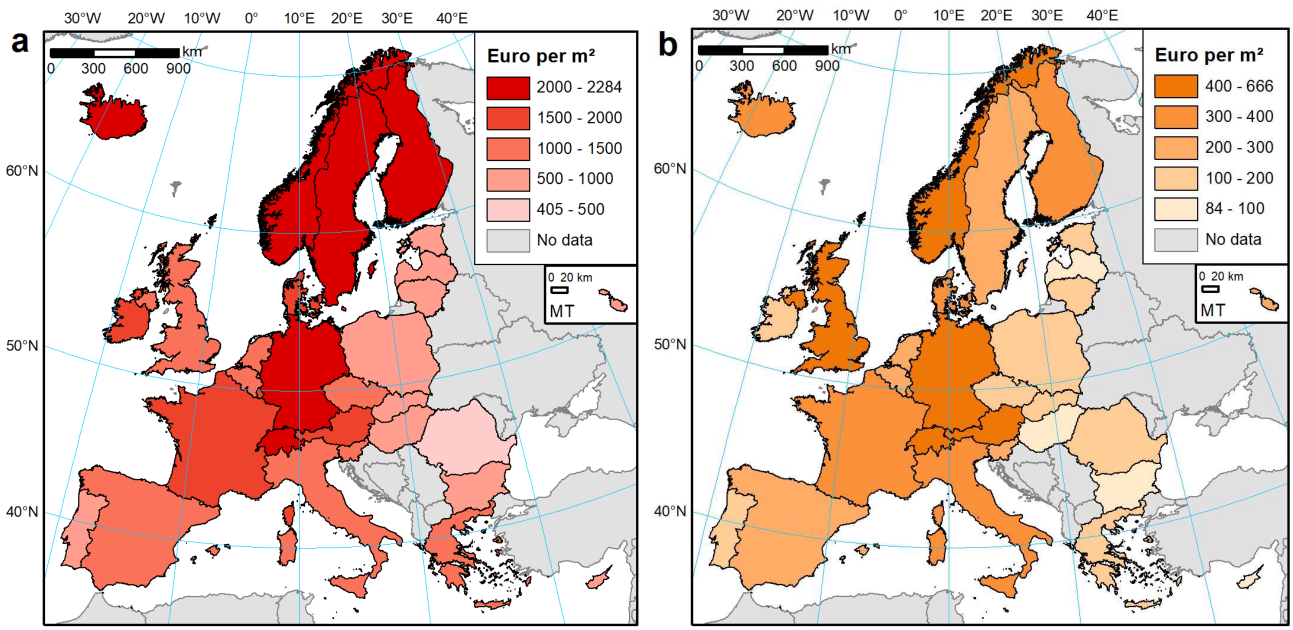

Figure 5. Value of (a) residential buildings and (b) household contents per m^2 of floor space as of 2017. Country boundaries from EuroGeographics (Eurostat, 2019b).

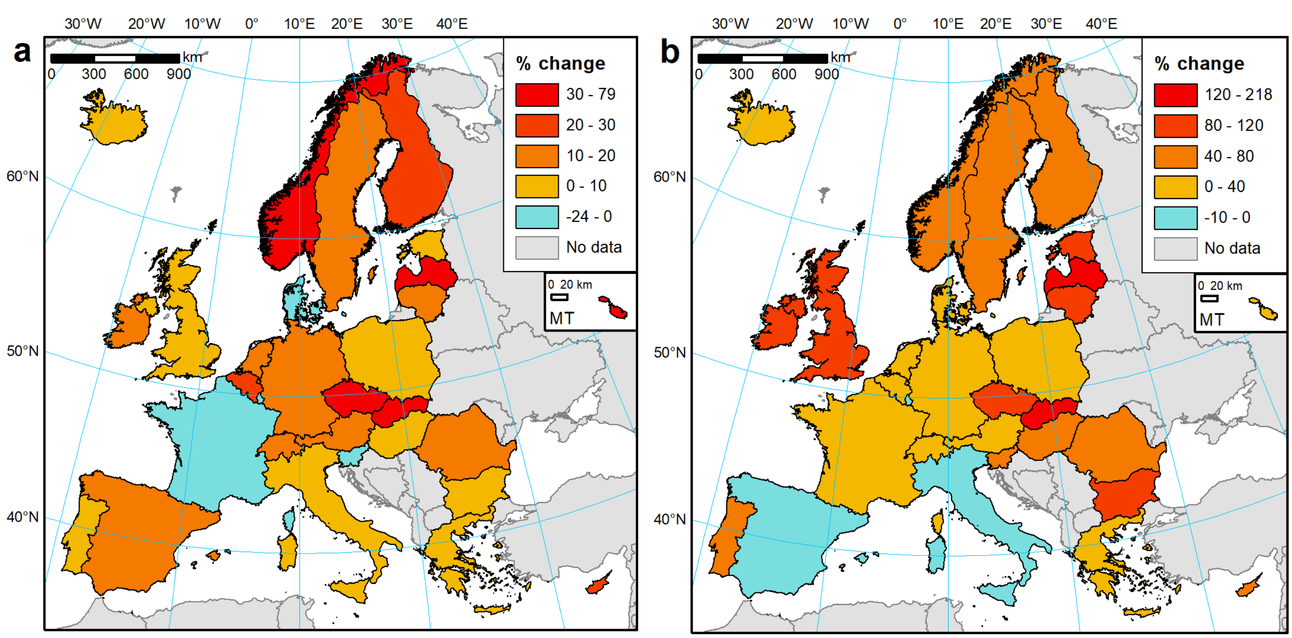

Figure 6. Change in the value of (a) residential buildings and (b) household contents per m^2 of floor space, 2000–2017, in constant prices. Country boundaries from EuroGeographics (Eurostat, 2019b).

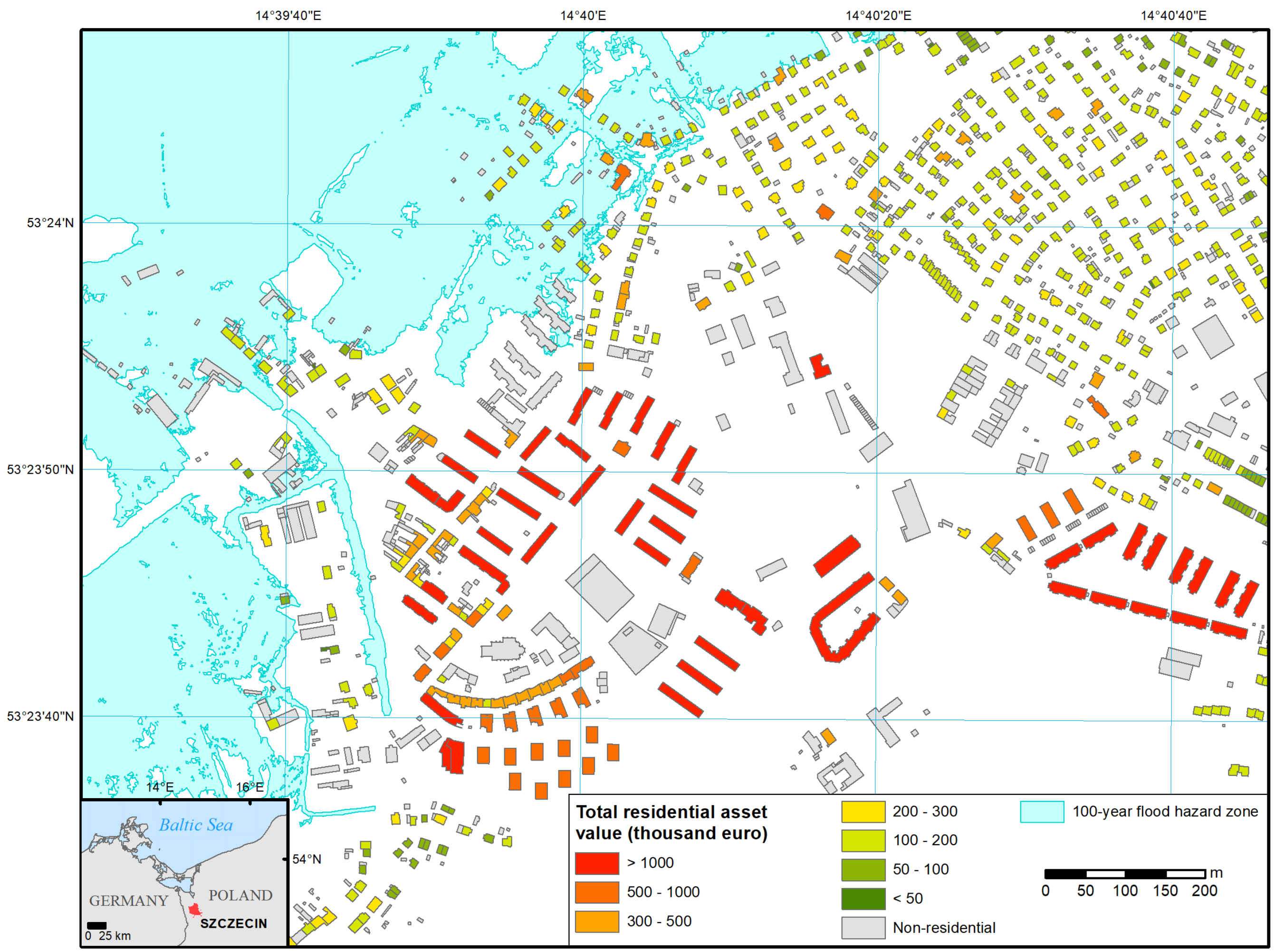

Figure 7. Estimated residential asset values in a low-lying part of the city of Szczecin, Poland. Flood hazard zone from Paprotny and Terefenko (2017). Building geometry from ©OpenStreetMap contributors 2019. Distributed under a Creative Commons BY-SA License.

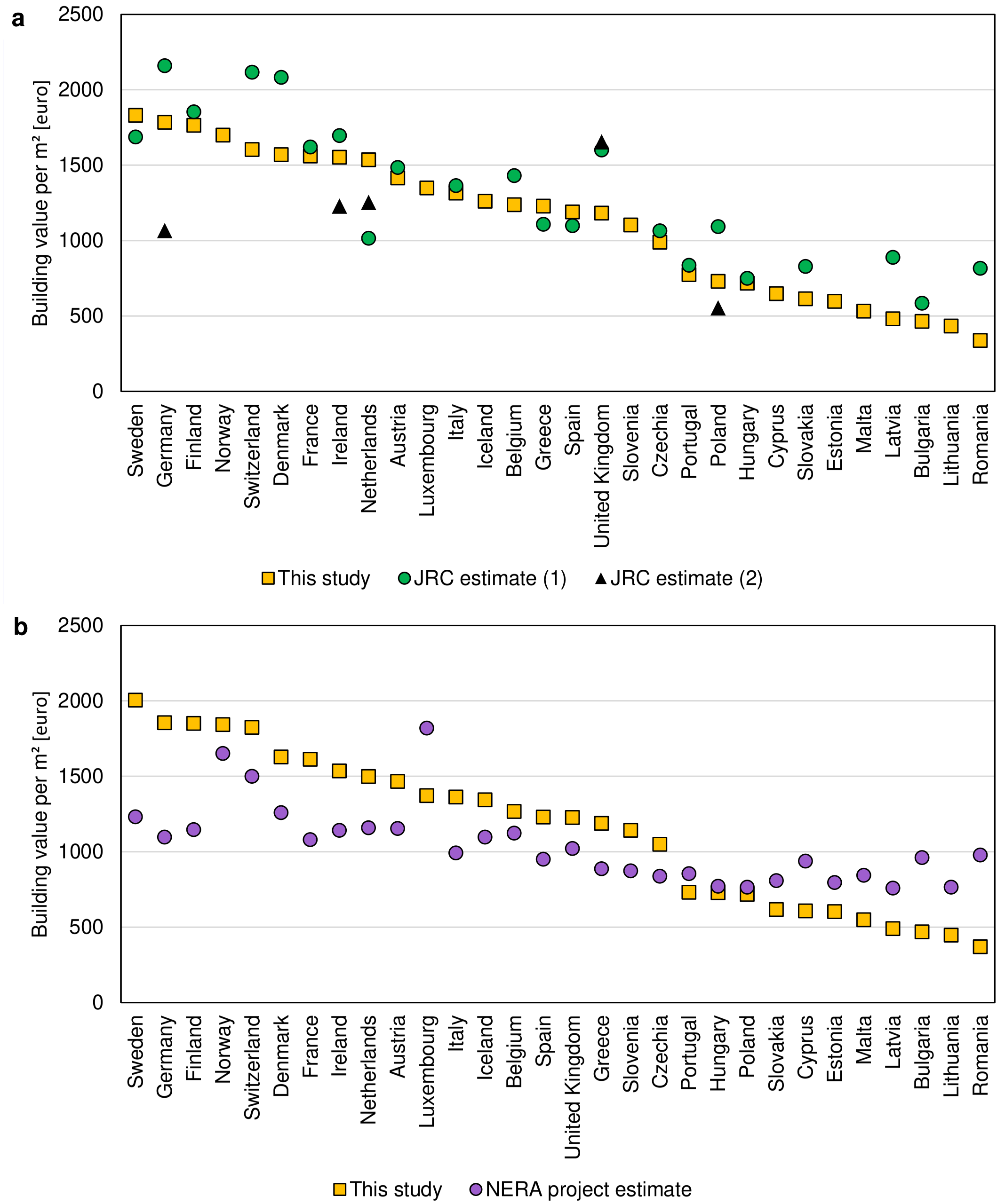

Figure 8. Comparison of residential building values per m^2 of floor space estimated in this study with (a) two estimates by the Joint Research Centre (Huizinga et al., 2017) for year 2010 and (b) estimates from NERA project (Ozcebe et al., 2014) for year 2011.

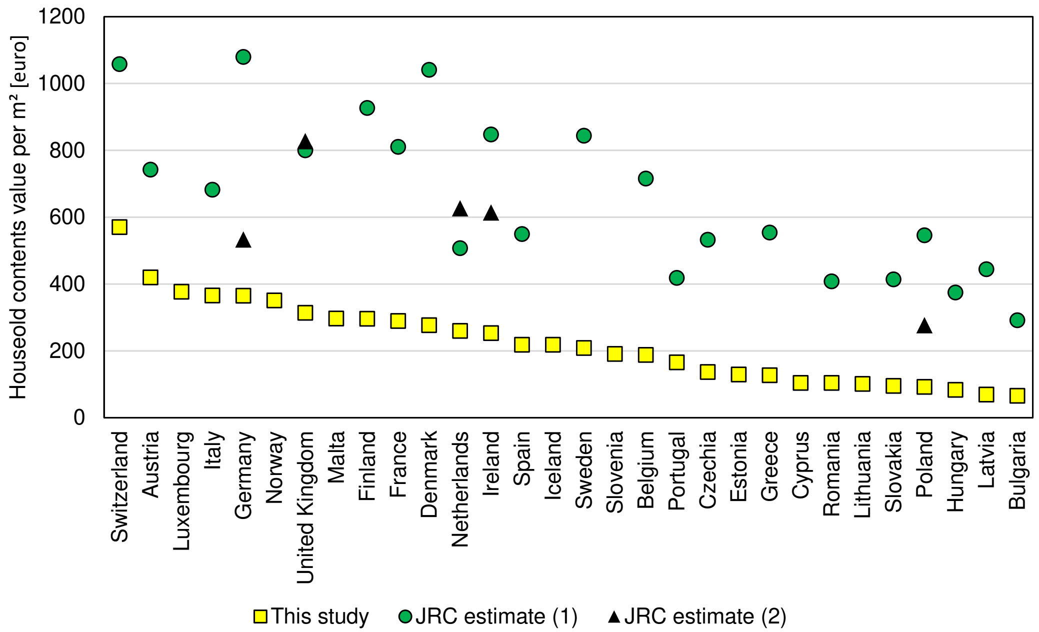

Figure 9. Comparison of household contents values per m^2 of floor space estimated for the year 2010 in this study with two estimates by the Joint Research Centre (Huizinga et al., 2017).

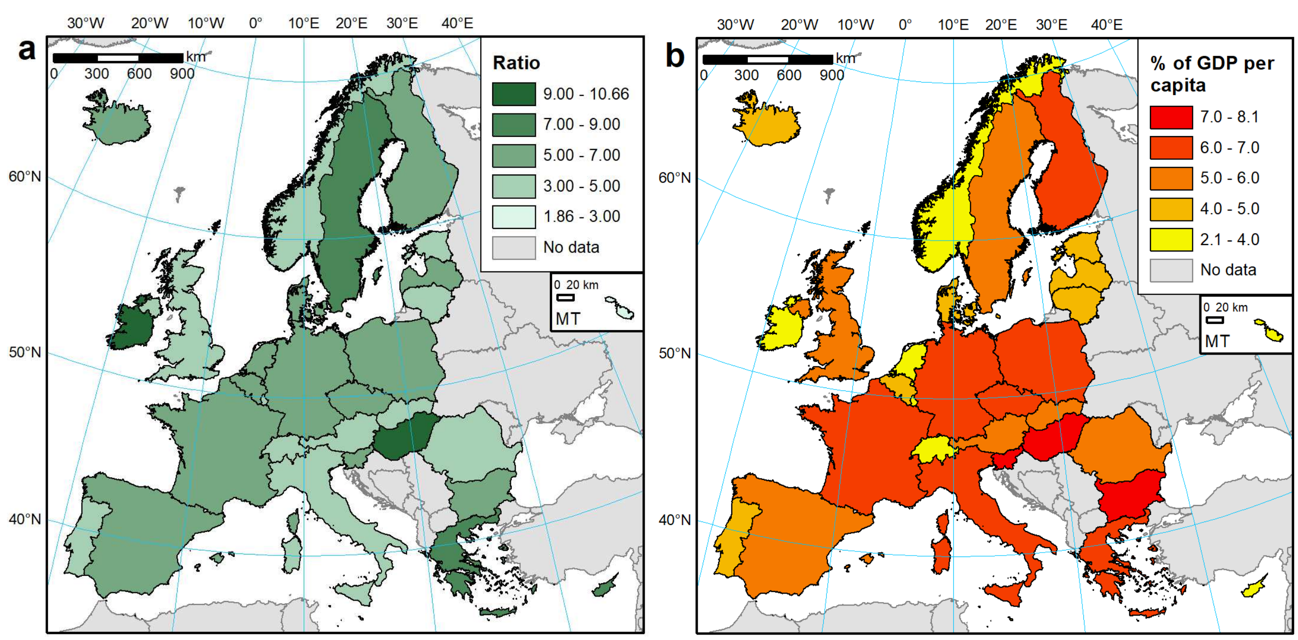

Figure 10. (a) Ratio between average building structure and household contents value per m^2, 2017; (b) Total residential assets (building and contents) as % of GDP per capita, 2017. Country boundaries from EuroGeographics (Eurostat, 2019b).

Table 1. Variables considered for the building height prediction model. Abbreviations are shown for variables included in the final model (Fig. 2).

Variable	Dataset	Source
Building height (~~H~~H) [m]	Building Height 2012	Copernicus Land Monitoring Service (2019)
Population per 1 km grid cell (2011 census) (~~POP~~P)	GEOSTAT 2011	Eurostat (2019b)
Population per 100 m grid cell (2011 census)	HANZE database	Paprotny et al. (2018a)
Population in an urban cluster (2011 census)	Urban Clusters 2011	Eurostat (2019b)
Distance from centre of an urban cluster [km]	Urban Clusters 2011	Eurostat (2019b)
Soil sealing per 100 m grid cell (~~IMD~~S) [%]	Imperviousness 2012	Copernicus Land Monitoring Service (2019)
Build-up surfaces per 100 m grid cell [%]	European Settlement Map 2012	Copernicus Land Monitoring Service (2019)
Building footprint area (~~B~~B) [m^2]	OpenStreetMap	OpenStreetMap (2019)

Table 2. Validation statistics for the building height prediction model (mean value of the uncertainty distribution) for ~~various sets~~ different cities. For all cities, the results are an average of ~~residential buildings~~results for a 10-fold cross-validation. For individual cities, the results are an out-of-sample validation (i.e. the model's sample excluded the city that was validated).

~~Dataset~~ Area	N	R^2	MAE [m]	MBE [m]	SMAPE	R
~~Residential building heights,30 European capitals~~ All cities (cross-validation)	23,736	0.35	3.25	0.09	0.17	
Amsterdam	24,~~212~~ 506	0.31	2.50	-0.17	0.15	
Athens	18,177	0.25	4.38	-1.70	0.16	
Berlin	25,526	0.49	3.65	-1.29	0.18	
Bratislava	926	0.42	6.81	-4.61	0.30	
Brussels	19,845	0.12	3.77	-1.00	0.17	
Bucharest	1695	0.36	~~3.24 m~~ 6.01	~~0.08 m~~ 1.00	0.28	
Budapest	1963	0.37	4.14	-1.72	0.19	
Copenhagen	10,747	0.24	2.55	2.00	0.17	~~9.5~~
Dublin	12,648	0.09	1.69	1.13	0.12	
Helsinki	8053	0.34	2.62	1.01	0.17	
Lisbon	3486	0.10	5.37	-0.60	0.20	
Ljubljana	1196	0.19	3.28	1.97	0.22	
London	22,170	0.10	3.36	2.65	0.18	
Luxembourg	582	0.19	2.26	-0.11	0.12	
Madrid	4909	0.13	6.19	-1.43	0.20	
Nicosia	283	0.05	3.23	-0.70	0.18	
Oslo	4750	0.45	2.76	1.68	0.18	
Paris	23,441	0.23	3.03	0.99	0.16	
Prague	6802	0.47	3.92	-1.86	0.19	
Reykjavik	2364	0.05	2.99	2.05	0.22	
Riga	1423	0.29	4.31	-1.57	0.21	
Rome	5397	0.36	3.97	-1.69	0.16	
Sofia	4127	0.39	4.35	-0.56	0.21	
Stockholm	8748	0.25	2.23	0.62	0.16	
Tallinn	1386	0.39	3.48	0.58	0.21	
Valletta	123	0.13	4.32	0.24	0.18	
Vienna	8690	0.50	2.89	-0.11	0.16	
Vilnius	757	0.42	2.79	-0.91	0.17	
Warsaw	7662	0.24	3.05	-0.14	0.17	
Zagreb	4979	0.17	2.58	0.31	0.16	

Table 3. Validation statistics for the building height prediction model (mean value of the uncertainty distribution) for various sets of residential buildings.

Dataset	N	R^2	MAE	MBE	SMAPE	RM
Number of floors in residential buildings, Polish ~~coastal zone~~ coast	62,580	0.33	~~0.64~~ 0.65	~~-0.07~~ -0.06	0.16	1
of which: houses with 1 flat	54,410	0.13	~~0.57~~ 0.58	-0.10	0.16	0
houses with 2 flats	1145	~~0.05~~ 0.04	~~0.62~~ 0.64	~~-0.05~~ -0.04	0.16	0
houses with 3 or more flats	7025	~~0.17~~ 0.16	~~1.19~~ 1.24	~~0.12~~ 0.18	0.16	1
Floor space area, detached houses, Meuse flood 1993	3043	~~0.42~~ 0.41	~~53.8~~54.0 m^2	-17.3 m^2	0.18	~~159~~83.5
Floor space area, all houses, German floods 2002–2014	~~2330~~ 2868	~~0.34~~ 0.33	~~122~~119 m^2	~~32.3~~32.9 m^2	0.26	~~219~~206
of which: detached houses	~~1351~~ 1556	0.15	~~92.1~~94.5 m^2	~~31.1~~34.4 m^2	~~0.33~~ 0.26	~~167~~138
semi-detached houses	~~443~~ 662	0.20	~~112~~100 m^2	~~50.0~~43.2 m^2	~~0.26~~ 0.25	~~193~~147
multi-family houses	~~536~~ 647	~~0.31~~ 0.30	~~207~~196 m^2	~~20.5~~19.3 m^2	0.26	~~382~~346

Table 4. Hit rate of predictions of the number of floors for Polish residential buildings at risk of sea level rise and coastal floods.

% of predicted floors per observed floor class		Predicted number of floors							
		1	2	3	4	5	6	7+	Total
Observed number of floors	1	**~~69.5~~69.8**	~~25.3~~ 24.9	~~3.9~~ 4.1	~~1.0~~ 1.1	0.2	~~0.0~~ 0.1	0.0	100.0
	2	~~38.7~~ 39.4	**~~42.9~~41.7**	~~14.5~~ 14.7	~~3.2~~ 3.4	0.6	0.1	0.0	100.0
	3	~~10.1~~ 10.2	~~48.8~~ 47.7	**~~25.1~~25.4**	~~9.6~~ 9.7	~~5.1~~ 5.2	~~1.2~~ 1.3	~~0.2~~ 0.4	100.0
	4	~~1.9~~ 2.1	~~18.2~~ 17.6	~~25.0~~ 24.5	**~~24.8~~24.2**	~~18.1~~ 17.5	~~8.1~~ 8.6	~~3.9~~ 5.4	100.0
	5	0.2	~~5.5~~ 5.9	~~14.7~~ 14.0	~~29.5~~ 27.3	**~~26.3~~25.7**	~~14.9~~ 15.6	~~8.8~~ 11.3	100.0
	6	0.9	5.4	~~8.0~~ 7.1	~~18.8~~ 17.9	~~30.4~~ 33.9	**~~24.1~~19.6**	~~12.5~~ 15.2	100.0
	7+	0.0	0.4	11.3	~~22.5~~ 22.1	~~31.3~~ 29.6	~~20.4~~ 20.0	**~~14.2~~16.7**	100.0