https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

Building-level exposed asset value modelling for Germany

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Abstract

This study addresses the challenges of exposure modelling at the building or object-level in Germany, motivated by the need for harmonized, open-access data in next generation risk assessments. While aggregated exposure data suffice for many applications, detailed object-level data are increasingly essential for tasks such as local risk management and impact forecasting. However, this object-level information is often proprietary, protected by regulation, poorly documented, and fragmented because data on building usage, structural type, or replacement costs is often not readily available or not compiled in one dataset. To address this gap, we present an evaluation of potential exposure modelling frameworks utilizing various disaggregation approaches and source data from cadastre-derived, crowd-sourced, national accounts, and fit-for-purpose datasets. Using information collected from an area recently affected by a flood disaster and a weighted scoring model, we evaluate the ability of candidates to assign a building's economic sector and asset value against our hand-labelled benchmark dataset. Ultimately, we find an exposure modelling framework disaggregating national-accounts onto cadastre-derived building footprints slightly out-performs other candidates owing mainly to its transparency and adaptability. However, we conclude that all but the land-use derived candidate are defensible exposure modelling frameworks — so long as some relevant validation is performed. The frameworks presented here enable the transparent, reproducible, and maintainable multi-sector object-level exposure modelling necessary for the next generation of risk analysis and impact forecasting.

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1 Introduction

Natural hazards have impacted billions of people globally over recent decades. To mitigate these impacts, communities and governments rely on risk models which provide critical information for risk management [Messner, 2007,

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

Merz and Thieken, 2004]. These models typically conceptualize risk as arising from the interaction of three components: hazard, vulnerability, and exposure [Crichton, 1999]. In this context, exposure refers to the assets at risk from natural hazards, such as buildings, goods, infrastructure, and other elements of value [Merz et al., 2010, Wieland et al., 2015]. Impact forecasting, which predicts the spatially explicit consequences of an imminent event (e.g., the number and location of affected people and buildings, expected damage, or disruption of services), requires detailed exposure and vulnerability information to translate hazards into impacts, thereby motivating object-level (building-scale) exposure models [Apel et al., 2022]. Exposure modelling aims to identify and quantify these assets, focusing on variables related to natural hazards risk like building size, construction type, construction materials, and asset monetary value [Paprotny et al., 2021, Gerl et al., 2016]. The selection of exposure variables is generally driven by the modelling objectives and availability, underscoring the importance of tailored approaches to risk assessment and impact forecasting.

Empirical studies consistently identify *asset monetary value* as a key predictor of flood losses [Gerl et al., 2016]. This asset value is usually expressed as replacement cost (RC) or depreciated cost (DC). RC denotes the expense of rebuilding with new materials, whereas DC captures age-related depreciation. The perpetual inventory method is commonly used to calculate DC by taking a historic estimate of the building stock (e.g., by federal state in 1946) and adjusting it annually for new construction, demolition, and other flows to arrive at a net asset value (NAV) [Schmalwasser and Schidlowski, 2006]. However, there is no universally agreed framework for these categories, and definitions and methods vary between jurisdictions (see Sect. S1). Loss modelling has therefore applied RC to estimate the total economic exposure or reconstruction and DC to approximate owners' financial losses for insurance compensation [Daniell, 2014]. Other categories such as market value (the price at which a building can be traded in the marketplace) and insured value (the value assigned to a building for the purpose of insurance) appear less often in natural hazard studies [Merz et al., 2010, Gerl et al., 2016]. Other variables of importance include building volume, often determined by multiplying footprint area (ground contact area) by height, gross floor area (total area of all storeys, excluding the roof), and usable floor area (space available for use, excluding walls) [Zschiesche, 2021].

Traditional hazard exposure models often rely on aggregated approaches, resolving exposed assets at coarse spatial scales such as community, block-level, or grid-based [Hall et al., 2005, Sairam et al., 2021]. These aggregated approaches have been useful in large-scale analysis, but may not provide the accuracy required to support local risk management [Röthlisberger et al., 2018, Bryant et al., 2023, Sieg and Thieken, 2022]. Drawing on local case studies, Wünsch et al. [2009] and Molinari and Scorzini [2017] show that, although the procedure for estimating exposed assets influences modelled losses, the spatial resolution of the asset data has an even greater influence.

In contrast to aggregated approaches, object-level exposure modelling evaluates individual assets explicitly, such as the value of single buildings, offering finer granularity or resolution and potentially greater accuracy in damage assessments [Röthlisberger et al., 2018]. The potential for this higher resolution to improve accuracy in loss modelling is a function of the spatial variability or spatial correlations of the hazards and vulnerabilities considered. For example, flood intensities and vulnerability characteristics (e.g., building height) can vary over short distances (e.g., between buildings and streets), making flood exposure models particularly sensitive to resolution [Thieken et al., 2006, Bryant et al., 2025, 2023]. Similarly, tsunami inundation intensities exhibit short spatial correlation lengths, whereas seismic ground motion remains strongly correlated over much larger distances [Gomez-Zapata et al., 2021]. Consequently, building-level exposure is considered more important for tsunami loss models, while sub-kilometre-scale resolution may be more reasonable for earthquake loss models [Dabbeek et al., 2021].

The major challenge facing object-level exposure modelling is that available data, like census information aggregated to administrative units, is often coarse and poorly aligned with hazard data. To address this spatial mismatch, regional statistics can be disaggregated into finer spatial units using ancillary data like land use, population, or nighttime lights [Wu et al., 2018, Gómez Zapata et al., 2022]. These methods have been applied at local [Custer and Nishijima, 2018, Figueiredo and Martina, 2016, Sieg and Thieken, 2022, Wu et al., 2019], regional [Wünsch et al., 2009], national [Kleist et al., 2006, Röthlisberger et al., 2018, Thieken et al., 2006, Wu et al., 2018], and continental scales [Paprotny et al., 2020b,a, Paprotny and Mengel, 2023, Dabbeek et al., 2021]. For example, Figueiredo and Martina [2016] utilized open building data and census data to disaggregated residential floor area onto a 50 m

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

gridded exposure model to show that coarse exposure models over-estimate. Similarly, Bryant et al. [2025] used a global flood model to demonstrate the influence of aggregating exposed assets in loss models, showing how typically concave non-linear flood damage functions lead aggregated models to over-estimate.

Many asset-scale exposure models treat building geometry (i.e., floor area or building volume) as a final multiplier, applied transparently to scale a unit cost (e.g., €/m^2 or €/m^3) to obtain asset value (€). For example, Paprotny et al. [2020b] disaggregated national gross fixed asset values of dwellings for 22 EU countries to derive national €/m^2 averages from floor area estimates. Similarly, using public census data, expert knowledge, and engineering manuals, the European Seismic Risk Model 2020 (ESRM20) provides an open-source continental-scale exposure model that estimates occupancy types and typical per-asset replacement costs from country-wide unit costs (€/m^2) (see Table S8) [Crowley et al., 2021]. Building on the ESRM20 exposure model, Nievas et al. [2023] developed EHRE, a high-resolution exposure model for Europe that assigns probabilistic ESRM20 building classes to OpenStreetMap (OSM) [OpenStreetMap contributors, 2017] building footprints, while retaining the ESRM20 per-building replacement costs.

Despite recent advancements in disaggregation and exposure modelling, few attempts at validation or comparison have been published [Röthlisberger et al., 2018, Sieg et al., 2023, Sieg and Thieken, 2022, Thieken et al., 2006, Wünsch et al., 2009]. Validating against loss records, Schröter et al. [2018] compare cadastre-derived predictors against post-event survey loss models and conventional depth–damage curves to show that these predictors enable object-level loss estimates with accuracy comparable to survey-based models and substantially better than depth–damage curves. However, we are aware of no published direct comparison or validation of locally explicit building asset values. To address these gaps, our study aims to develop and compare several models for object-level exposure estimations applicable to Germany. Specifically, the objectives are to survey and identify potential data sources, design a set of candidate exposure models, and quantitatively and transparently evaluate these to identify a robust, reproducible model for multi-sector risk analysis and impact forecasting.

2 Methods

Our study first developed and processed candidate *sector classification* and *asset value* models, fundamental components of most exposure models. These candidate models were then evaluated using a hand-labelled benchmark dataset we built for our study area.

2.1 Study Area

Our study focuses on the Ahrweiler District ("Landkreis Ahrweiler") in western Germany (Figure 1). In July 2021, the region experienced a severe flood event that caused significant economic losses and fatalities [Lehmkuhl et al., 2022] (see Figure 2). Ahrweiler's history of flooding spans centuries, with over 70 floods recorded in the past 500 years [Brühl, 2025], the first one being reported in 1348 [Seel, 2025].

The service sector in Ahrweiler constitutes the most important economic sector with a share of 70.9% of the GDP; followed by manufacturing industry (27.8%); and agriculture, forestry, and fishing (1.2%) [Rheinland-Pfalz, 2025]. Land use is 53.3% forest and vegetation, 31.1% agriculture, 7.2% settlements (3.3% residential, 1.0% industrial, 1.6% recreational), 6.8% infrastructure, and the remainder water bodies and other uses [Rheinland-Pfalz, 2025]. Public records show over 40,000 residential buildings with 88.8% being detached and semi-detached houses (as of 2023) and roughly 6,000 registered companies [Rheinland-Pfalz, 2025].

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

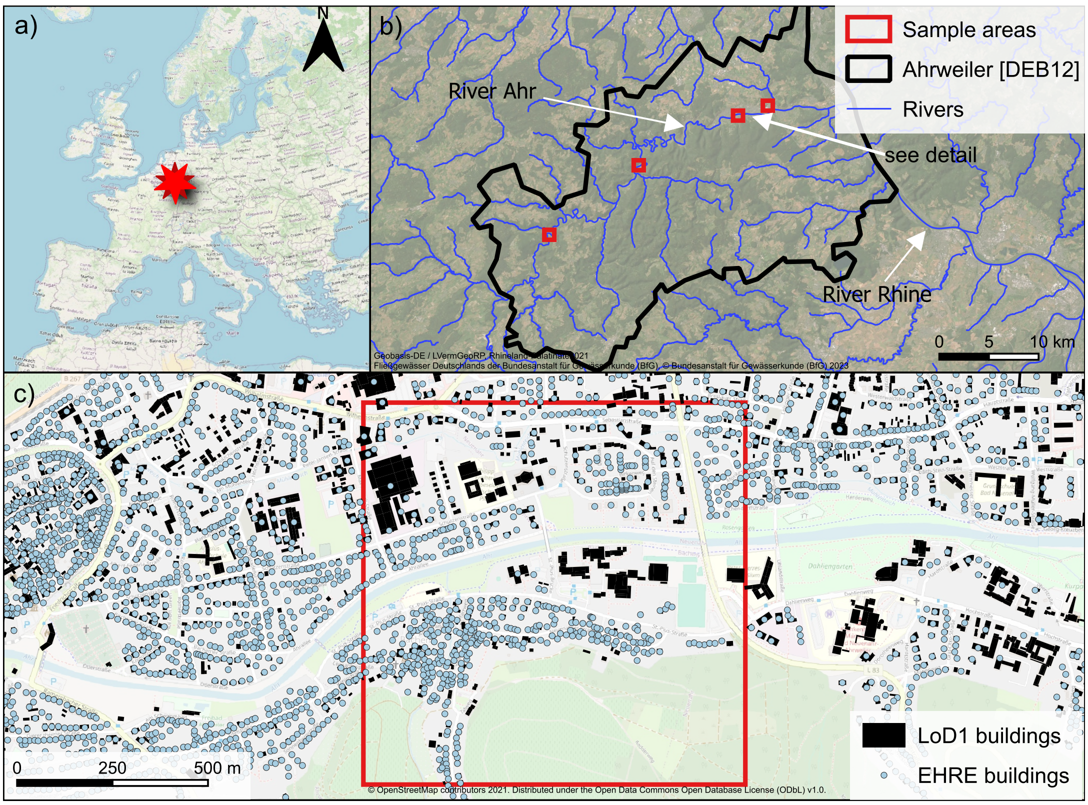

Figure 1: Study area maps showing: a) study location; b) study boundary (NUTS-3 name [and code]); and c) typical detail of village area with building locations from datasets discussed in the text. Map data from OpenStreetMap (ODbL) — openstreetmap.org/copyright.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

Figure 2: Overview of typical buildings during the 2021 floods. Image © Christian / Adobe Stock (ID: 447651476), licensed by GFZ Helmholtz Centre for Geosciences Potsdam.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

2.2 Data

To develop and process our candidate models, we first gathered freely available building-exposure and asset-value datasets, with a focus on building fixed asset values, that is, considering the structural and non-structural architectural components of the buildings, but not their movable contents/equipment. A systematic search using Google [Google, 2025a] and Google Scholar [Google, 2025b] yielded the datasets summarized in Table S2, from which we then selected those datasets listed in Table 1 for further analysis (see Sect. S2 for details). The three asset value candidate datasets considered here are the Basic European Assets Map (BEAM), the European High Resolution Exposure (EHRE) model, and data derived from the European Statistical Office (Eurostat). While the raw EHRE data is object-level and model-ready, the BEAM and Eurostat data require additional processing with ancillary data as described in the following sections.

Table 1: Summary of datasets and sources used in this study. RC: Replacement Cost, NAV: Net Asset Value, GVA: Gross Value Added, NUTS: Nomenclature of Territorial Units for Statistics.

name	spatial relation	attributes	classification	access	vintage	reference
Eurostat GVA Regional	tabular (NUTS 3)	GVA €	6 sector groups (Table S3)	free access	2018	Eurostat [2025b]
Eurostat Capital Stocks	tabular (national)	RC € for *Other buildings and structures*	10 sector groups	free access	2018	Eurostat [2025a]
Insee Capital Stocks	tabular (national)	gross fixed capital € for *Other buildings and structures* and *Buildings other than dwellings*	10 sector groups	free access	2018	Insee [2022]
Paprotny [2022]	tabular (national)	RC €/m^2 for dwellings and household contents (2000–2020)	Residential only	free access	2022	Paprotny [2022]
BEAM	polygon	DC or NAV €/m^2 (see Table 2)	sector (residential; industrial; service; agriculture)	free access	2018	Copernicus [2020]
EHRE	point and polygon	RC € (structural components)	sector (residential; commercial; and industrial)	upon request	2020	Nievas et al. [2023]
LoD1	polygon	building function (i.e., use); geometry (height and area)	34 building functions	licensed	2022	BKG [2023]
OSM	polygon	landuse types	35 landuse types	free access	2024	OpenStreetMap contributors [2017]
CORINE	polygon	landuse types	19 landuse types	free access	2018	Copernicus [2018]
NUTS-regions	polygon	n/a	n/a	free access	2023	BKG [2024]
BKI book	tabular (book)	building construction costs, regionalization factors	24 building use types	for purchase	2021	BKI [2021]

2.2.1 Datasets from the Statistical Office of the European Union (Eurostat)

The Statistical Office of the European Union (Eurostat) provides harmonized economic data across member states, making it an invaluable source for national-level asset value estimates [Eurostat, 2013]. In Germany, this data is collected by each “Länderstatistikamt” (State Statistical Office) and organized by “Statistisches Bundesamt (Destatis)” (Federal Statistical Office) who provide the data to Eurostat [Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder, 2021]. Prior to 2025, data were usually organized using the Statistical Classification of Economic Activities in the European Community (NACE Rev. 2), a hierarchical scheme distinguishing 21 level one categories or sectors [European Commission, 2008]. For example, the *Gross value added (GVA) at basic prices by NUTS3 region* table [Eurostat, 2025b] provides an estimate for the economic output minus consumption by allocating national totals to regions, using as much regional data as possible while maintaining consistency with national totals [Euro-

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Preprint. Discussion started: 13 November 2025

pean Commission. Statistical Office of the European Union, 2013]. This table provides GVA estimates per year for Nomenclature of Territorial Units for Statistics (NUTS) 3 regions (roughly 400 in Germany) for six economic sector groups (see Table S3). Providing a more refined discretization by asset types, the *Capital stocks by industry (NACE Rev.2) and detailed asset type* table [Eurostat, 2025a] estimates the value of fixed assets per year at national scale for 21 NACE (level-one) sectors. Values are provided on a gross or net basis; gross denotes the value of all fixed assets still in use valued at current replacement cost (as if new), whereas net deducts accumulated consumption of fixed capital. The table provides gross values for the asset category *Other buildings and structures* (AN.112) which is an aggregate of the categories shown in Table S4. Therefore, the published AN.112 category lump together many assets *not* of interest to exposure modelling of non-residential building assets (e.g., railways), and generally require some disaggregation (e.g., to AN.1121) if used as such [Paprotny et al., 2020a].

2.2.2 Basic European Asset Map (BEAM)

The Basic European Asset Map (BEAM) was developed by the European Commission Joint Research Centre to “estimate, evaluate and compare real and potential damages caused by natural disasters all across Europe” and provides €/m^2 asset values mapped to land use polygons for 11 asset layers using the “net concept, which reflects the depreciated construction costs (not restoration costs or insured assets)” [Copernicus, 2020]. From these 11 layers, we focus here on those related to building asset values listed in Table 2. For residential buildings, BEAM estimates depreciated construction costs (DC) by multiplying €/m^2 construction costs by a depreciation rate, before disaggregating to land use polygons with regional unit counts and density factors. In contrast, for non-residential buildings, BEAM estimates NAV by allocating national totals to NUTS 2 regions before disaggregating to land use polygons using employee counts and density factors. While the BEAM data product is freely available and their methods are (briefly) summarized in IABG mbH and geomer GmbH [2020], all factors mentioned above and the software pipeline are unpublished and proprietary.

BEAM sector	BEAM asset layer	Cost basis	BEAM group
residential	private housing: buildings & equipment	DC	settlement
industrial	industry immobile (building & equipment)	NAV	economy
service	services immobile (building & equipment)	NAV	economy
agricultural	agriculture immobile (building & equipment)	NAV	agriculture

Table 2: BEAM asset layers [Copernicus, 2020] included in our study. Note that for our analysis, asset values are multiplied by the factors shown in Table S7 to isolate the “building” portion (see text for details). DC: depreciated (construction) cost; NAV: net asset value.

2.2.3 European High Resolution Exposure (EHRE) model

The European High Resolution Exposure (EHRE) model presented in Nievas et al. [2023] is a European-wide exposure model that results from the combination of (i) the aggregated exposure model of ESRM20 [Crowley et al., 2021, 2020], (ii) data on individual buildings from OSM, processed as OpenBuildingMap (OBM) [GFZ, 2024, Schorlemmer et al., 2020], and (iii) remote sensing-derived built-up areas from the Global Human Settlement Layer (GHSL) [Corbane et al., 2018]. It represents buildings as a combination of individual OSM building footprints and, in regions where OSM is deemed incomplete, “remainder” estimates, which are represented on a ≈ 100 m grid. EHRE inherits all the occupancy cases, structural classes (GEM Building Taxonomy v3.0 [Silva et al., 2022]), number of building occupants, and replacement costs per building from the ESRM20 model. For Germany, these estimates are largely based on census data retrieved in 2011 [Crowley et al., 2020]. Individual building footprints are assigned by EHRE a series of potential structural classes and their associated probabilities. ESRM20 replacement costs (RC), referenced to 2020, are obtained by applying country- and occupancy-specific reconstruction costs (€/m^2, see Table S8), adjusted by material-dependent modifiers (0.95–1.05) which are then multiplied by the average usable floor area of each building class in a region. In EHRE, these regional values are maintained and object-distributed, not adjusting for the geometry (i.e., area) of OBM buildings. In other words, ESRM20 estimates regional exposure on administrative units (totals and averages), whereas EHRE distributes these values to the building scale by linking ESRM20 classes and costs to individual OSM footprints (and filling gaps with aggregated remainder buildings).

EHRE inherits the occupancy types of individual OSM footprints from OBM, which assigns them by: (i) retrieval of all OSM tags associated with the building, (ii) mapping of the OSM tags onto GEM Taxonomy occupancy types, and (iii) a final rule-based selection. Extracts of the EHRE model are available upon request, and the whole suite of software used to create it is publicly available and open-source (see Nievas et al. [2023] for details).

2.2.4 Ancillary datasets

The Level of Detail 1 (LoD1) dataset provided by the *Bundesamt für Kartographie und Geodäsie (BKG)* ("Federal Agency for Cartography and Geodesy") [BKG, 2023] provides information on buildings across Germany. It includes polygons of all buildings that are recorded in the *Amtliche Liegenschaftskatasterinformationssystem (ALKIS)* ("Official Real Estate Cadastre Information System") of all German federal states [AdV, 2023] as of 2022. LoD1 is cadastre-derived, drawing directly on authoritative land parcel and building records maintained by state cadastral offices, ensuring national coverage, legal consistency, and administrative validity. Information on individual building use types (called "[building] function") is given for each individual building as well as the building height. In the LoD1 dataset, roof shapes are assumed to be flat, consequently, heights of complex buildings are averaged. LoD1 building use or function is recorded by the cadastral authorities of the federal states, based on information such as building permit applications [Waldhof, 2025]. For the below analysis, geometries with non-building functions (e.g. stadiums, water tanks, bridges) were discarded.

Another source we use for building data is OpenStreetMap (OSM) [OpenStreetMap contributors, 2017], a global editable map database built and maintained by volunteers. It describes a large number of geographic features, including individual building footprints, roads and land use polygons, providing 35 land use classes in our study area. Further land use information was obtained from Coordination of Information on the Environment (CORINE) Land Cover data [Copernicus, 2018] which includes a pan-European land cover and land use inventory with 44 classes, 19 of which are found in our study area.

Benchmark construction cost information was sourced from *Baukosten Gebäude Neubau 2021* (BKI) ("Construction costs for new buildings 2021") [BKI, 2021]. BKI [2021] provides construction cost values of 75 different building use types as €/m^3 (see Table S9), based on a database of several thousand invoiced projects for new buildings collected by architectural associations in Germany. The book is available for purchase online for personal use and is intended to provide a realistic basis for reliable cost estimation of construction projects for architects, engineers, building contractors and experts.

2.3 Candidate Models

In loss modelling, the variables selected for exposure models are typically guided by vulnerability research and the availability of data. This commonly leads building-related models to include categorical dimensions such as *use*, *construction type*, and *economic sector*. These categories provide informative predictors of vulnerability behaviour (e.g., via stratified modelling) and, in the case of economic sector classification, useful dimensions for communicating results to stakeholders. In practice, sector classification (e.g., residential, industrial, service) is frequently applied deterministically to each asset by transferring labels from a related, more granular categorical source (e.g., building function or land use) with a simple lookup table or reclassification schema. While there is no standard sector classification label set for building use, common frameworks include NACE 2.0 with its 21 economic areas (see Table S3) or a more basic framework like the one employed by BEAM (Table 2). Here, we adapt or develop four candidate exposure models or workflows for assigning sector labels to building assets, the results of which are evaluated against our hand-labelled benchmark. From these, the three best performing are further developed into candidate asset value models formulated on the BEAM, Eurostat, and EHRE datasets as described below. All resulting derived datasets are provided in Buhrmann [2025b] and Buhrmann [2025a].

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

2.3.1 LoD1+Eurostat

The first workflow we consider uses the granular per-asset building function information obtained from the LoD1 dataset and a reclassification schema (Supplementary Data Table 1) to map these to the six sectors provided by Eurostat [2025b] (see Table S3).

To obtain asset-value estimates from this per-asset sector-classified layer, we adopted the method of Paprotny et al. [2020a] for non-residential and Paprotny et al. [2020b] for residential RC as shown in Fig. 3. Accordingly, to obtain an estimate per-sector of the regional RC for non-residential buildings for our year of interest from published data, Paprotny et al. [2020a] disaggregates both spatially (national to regional) and categorically (AN.112 to AN.1121). These disaggregations are achieved using simple ratios obtained from ancillary data tables:

$$RC_{r,s,y,\mathrm{AN.1121}} = RC_{n,s,y,\mathrm{AN.112}} \times \frac{GVA_{r,s,y}}{GVA_{n,s,y}} \times \frac{GFC_{n,s,y,\mathrm{AN.1121}}}{GFC_{n,s,y,\mathrm{AN.112}}} \tag{1}$$

where $RC_{r,s,y,\mathrm{AN.1121}}$ is the *Buildings other than dwellings* (AN.1121; Table S4) RC for a NUTS 3 region r in sector s for year y; $RC_{n,s,y,\mathrm{AN.112}}$ is the national gross RC for *Other buildings and structures* (AN.112) assets from Eurostat [2025a]; $GVA_{n,s,y}$ is the national and $GVA_{r,s,y}$ is the NUTS 3 regional GVA from Eurostat [2025b]; and $\mathrm{GFC}_{n,s,y,\mathrm{AN.112}}$ and $\mathrm{GFC}_{n,s,y,\mathrm{AN.1121}}$ are the gross fixed capital for *Other buildings and structures* (AN.112) and *Buildings other than dwellings* (AN.1121) respectively obtained from Insee [2022] [Paprotny, Dominik, 2025]. Values for each variable are provided per-sector group in Table S5 and S6. Within our NUTS 3 region, these values were finally distributed to individual buildings proportional to building volume (m^3), computed by multiplying LoD1 footprint area by height attributes.

For residential buildings, asset values were calculated by multiplying LoD1 footprint area by the national value of 2.478 €/m^2 taken from Paprotny [2022] who calculated this value by dividing the national gross replacement cost of the dwelling stock, derived from Eurostat national accounts and perpetual inventory method estimates from 2018, by the total residential floor area in Germany [Paprotny et al., 2020b].

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

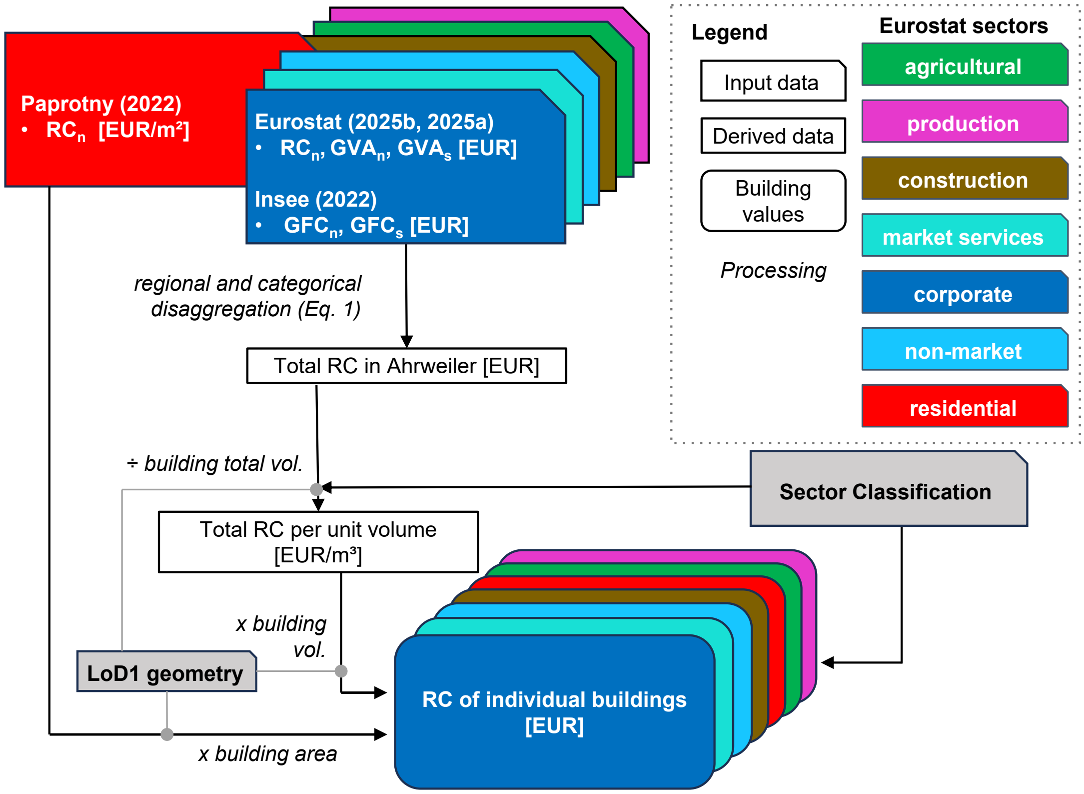

Figure 3: LoD1+Eurostat asset value model workflow adapted from Paprotny et al. [2020a,b].

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

2.3.2 LoD1+BEAM

The second workflow considered here provides a similar classification based on LoD1 function data, but uses BEAM data to disaggregate asset values. Accordingly, a separate reclassification schema was used to map the LoD1 function values to one of the four sectors: residential, industrial, service, or agriculture (Supplementary Data Table 1).

As the BEAM dataset provides a relatively coarse land use polygon scale €/m^2 asset value, we opted to back-calculate a regional aggregate €, then re-distribute this to individual buildings by volume for each sector. To subtract the equipment values included in BEAM from our building value estimate, per-sector multipliers adapted from [Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder, 2023] and shown in Table S7 were used. See Fig. 4 for a visualization of the workflow.

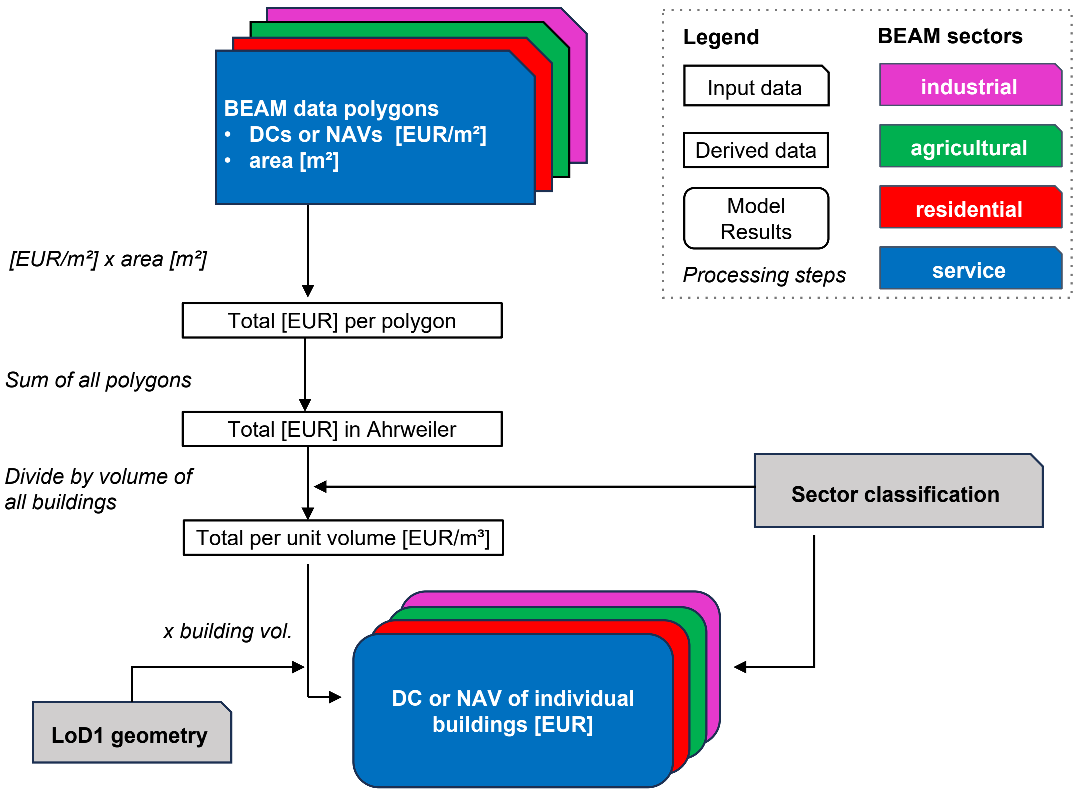

Figure 4: LoD1+BEAM asset value model workflow.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

2.3.3 EHRE

Buildings in EHRE come pre-classified deterministically into five occupancy cases: residential, commercial, industrial, mixed, and other. The mixed category, used for buildings with a combination of uses, we re-label “ambiguous” to match the benchmark data. The “other” category EHRE uses for a set of OBM buildings whose occupancy is not represented in ESRM20 (e.g., hospitals, schools, assembly buildings), which are not assigned any structural classes or replacement values. For the residential, commercial, and industrial buildings, EHRE provides a set of stochastic structural classes and replacement values for each building. To obtain a single deterministic building asset value for comparison against the other models, we sum and collapse these classes to a single replacement value, then multiply by the structural and non-structural factors shown in Table S8 (effectively excluding the “contents” component). The workflow is visualized in Fig. 5 and the source EHRE data extract is provided in Nievas [2025].

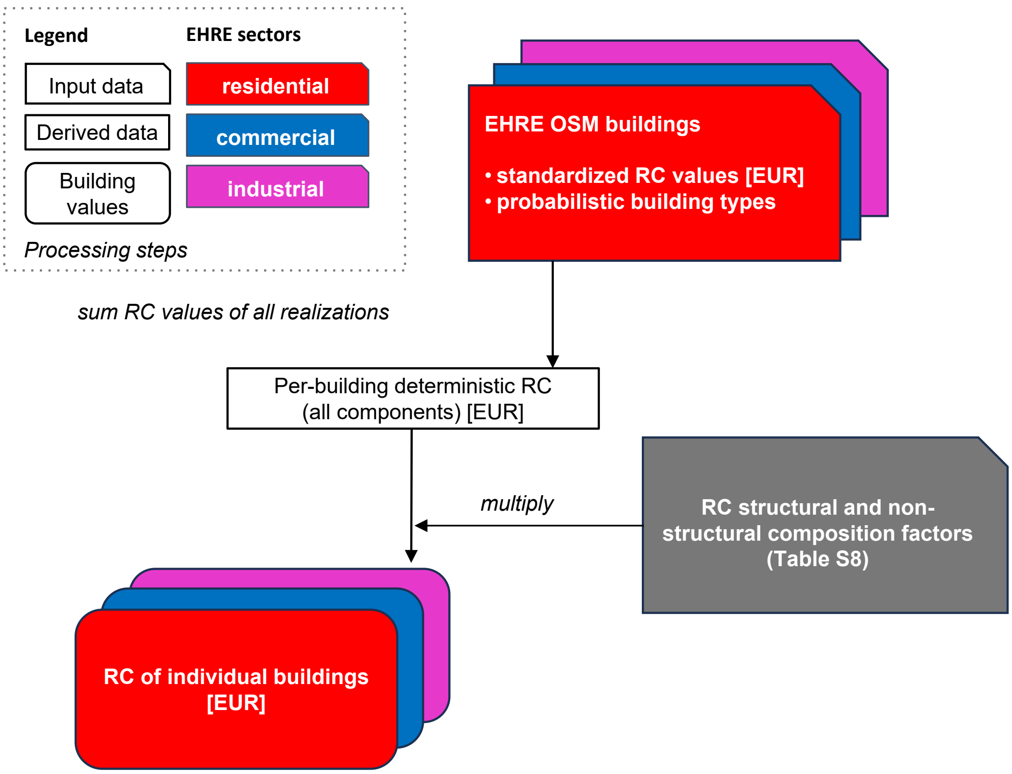

Figure 5: EHRE asset value model workflow adapted from Nievas et al. [2023].

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

2.3.4 OSM land use classification

For comparison against the above workflows that leverage building-specific attributes for sector classification, we developed an alternative classification approach based solely on open-source land use data using hierarchical imputation of first OSM polygons and then CORINE gridded land use data. First, the land use classes of both datasets were classified into one of BEAM's economic sectors using the lookup table from Supplementary Data Table 1 before spatially joining onto LoD1 building locations. This results in most assets sourcing land use information from the OSM polygons, but in some areas where these are missing the CORINE value is taken. The land use based workflow is shown in Figure 6.

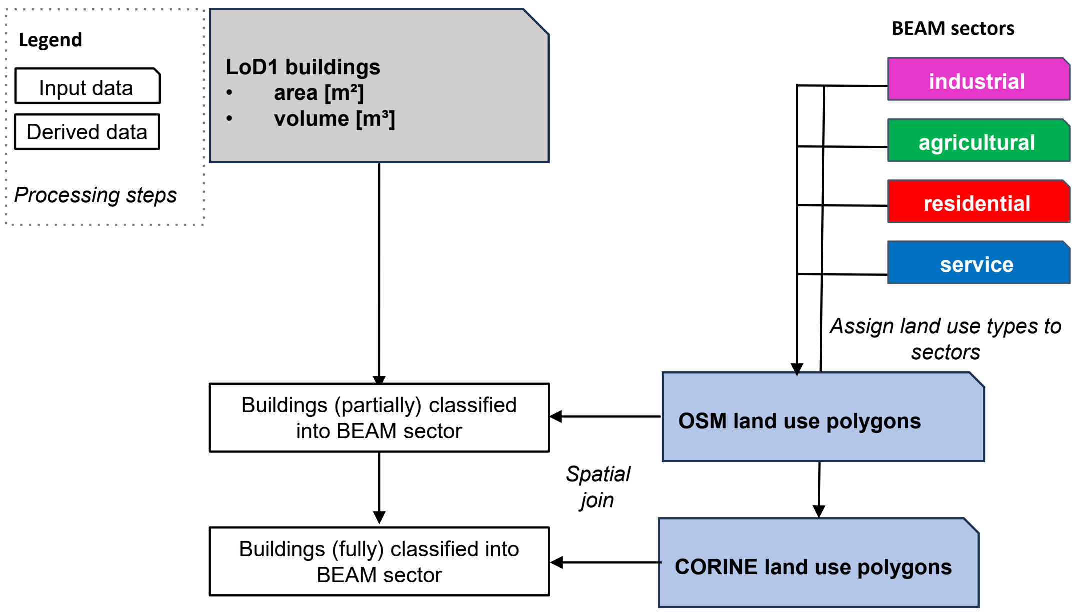

Figure 6: OSM land use classification model workflow.

2.4 Benchmark Dataset

To develop our benchmark dataset, we selected four representative study plots based on knowledge of the region (Figure 1). From these, a dataset of 844 sample buildings focusing on the four study plots and the village of Bad Neuenahr-Ahrweiler was created by hand (based on LoD1 geometries) representing typical residential and non-residential buildings in Ahrweiler [Buhrmann, 2025b]. Assets were classified into 24 building use types from BKI [2021], which we further categorized into the three basic sectors *residential*, *industrial*, and *service* and a fourth *ambiguous* category as a catch-all for building use types (e.g., "commercial buildings, with apartments") whose sector assignment is ambiguous (see Supplementary Data Table 1). Building classifications were determined through detailed visual inspections using Google Earth [Google, 2024a], Google Street View [Google, 2024b], Mapillary [Meta Platforms Ireland Limited, 2024], and ImmoScout24 [Immobilien Scout GmbH, 2024] in March 2024, comparing 3D representations to descriptions and images in BKI [2021] and site visits (see Sect S4 for details). New construction costs per-asset were calculated by multiplying unit construction costs from BKI [2021] (see Table S9), the regional cost factor (0.986), and individual building volumes from LoD1. The workflow is summarized in Fig S1.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

3 Results & Discussion

This section presents and discusses the evaluation results of the candidate sector classification and asset value models.

3.1 Sector Classification

The differences in classification results between the four classification models against the four sectors of the benchmark dataset for the 844 sample buildings are summarized in Fig. 7 with per-label performance metrics provided in Table S11 and mean values for each model in Table S12.

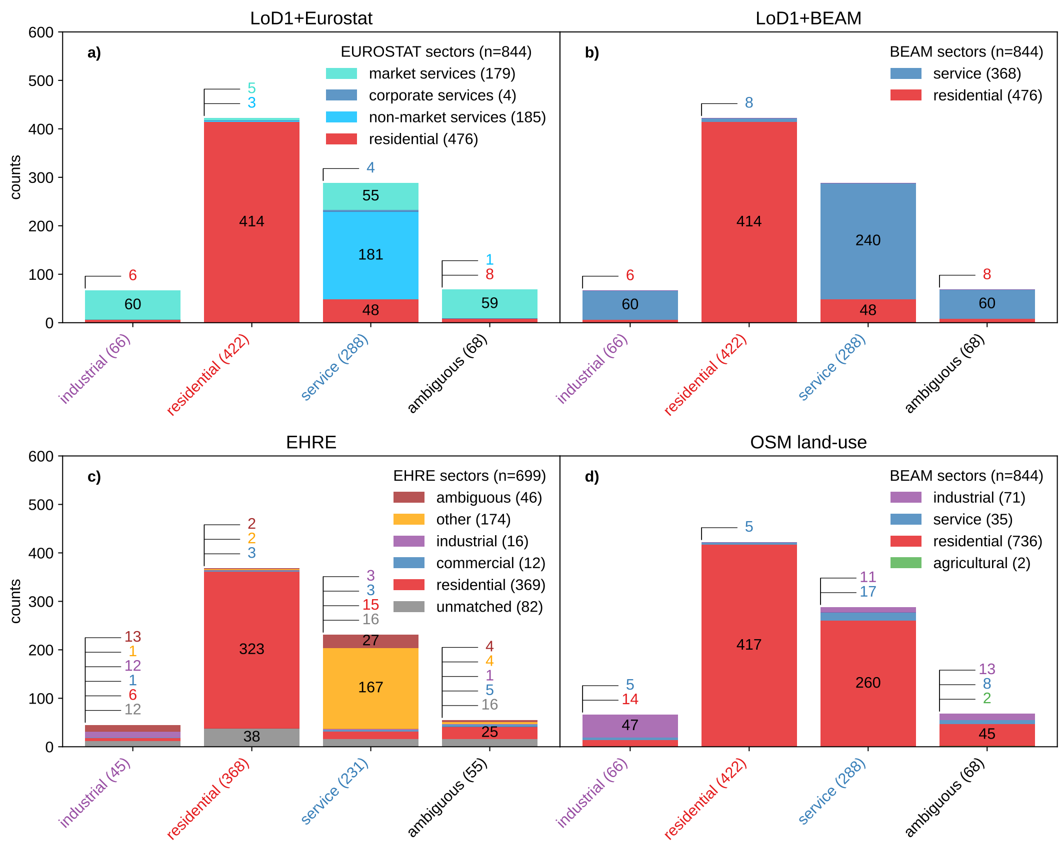

Figure 7: Sample building sector classification results against the benchmark dataset for four candidate models. Bars labelled by building count and grouped by the three economic sectors of the benchmark dataset plus a fourth *ambiguous* category. Bars are coloured by the sector classification of each candidate model. Note that EHRE (panel c) is natively OSM-indexed (unlike the others which are LoD1 indexed), leading to *unmatched* records (n=82). EHRE also treats some benchmark building collections as single-part, leading to the anomalous total building count (n=699) (see text for details).

Examining performance across all four models shows LoD1+Eurostat (Fig. 7a) and LoD1+BEAM (Fig. 7b) perform best ($F_1 = 0.71$; Table S12). Both these models are in perfect agreement with each other (assuming equiv-

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

alence of all Eurostat "services" labels per Table S10) as both models share a LoD1 "function" basis and vary only in their terminal category assignments (see Supplementary Data Table 1). This LoD1 data assigns roughly 75% of the non-residential buildings in our benchmark dataset to "Building for business or trade" which we map to "market service" and "service" in the Eurostat and BEAM models respectively. However, our manual classification of these buildings in the benchmark dataset describes many as *industrial* or *ambiguous*. In other words, while some rare buildings with specific uses are well classified in LoD1 (e.g., Schools, Churches, Fire Departments), there is insufficient resolution to differentiate between the more numerous industrial and service buildings. Beyond this, the two additional categories in the Eurostat model compared to the BEAM (six vs. four) give Eurostat slightly more resolution. The utility of this can be seen in the *non-market services* category (Fig. 7a), 97% of which match the benchmark *service* classification. However, because we opted for a simple four category benchmark, this advantage is not reflected in the performance metrics of Table S12.

The OSM land use model (Fig. 7d) performs the worst of all models ($F_1 = 0.45$), chiefly by over-assigning buildings to the *residential* sector. For example, about 90% of benchmark buildings labelled as *service* are misclassified as *residential* by this model. This bias arises from the application of coarse land use polygons downscaled to individual buildings in dense, predominantly residential areas that contain a small number of *service* buildings. In such settings, buildings belonging to a minority-sector (e.g., *service*) are misclassified to the dominant residential land use during the polygon-to-object translation.

To compare against the EHRE model (Fig. 7c), which is OSM geometry indexed, it was necessary to spatially join these records to the LoD1-based benchmark dataset. Because LoD1 is designed for 3D building representation, some objects that are single-part in EHRE are multi-part in LoD1. To provide a fair comparison, LoD1 building part geometries were merged in these cases. Further, we slightly shifted $< 1\%$ of LoD1 features to match EHRE geometry in obvious (and rare) cases. This yielded 617 record matches and 82 orphaned benchmark records (unmatched EHRE records were discarded like the other models). The orphaned records could be attributed to the different vintage of underlying data or the treatment of incomplete data. For example, while LoD1 does not provide any treatment of uncertainty or missing buildings, EHRE uses a built-up-area ratio to estimate a missing-fraction and assigns information related to these "remainder" buildings to a roughly 100x100m grid cell. Considering these disparate geometries, EHRE had comparable performance to the other non-land-use based models in the residential ($F_1 \approx 0.92$) sector. The *service* sector benchmark labels however EHRE generally assigned to the *other* category, which EHRE uses as a catch-all for buildings whose occupancy type is unknown in OBM (because of a lack of OSM tags, or lack of OBM rules to translate those tags into a final occupancy type) and buildings whose OBM occupancy type does not correspond to any of the three ESRM20 occupancy cases (residential, commercial, industrial). EHRE's application of these *other* labels we consider *omission errors* (because replacement values are omitted from these assets) rather than *commission errors* (active assertion of the wrong label). If we were to instead map this *other* category to *service*, EHRE's weighted score for this sector would increase enough to surpass the LoD1-based models ($F_1 \approx 0.72$). Further, as our evaluation only considers asset-to-asset comparisons, we do not consider any of the residential or commercial remainder buildings imputed by EHRE (Table 3).

Looking at the three classification sectors of the benchmark dataset (industrial, residential, and service), shows the variability in performance across the four candidate models. The highest classification agreement was observed for residential buildings, with all four models classifying nearly all sample buildings consistently (recall ≥ 0.98); over-estimation was more challenging, especially for OSM land use (Fig. 7d; precision ≈ 0.57) as discussed above. For the service sector, the LoD1 function-based models (Fig. 7a,b) had reasonable true positive capture (recall ≈ 0.83), but over-classified *industrial* and *ambiguous* buildings as *service* (precision ≈ 0.65). For industrial assets, the OSM land use model performed best (F1 ≈ 0.68), suggesting industrial land use is relatively distinct and well mapped in OSM for our study area. The industrial group in the EHRE model is comprised mostly of industrial (n=12), unmatched (n=12), and mixed (n=13) buildings, which suggests reasonable performance considering the mixed category includes some industrial occupancy types. On the other hand, the LoD1-based models failed to map any industrial assets owing to the lack of any such labels in the dataset (see Supplementary Data Table 1).

The final benchmark category *ambiguous* was used as a catchall for unclear or mixed building use in our hand labelling. As the two LoD1-based models (Fig. 7a,b) do not have any mixed or ambiguous categories, these bench-

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

mark buildings were generally mapped as *service*. This pattern arises because many of these buildings are mixed use (*commercial buildings with apartments*, *warehouse buildings, without mixed use*, and *single-, multiple- and multi-storey garages*) which LoD1 labels *Building for business or trade*. EHRE on the other hand does have a *mixed* category; however, most these assets (n=46) we found to be clearly *industrial* or *service* in our benchmark (rather than ambiguous).

In summary, the LoD1 function-based models (Fig. 7a,b), with their government-collected per-asset data (and unfortunate use restrictions) unsurprisingly provided the closest match to our hand-labelled benchmark dataset, despite being unable to identify any industrial or ambigious buildings. The open-source object-based EHRE also performed well (Fig. 7c), especially if the *other* category is considered *service*. Lastly, the open-source hierarchical imputation OSM land use based model (Fig. 7d) performed the worst against our benchmark, primarily through the over-assignment of *residential* labels; therefore, we exclude this model from the subsequent sections.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

3.2 Regional Total Asset Values

Extending three of the above sector classification label sets by joining asset values from regional datasets, Table 3 provides a summary of resulting asset values aggregated to the Ahrweiler District.

Table 3: Building asset value model results per sector for Ahrweiler (DEB12; Fig. 1). Sectors with no buildings are omitted. See text for model descriptions. NAV: net asset values; RC: replacement costs; DC: depreciated (construction) costs.

LoD1+Eurostat (RC)

sector	building count	aggregate €	unit value
residential	44,819	1.14×10^{10}	2,478 €/m^2
production	19	5.53×10^{8}	52,517 €/m^3
market services	14,905	4.90×10^{8}	21 €/m^3
corporate services	94	5.48×10^{8}	2,391 €/m^3
non-market services	1919	1.35×10^{9}	251 €/m^3
TOTAL	61,756	1.43×10^{10}	

LoD1+BEAM

sector	building count	aggregate €	unit value (€/m^3)
residential (DC)	44,819	5.33×10^{9}	118
service (NAV)	16,918	7.64×10^{9}	295
industrial (NAV)	19	4.78×10^{8}	104,034
TOTAL	61,756	1.34×10^{10}	

EHRE (RC)

sector	building count	aggregate €
residential	53,077	1.23×10^{10}
commercial	813	1.68×10^{9}
industrial	600	5.66×10^{8}
residential (remainder)	10,202.2	2.36×10^{9}
commercial (remainder)	364.72	7.48×10^{8}
TOTAL	65,056.92	1.77×10^{10}

Comparing across models, we find large variations in estimated asset value district-wide aggregates. This echoes the findings of [Röthlisberger et al., 2018], who showed that model estimates can diverge by factors up to 50–200 at 10 km^2 aggregation in Switzerland. Comparing our findings for the residential-sector for the two LoD1 function-based models with identical assets (LoD1+BEAM and LoD1+Eurostat), we find the Eurostat-based RC estimate more than double that of BEAM's DC. Computationally, this arises primarily from disaggregating with BEAM's 117.50 €/m^3 DC vs. Paprotny [2022]'s 2.478 €/m^2 RC (Table 3); which is unsurprising considering BEAM includes depreciation whereas [Paprotny, 2022] does not. More surprising, considering these different cost-bases, the non-residential sectors counterbalance the residential differences, such that the total (all-sector) sums of the two LoD1-based models happen to fall within $\approx 7\%$. Looking at the unit costs, both LoD1-based models produced some implausible values as a result of disaggregating regional values onto sectors poorly represented by LoD1. For example, LoD1+Eurostat's *production* unit cost is two orders of magnitude beyond any of the BKI unit costs (Table S9) while LoD1+BEAM's *industrial* sector, with only 19 buildings, is three orders of magnitude beyond. Similarly, LoD1+Eurostat's *market services* unit cost is an order of magnitude lower than any of the BKI values.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

This suggests our sector mapping (Supplementary Data Table 1) and LoD1 function data are not well matched to the Eurostat reporting structure in our region.

The EHRE model estimates a larger residential RC (12.3 B€) even without the remainder buildings (2.4 B€) owing to the higher building counts, despite the lower ESRM20 multipliers (see Table S8), while the non-residential building stock in EHRE is the smallest of all models (3.0 B€).

While these total asset value figures are not directly comparable to loss model estimates, the large disparities found here suggest exposure model asset values contribute a similar level of uncertainty to that of other components in a risk model chain. For example, BN-FLEMOps has a Mean Absolute Error around 15% [Wagenaar et al., 2018] and FLEMOps 24% [Thieken et al., 2008] when comparing modelled to observed losses.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

3.3 Per-Asset Values

Comparing asset-to-asset, Figure 8 presents the two LoD1-geometry distributed asset value models against the BKI [2021] construction-cost benchmark (also LoD1-geometry distributed). This figure shows a near-linear relationship between modelled and benchmark asset values for all sectors, which is intuitive if we consider that both the models and the benchmark are geometry-based; i.e, they differ mainly in the unit cost multipliers applied to the building area or volume (see Table 3 and Table S9 for unit costs). Setting aside the sectors with implausible disaggregated unit rates (e.g., *market services* and *corporate services*), all assets in the LoD1+Eurostat model underestimate the benchmark. This can also be seen (partially) by comparing the *non-market services* unit cost (348 €/m^3) to the BKI service unit costs (Table S9); nearly all of which are higher. This underestimation in our LoD1+Eurostat model likely arises from its reliance on stock-average values [Paprotny et al., 2020a], in contrast to the new-build construction cost averages reported by BKI. Similarly, all *residential* BEAM assets underestimate their BKI counterparts, with a unit cost of 118 €/m^3, lower than any reported by BKI. While this is unsurprising considering BEAM includes a depreciation factor, the over-assignment of *residential* labels discussed earlier, or inaccurate building volumes could also influence the discrepancy. In contrast, the LoD1+BEAM *service* assets are less biased, with the 295 €/m^3 falling within BKI's wide range (Table S9); however, this results in higher variance than the other sectors.

Unlike the LoD1-based models and the benchmark data, EHRE is object- rather than geometry-distributed, assigning asset values using probabilistic construction types from ESRM20's regional totals. In other words, EHRE preserves regional average replacement costs (from ESRM20) whereas the LoD1-based models considered here preserve asset-level unit costs. Further, because EHRE's OSM geometry basis provides a simpler more consolidated footprint-based representation of buildings, whereas LoD1 — designed for 3D buildings — represents complex buildings with multiple features, building-by-building value comparison is subjective and challenging (unlike categorical comparison). Our early attempts at this failed to find a satisfactory definition of a *building object* between the two datasets (esp. for large complex structures), but in general we found EHRE strongly under-estimates residential and industrial replacement costs, while sometimes over- or under-estimating commercial ones relative to the benchmark. The open-source nature of EHRE and the ESRM20 exposure model it builds upon mean, however, that the performance of the EHRE model in this regard could be improved, firstly, by changing the average replacement cost per area and, secondly, by using the area of the OSM building footprints to calculate the replacement costs, instead of retaining the average replacement cost per building values of ESRM20 (which are based on average building areas).

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

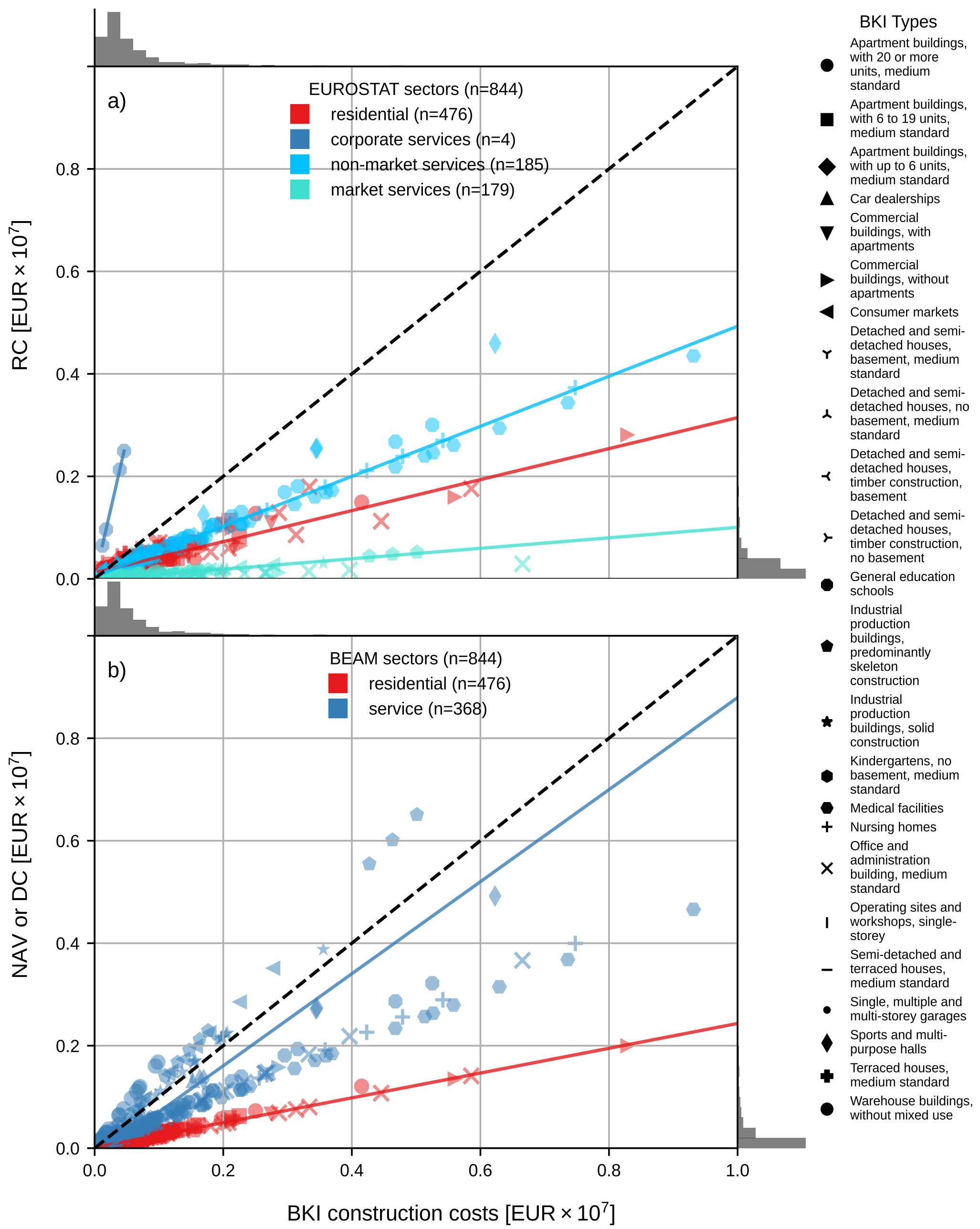

Figure 8: Asset values for (a) LoD1+Eurostat (RC) and (b) LoD1+BEAM (residential is DC while non-residential is NAV) models against the benchmark dataset. Data markers represent the BKI [2021] type and colours the model sector. Solid lines provide the linear trend of the respective sector while the dashed line shows a 1:1 reference. Distributions of respective asset values are shown as histograms adjacent to the axes. RC: Replacement Cost, NAV: Net Asset Value, DC: Depreciated Costs.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

3.4 Weighted Scoring Model

To provide a more robust basis for model selection we use a semi-quantitative Weighted Scoring Model (WSM) to communicate the relative strengths and weaknesses of the three asset value model candidates. Derived from the multiple-criteria decision-making mathematical framework, this technique is widely used to prioritize options by assigning weights to various criteria, which are then scored and ranked [Zionts, 1981]. For this, we developed the criterion and weights shown in Table S13 to inform decisions on model selection based on previous experience. As presented in Table 4, each model is subjectively scored on a scale of 0–10 for each criterion before scores are multiplied by their respective weights then summed.

Table 4: Scores and weights for the asset value models. See Table S13 for a description of each criterion.

Criteria	Weight	LoD1+Eurostat	LoD1+BEAM	EHRE
Benchmark classification	0.15	8	7	6
Benchmark values	0.15	7	8	4
Sustainability	0.1	7	4	5
Model parsimony	0.1	5	6	7
Transparency	0.1	7	3	7
Uncertainty handling	0.1	5	5	8
Breadth of asset types	0.15	6	8	7
Adaptability	0.15	9	5	7
Total score	1	6.9	6	6.3

Translating the sector and asset-value benchmark comparisons from above to the WSM, the LoD1+Eurostat model slightly out-performs the other candidates owing mainly to the benchmark performance, sustainability, and adaptability. Eurostat data are updated annually, offering a clear advantage, whereas the update cycles of BEAM are unclear and EHRE currently has no planned updates. Like BEAM, Eurostat data tables are web-hosted with open access; however, the LoD1 data requires a license (commonly provided for free to public bodies and research institutes under specific agreements), while commercial users typically obtain fee-based licences. Of the three workflows considered, LoD1+Eurostat is more onerous than LoD1+BEAM, requiring the downloading and disaggregation of regional and categorical estimates (see Eq. 1). EHRE on the other-hand is already disaggregated to per-asset stochastic classes; therefore pre-processing is only required if the user desires deterministic values (like our study). Considering the transparency of the underlying data, BEAM is substantially more opaque than the other candidates, with no source code or parameter values provided and documentation only a short paragraph, in some cases without references. In contrast, we find the LoD1+Eurostat and EHRE models to be similarly transparent, both relying on large-scale opaque source data (e.g., OSM, LoD1) but with subsequent calculations performed transparently. For example, the EHRE source code is published [Nievas et al., 2023] while the simpler LoD1+Eurostat methods are described by Fig. 3 and Eq. 1. EHRE is the only model to explicitly consider uncertainty, both through the incorporation of probabilistic building types and the use of "remainder" layers and the "other" building sector. Finally, while our study focuses on building structural asset values, numerous other asset types are often incorporated into exposure models (e.g., population, building contents). In this regard, LoD1+Eurostat provides the narrowest set of asset types as it is the least pre-processed for exposure modelling. However, this minimal processing affords the greatest flexibility for LoD1+Eurostat, which provides data for any year across the Eurozone, allowing advanced modellers to tune the exposure model for their context.

3.5 Limitations and recommendations

With this study, we provide the first per-asset evaluation of asset value models for exposure modelling. Although extending these workflows to other regions in Germany would be straightforward, the need for a labour-intensive hand-labelled benchmark restricted our evaluation to a single region, meaning the findings are only transferrable

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

to regions with construction practices, economic conditions, and exposure distributions comparable to Ahrweiler. Future studies with more resources should consider extending the breadth and coverage of our benchmark dataset. Similarly, we chose to focus on asset values and sector classification as the simplest means for comparing diverse workflows; however, exposure models typically include additional variables like building size, construction type, construction materials, etc. Including these, and non-building assets, in the benchmark and evaluation would provide a more complete comparison. However, as the significance of each of these variables will depend on the particulars of the hazard in question and its associated vulnerability model, the usefulness of such a general study (rather than one specific to a particular case) should be carefully considered.

The dependency of our benchmark on the underlying BKI [2021] data, which only provides average new construction costs in Germany, makes the comparison less useful for certain disaster modelling applications like estimating insurance claims or disaster reconstruction for a heterogeneous set of buildings. More useful would be observed replacement costs from disaster affected buildings; however, this information is notoriously difficult to collect and plagued with uncertainty when self-reported [Rözer et al., 2019]. Similarly, because we opted to provide a broad evaluation, we include asset value workflows with different cost basis (RC, DC, NAV) and years (2018, 2020, and 2022), making our findings less conclusive. Aligning cost bases or developing standardized conversion approaches could improve the appearance of the evaluation, but at the expense of attribution and interpretability.

While our work only considers classical disaggregation workflows built on standard accounting and cadastral datasets, the challenges reported here suggest opportunities for employing machine learning and remote sensing based methods, especially for asset classification. For example, Gouveia et al. [2024], Silva et al. [2024] trained algorithms on labelled images of buildings with promising results.

Lastly, during data collection and publication we struggled to obtain and release asset-level data, a challenge commonly faced by European exposure modellers. This type of building-level economic data is generally considered to be privacy protected under the EU's General Data Protection Regulation [Union, 2016]. While many benefits arise from such protections, policy makers should consider the burden this places on asset-level disaster modelling [McLennan et al., 2020].

4 Conclusions

This study developed and benchmarked object-level asset value models for a region in Germany, examining various disaggregation approaches from cadastre-derived (LoD1), crowd-sourced (OSM), national accounts (Eurostat), and fit-for-purpose datasets (EHRE and BEAM). We adapted and extended four exposure modelling workflows to develop asset-level models, then evaluated these with our hand-labelled benchmark dataset.

From this, we found that the cadaster-derived LoD1-based models performed best overall against the benchmark at labelling a building's sector ($F_1 = 0.71$), but lacked the resolution necessary to identify industrial uses. Aggregate, region-wide values diverged between the candidate models (up to an order-of-magnitude at the sector level), suggesting an under-appreciated level of uncertainty — comparable to uncertainties reported in other aspects of risk modelling, like vulnerability — and emphasizing the need for local validation. Similarly, we found implausible unit rates when disaggregating regional sector totals onto LoD1 functions that poorly represent our local sector mix (e.g., unit costs three orders of magnitude beyond comparable published values), signalling the importance of aligning regional data with building-level data. Setting these implausible unit rates aside, we found both Eurostat and BEAM based models generally underestimate the new construction costs reported by our benchmark. This reflects, respectively, Eurostat's reliance on stock-average replacement costs rather than new-build price lists, and BEAM's inclusion of depreciation in construction costs. Extending this evaluation using a scoring model to examine less-quantitative factors important for exposure modelling like sustainability, transparency, and adaptability, we find all candidate models (except the land use based model) score similarly. However, the LoD1- and Eurostat-based model performs slightly better, mainly due to its ease of adaptation across regions and time periods, and the relative simplicity of maintaining and updating it.

These findings suggest that, other than the land-use-based model, any of the three workflows considered here can provide a defensible asset-level exposure model in Germany, albeit with different cost basis. Modellers should select

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

the workflow that aligns with their sustainability, adaptability, sophistication, and cost-basis needs and perform local validation. In summary, we find transparent, maintainable workflows, not coarse land use proxies, yield the most reliable object-level exposure when grounded in local validation.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

Code/Data Availability

Source datasets used for the analysis are listed in Table 1 and are freely available at the web links provided; with the exception of the EHRE data extract which is provided in Nievas [2025]. All sector mappings we employ are provided in Supplementary Data Table 1. Results for the three candidate asset value models (and their corresponding sector classification) are openly provided in Buhrmann [2025b] with geometry provided in Buhrmann [2025a] (upon request to preserve privacy). Software to develop the models and perform the analysis is provided in Buhrmann [2025c].

Author Contribution

CRediT Role	AB	CN	NS	JD	HK	SB
Conceptualization	TRUE				TRUE	TRUE
Data curation	TRUE	TRUE				TRUE
Formal analysis	TRUE					TRUE
Funding acquisition					TRUE	
Investigation	TRUE					TRUE
Methodology	TRUE					TRUE
Project administration						TRUE
Resources						
Software	TRUE		TRUE			TRUE
Supervision					TRUE	TRUE
Validation						
Visualization	TRUE					TRUE
Writing (original draft)	TRUE	TRUE				TRUE
Writing (review editing)	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

Competing interests

Some authors are members of the editorial board of journal NHESS

References

AdV. Alkis: Amtliches liegenschaftskatasterinformationssystem, 2023. URL `https://www.adv-online.de`. AdV stands for: Arbeitsgemeinschaft der Vermessungsverwaltungen der Länder der Bundesrepublik Deutschland. Managed by the German cadastral authorities. Data was not accessed directly for this study.

Heiko Apel, Sergiy Vorogushyn, and Bruno Merz. Brief communication: Impact forecasting could substantially improve the emergency management of deadly floods: Case study July 2021 floods in Germany. *Natural Hazards and Earth System Sciences*, 22(9):3005–3014, September 2022. ISSN 1684-9981. doi: 10.5194/nhess-22-3005-2022.

Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder. Methodenbeschreibung ESVG 2010 / revision 2019: Volkswirtschaftliche gesamtrechnungen der länder [method description ESA 2010 / revision 2019: National accounts of the länder]. Technical report, Statistisches Landesamt Baden-Württemberg, Stuttgart, 2021.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder. Anlagevermögen in den Ländern der Bundesrepublik Deutschland 1991 bis 2020, 2023. URL https://www.statistikportal.de/de/vgrdl/ergebnisse-laenderebene/investitionen-anlagevermoegen#alle-ergebnisse.

Bundesamt für Kartographie und Geodäsie BKG. 3D-Gebäudemodell LoD1, April 2023. URL http://sg.geodatenzentrum.de/web_public/nutzungsbedingungen.pdf.

Bundesamt für Kartographie und Geodäsie BKG. NUTS-Gebiete 1:5 000 000, Stand 31.12. (NUTS5000 31.12.), January 2024. URL https://gdz.bkg.bund.de/index.php/default/digitale-geodaten/verwaltungsgebiete/nuts-gebiete-1-5-000-000-stand-31-12-nuts5000-31-12.html.

BKI. *BKI Baukosten 2021 Neubau [BKI construction costs 2021 new buildings]*. BKI Baukosteninformationszentrum Deutscher Architektenkammern GmbH, Stuttgart, 2021. ISBN 978-3-481-04275-2. URL www.bki.de.

Seth Bryant, Heidi Kreibich, and Bruno Merz. Bias in Flood Hazard Grid Aggregation. *Water Resources Research*, 59(9):e2023WR035100, 2023. ISSN 1944-7973. doi: 10.1029/2023WR035100.

Seth Bryant, Jody Reimer, Heidi Kreibich, and Bruno Merz. Aggregating flood damage functions: The peril of Jensen's gap. *Journal of Flood Risk Management*, 18(1):e13053, 2025. ISSN 1753-318X. doi: 10.1111/jfr3.13053.

Graf Brühl. Ahrtal: Siebzig Hochwasser in fünfhundert Jahren | GRAF BRÜHL Onlinemagazin, 2025. URL https://grafbruehl.com/magazin/ahrtal-hochwasser-chroniken/.

Aaron Buhrmann. Geometry data for "building-level exposed asset values for germany", October 2025a. URL https://doi.org/10.5281/zenodo.17250008.

Aaron Buhrmann. Sanitized data for "building-level exposed asset values for germany", October 2025b. URL https://doi.org/10.5281/zenodo.17249978.

Aaron Buhrmann. Software for exposure modelling for ahrweiler, October 2025c. URL https://doi.org/10.5281/zenodo.17350703.

Copernicus. Germany BEAM update, April 2020. URL https://emergency.copernicus.eu/mapping/ems/germany-beam-update.

Land Monitoring Service Copernicus. CORINE Land Cover 2018 (vector/raster 100 m), Europe, 6-yearly, 2018. URL https://land.copernicus.eu/en/products/corine-land-cover/clc2018#download.

Christina Corbane, Aneta Florczyk, Martino Pesaresi, Panagiotis Politis, and Vasileios Syrris. GHS built-up grid, derived from Landsat, multitemporal (1975-1990-2000-2014), R2018A, July 2018. URL http://data.europa.eu/89h/jrc-ghsl-10007.

David Crichton. The risk triangle. *Natural disaster management*, 102(3):102–103, 1999.

Crowley, Dabbeek, Despotaki, Rodrigues, Martins, Silva, Romão, Pereira, Weatherill, and Danciu. *European Seismic Risk Model (ESRM20)*. Eucentre, IT, 2021. URL https://doi.org/10.7414/EUC-EFEHR-TR002-ESRM20.

Helen Crowley, Venetia Despotaki, Daniela Rodrigues, Vitor Silva, Dragos Toma-Danila, Evi Riga, Anna Karatzetzou, Stavroula Fotopoulou, Zeljko Zugic, Luis Sousa, Sevgi Ozcebe, and Paolo Gamba. Exposure model for European seismic risk assessment. *Earthquake Spectra*, 36(1_suppl):252–273, October 2020. ISSN 8755-2930, 1944-8201. doi: 10.1177/8755293020919429. URL https://journals.sagepub.com/doi/10.1177/8755293020919429.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

Rocco Custer and Kazuyoshi Nishijima. Probabilistic disaggregation of a spatial portfolio of exposure for natural hazard risk assessment. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, 12(1):1–13, January 2018. ISSN 1749-9518, 1749-9526. doi: 10.1080/17499518.2017.1371761. URL https://www.tandfonline.com/doi/full/10.1080/17499518.2017.1371761.

Jamal Dabbeek, Helen Crowley, Vitor Silva, Graeme Weatherill, Nicole Paul, and Cecilia I. Nievas. Impact of exposure spatial resolution on seismic loss estimates in regional portfolios. *Bulletin of Earthquake Engineering*, 19(14):5819–5841, November 2021. ISSN 1573-1456. doi: 10.1007/s10518-021-01194-x.

James Daniell. *Development of socio-economic fragility functions for use in worldwide rapid earthquake loss estimation procedures*. PhD thesis, Karlsruher Institut für Technologie, 2014.

European Commission. *NACE Rev. 2: Statistical Classification of Economic Activities in the European Community*. Publications Office of the European Union, Luxembourg, 2008. ISBN 978-92-79-04741-1.

European Commission. Statistical Office of the European Union. *Manual on Regional Accounts Methods*. Publications Office of the European Union, Luxembourg, 2013. ISBN 978-92-79-27293-6.

Eurostat. *European System of Accounts:ESA 2010*. Publications Office, LU, 2013. URL https://data.europa.eu/doi/10.2785/16644.

Eurostat. Capital stocks by industry (NACE Rev. 2) and by asset type (nama_10_nfa_st), 2025a. URL https://ec.europa.eu/eurostat/databrowser/view/nama_10_nfa_st/default/table. Accessed: 19 August 2025.

Eurostat. Gross value added at basic prices by NUTS 3 regions (nama_10r_3gva), 2025b. URL https://ec.europa.eu/eurostat/databrowser/view/nama_10r_3gva/default/table. Accessed: 19 August 2025.

R. Figueiredo and M. Martina. Using open building data in the development of exposure data sets for catastrophe risk modelling. *Natural Hazards and Earth System Sciences*, 16(2):417–429, February 2016. ISSN 1684-9981. doi: 10.5194/nhess-16-417-2016. URL https://nhess.copernicus.org/articles/16/417/2016/.

Tina Gerl, Heidi Kreibich, Guillermo Franco, David Marechal, and Kai Schröter. A Review of Flood Loss Models as Basis for Harmonization and Benchmarking. *PLOS ONE*, 11(7):e0159791, July 2016. ISSN 1932-6203. doi: 10.1371/journal.pone.0159791. URL https://dx.plos.org/10.1371/journal.pone.0159791.

Helmholtz-Zentrum Potsdam Deutsches GeoForschungsZentrum GFZ. OpenBuildingMap, May 2024. URL https://www.openbuildingmap.org/.

Juan Camilo Gomez-Zapata, Nils Brinckmann, Sven Harig, Raquel Zafrir, Massimiliano Pittore, Fabrice Cotton, and Andrey Babeyko. Variable-resolution building exposure modelling for earthquake and tsunami scenario-based risk assessment: An application case in Lima, Peru. *Natural Hazards and Earth System Sciences*, 21(11):3599–3628, November 2021. ISSN 1684-9981. doi: 10.5194/nhess-21-3599-2021. URL https://nhess.copernicus.org/articles/21/3599/2021/.

Juan Camilo Gómez Zapata, Massimiliano Pittore, Fabrice Cotton, Henning Lilienkamp, Simantini Shinde, Paula Aguirre, and Hernán Santa María. Epistemic uncertainty of probabilistic building exposure compositions in scenario-based earthquake loss models. *Bulletin of Earthquake Engineering*, 20(5):2401–2438, March 2022. ISSN 1570-761X, 1573-1456. doi: 10.1007/s10518-021-01312-9. URL https://link.springer.com/10.1007/s10518-021-01312-9.

Google. Google search engine. https://www.google.com, 2025a. Accessed: 2025-01-17.

Google. Google scholar. https://scholar.google.com, 2025b. Accessed: 2025-01-17.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

LLC Google. Google Earth, May 2024a. URL https://www.google.com/intl/de_in/earth/.

LLC Google. Google Streetview, May 2024b. URL https://www.google.com/maps/.

Feliz Gouveia, Vítor Silva, Jorge Lopes, Rui S. Moreira, José M. Torres, and Maria Simas Guerreiro. Automated identification of building features with deep learning for risk analysis. *Discover Applied Sciences*, 6(9), August 2024. ISSN 3004-9261. doi: 10.1007/s42452-024-06070-2. URL https://link.springer.com/10.1007/s42452-024-06070-2.

Jim W. Hall, Paul B. Sayers, ., and Richard J. Dawson. National-scale Assessment of Current and Future Flood Risk in England and Wales. *Natural Hazards*, 36(1-2):147–164, September 2005. ISSN 0921-030X, 1573-0840. doi: 10.1007/s11069-004-4546-7. http://link.springer.com/10.1007/s11069-004-4546-7.

IABG mbH and geomer GmbH. Germany BEAM Update - Final Report. Technical report, copernicus, August 2020. https://emergency.copernicus.eu/mapping/download/181929/EMSN076_Final-Report_v1_20082025.pdf?redirect=list-of-components/EMSN076.

Immobilien Scout GmbH. ImmoScout24, May 2024. URL https://www.immobilienscout24.de/.

Insee. Capital fixe et consommation de capital fixe en 2021 – Les comptes de la Nation en 2021, 2022. URL https://www.insee.fr/fr/statistiques/6438757?sommaire=6438793.

L. Kleist, A. H. Thieken, P. Köhler, M. Müller, I. Seifert, D. Borst, and U. Werner. 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(4):541–552, June 2006. ISSN 1684-9981. doi: 10.5194/nhess-6-541-2006. URL https://nhess.copernicus.org/articles/6/541/2006/.

Frank Lehmkuhl, Holger Schüttrumpf, Jan Schwarzbauer, Catrina Brüll, Michael Dietze, Peter Letmathe, Carolin Völker, and Henner Hollert. Assessment of the 2021 summer flood in Central Europe. *Environmental Sciences Europe*, 34(1):107, s12302–022–00685–1, December 2022. ISSN 2190-4707, 2190-4715. doi: 10.1186/s12302-022-00685-1. URL https://enveurope.springeropen.com/articles/10.1186/s12302-022-00685-1.

Stuart McLennan, Leo Anthony Celi, and Alena Buyx. COVID-19: Putting the General Data Protection Regulation to the Test. *JMIR Public Health and Surveillance*, 6(2):e19279, May 2020. doi: 10.2196/19279.

B. Merz, H. Kreibich, R. Schwarze, and A. Thieken. Review Article ‘Assessment of Economic Flood Damage. *Natural Hazards and Earth System Sciences*, 10(8):1697–1724, August 2010. ISSN 1684-9981. doi: 10.5194/nhess-10-1697-2010. URL https://nhess.copernicus.org/articles/10/1697/2010/.

Bruno Merz and Annegret H Thieken. Flood risk analysis: Concepts and challenges. *Österreichische Wasser-und Abfallwirtschaft*, 56(3-4):27–34, 2004.

Frank Messner. FLOODSite: Evaluating flood damages: Guidance and recommendations on principles and methods. Technical Report T09-06-01, Helmholz Unweltforschungszentrum (UFZ), 2007. http://repository.tudelft.nl/view/hydro/uuid:5602db10-274c-40da-953f-34475ded1755/.

Meta Platforms Ireland Limited. Mapillary, May 2024. URL https://www.mapillary.com/.

Daniela Molinari and Anna Rita Scorzini. On the Influence of Input Data Quality to Flood Damage Estimation: The Performance of the INSYDE Model. *Water*, 9(9):688, September 2017. ISSN 2073-4441. doi: 10.3390/w9090688. URL https://www.mdpi.com/2073-4441/9/9/688.

Cecilia Nievas. Ehre data extract for ahrweiler, October 2025. URL https://doi.org/10.5281/zenodo.17317039.

Cecilia Nievas, Marius Kriegerowski, Felix Delattre, Nicolas Garcia Ospina, Karsten Prehn, and Fabrice Cotton. The European High-Resolution Exposure (EHRE) Model. Technical report, GFZ German Research Centre for Geosciences, 2023. URL https://gfzpublic.gfz-potsdam.de/pubman/item/item_5022908.

OpenStreetMap contributors. Planet dump retrieved from https://planet.osm.org . https://www.openstreetmap.org, 2017.

Dominik Paprotny. Residential exposure to natural hazards in europe, 2000–2020, May 2022. URL https://doi.org/10.5281/zenodo.6573503.

Dominik Paprotny and Matthias Mengel. Population, land use and economic exposure estimates for Europe at 100 m resolution from 1870 to 2020. *Scientific Data*, 10(1):372, June 2023. ISSN 2052-4463. doi: 10.1038/s41597-023-02282-0. URL https://www.nature.com/articles/s41597-023-02282-0.

Dominik Paprotny, Heidi Kreibich, Oswaldo Morales-Nápoles, Attilio Castellarin, Francesca Carisi, and Kai Schröter. Exposure and vulnerability estimation for modelling flood losses to commercial assets in Europe. *Science of The Total Environment*, 737:140011, October 2020a. ISSN 00489697. doi: 10.1016/j.scitotenv.2020.140011. URL https://linkinghub.elsevier.com/retrieve/pii/S0048969720335312.

Dominik Paprotny, Heidi Kreibich, Oswaldo Morales-Nápoles, Paweł Terefenko, and Kai Schröter. Estimating exposure of residential assets to natural hazards in Europe using open data. *Natural Hazards and Earth System Sciences*, 20(1):323–343, January 2020b. ISSN 1684-9981. doi: 10.5194/nhess-20-323-2020. URL https://nhess.copernicus.org/articles/20/323/2020/.

Dominik Paprotny, Heidi Kreibich, Oswaldo Morales-Nápoles, Dennis Wagenaar, Attilio Castellarin, Francesca Carisi, Xavier Bertin, Bruno Merz, and Kai Schröter. A probabilistic approach to estimating residential losses from different flood types. *Natural Hazards*, 105(3):2569–2601, February 2021. ISSN 0921-030X, 1573-0840. doi: 10.1007/s11069-020-04413-x. URL http://link.springer.com/10.1007/s11069-020-04413-x.

Paprotny, Dominik. Replacement Costs: Germany - bryant.seth@gmail.com - Gmail [personal correspondence], October 2025.

Statistisches Landesamt Rheinland-Pfalz. Kommunaldatenprofil, 2025. URL https://www.statistik.rlp.de/fileadmin/dokumente/kreisdatenprofil/ergebnisse/20240724_KRS131_Ahrweiler.pdf.

Veronika Röthlisberger, Andreas P. Zischg, and Margreth Keiler. A comparison of building value models for flood risk analysis. *Natural Hazards and Earth System Sciences*, 18(9):2431–2453, September 2018. ISSN 1684-9981. doi: 10.5194/nhess-18-2431-2018. URL https://nhess.copernicus.org/articles/18/2431/2018/.

Viktor Rözer, Heidi Kreibich, Kai Schröter, Meike Müller, Nivedita Sairam, James Doss-Gollin, Upmanu Lall, and Bruno Merz. Probabilistic Models Significantly Reduce Uncertainty in Hurricane Harvey Pluvial Flood Loss Estimates. *Earth's Future*, 7(4):384–394, April 2019. ISSN 2328-4277, 2328-4277. doi: 10.1029/2018EF001074.

Nivedita Sairam, Fabio Brill, Tobias Sieg, Mostafa Farrag, Patric Kellermann, Viet Dung Nguyen, Stefan Lüdtke, Bruno Merz, Kai Schröter, Sergiy Vorogushyn, and Heidi Kreibich. Process-Based Flood Risk Assessment for Germany. *Earth's Future*, 9(10):e2021EF002259, 2021. doi: 10.1029/2021EF002259. https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2021EF002259.

Dr Oda Schmalwasser and Michael Schidlowski. Measuring Capital Stock in Germany. *Wirtschaft und Statistik*, 2006.

Danijel Schorlemmer, Thomas Beutin, Fabrice Cotton, Nicolas Garcia Ospina, Naoshi Hirata, Kuo-Fong Ma, Cecilia Nievas, Karsten Prehn, and Max Wyss. Global Dynamic Exposure and the OpenBuildingMap - A Big-Data and Crowd-Sourcing Approach to Exposure Modeling, March 2020. URL https://meetingorganizer.copernicus.org/EGU2020/EGU2020-18920.html.

Kai Schröter, Stefan Lüdtke, Richard Redweik, Jessica Meier, Mathias Bochow, Lutz Ross, Claus Nagel, and Heidi Kreibich. Flood loss estimation using 3D city models and remote sensing data. *Environmental Modelling & Software*, 105:118–131, 2018. ISSN 1364-8152. doi: 10.1016/j.envsoft.2018.03.032.

Karl August Seel. Die Ahr und ihre Hochwässer in alten Quellen, 2025. URL https://kreis-ahrweiler.de/kvar/VT/hjb1983/hjb1983.25.htm.

Tobias Sieg and Annegret H Thieken. Improving flood impact estimations. *Environmental Research Letters*, 17 (6):064007, June 2022. ISSN 1748-9326. doi: 10.1088/1748-9326/ac6d6c. URL https://iopscience.iop.org/article/10.1088/1748-9326/ac6d6c.

Tobias Sieg, Sarah Kienzler, Viktor Rözer, Kristin Vogel, Henning Rust, Axel Bronstert, Heidi Kreibich, Bruno Merz, and Annegret H. Thieken. Toward an adequate level of detail in flood risk assessments. *Journal of Flood Risk Management*, 16(3):e12889, September 2023. ISSN 1753-318X, 1753-318X. doi: 10.1111/jfr3.12889. URL https://onlinelibrary.wiley.com/doi/10.1111/jfr3.12889.

Vitor Silva, Svetlana Brzev, Charles Scawthorn, Catalina Yepes, Jamal Dabbeek, and Helen Crowley. A Building Classification System for Multi-hazard Risk Assessment. *International Journal of Disaster Risk Science*, 13 (2):161–177, April 2022. ISSN 2095-0055, 2192-6395. doi: 10.1007/s13753-022-00400-x. URL https://link.springer.com/10.1007/s13753-022-00400-x.

Vitor Silva, Romain Sousa, Feliz Ribeiro Gouveia, Jorge Lopes, and Maria Joao Guerreiro. A building imagery database for the calibration of machine learning algorithms. *Earthquake Spectra*, 40(2):1577–1590, May 2024. ISSN 8755-2930, 1944-8201. doi: 10.1177/87552930241229103. URL https://journals.sagepub.com/doi/10.1177/87552930241229103.

A. H. Thieken, M. Müller, L. Kleist, I. Seifert, D. Borst, and U. Werner. Regionalisation of asset values for risk analyses. *Natural Hazards and Earth System Sciences*, 6(2):167–178, March 2006. ISSN 1684-9981. doi: 10.5194/nhess-6-167-2006. URL https://nhess.copernicus.org/articles/6/167/2006/.

A. H. Thieken, A. Olschewski, H. Kreibich, S. Kobsch, and B. Merz. Development and evaluation of FLEMOps – a new Flood Loss Estimation MOdel for the private sector. In *Flood Recovery, Innovation and Response I*, volume I, pages 315–324. WIT Press, London, England, June 2008. ISBN 978-1-84564-132-0.

European Union. Regulation (eu) 2016/679 of the european parliament and of the council of 27 april 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing directive 95/46/ec (general data protection regulation). Official Journal of the European Union, L 119, 4 May 2016, pp. 1–88, 2016. URL https://eur-lex.europa.eu/eli/reg/2016/679/oj.

Dennis Wagenaar, Stefan Lüdtke, Kai Schröter, Laurens M. Bouwer, and Heidi Kreibich. Regional and Temporal Transferability of Multi-Variable Flood Damage Models. *Water Resources Research*, April 2018. ISSN 00431397. doi: 10.1029/2017WR022233.

Julius Waldhof. AdV Online - Kontaktformular [#483]. E-mail message, April 2025. URL mailto:zshh@ldbv.bayern.de. E-mail sent to B. Buhrmann (buhrmann@gfz.de); cc: Florian Siegert, Margret Bellenberg, and Gerfried Westenberg.

M. Wieland, M. Pittore, S. Parolai, U. Begaliev, P. Yasunov, S. Tyagunov, B. Moldobekov, S. Saidiy, I. Ilyasov, and T. Abakanov. A Multiscale Exposure Model for Seismic Risk Assessment in Central Asia. *Seismological Research Letters*, 86(1):210–222, January 2015. ISSN 0895-0695, 1938-2057. doi: 10.1785/0220140130. URL https://pubs.geoscienceworld.org/srl/article/86/1/210-222/315454.

https://doi.org/10.5194/egusphere-2025-5172
Preprint. Discussion started: 13 November 2025

Jidong Wu, Ying Li, Ning Li, and Peijun Shi. Development of an Asset Value Map for Disaster Risk Assessment in China by Spatial Disaggregation Using Ancillary Remote Sensing Data. *Risk Analysis*, 38(1):17–30, January 2018. ISSN 0272-4332, 1539-6924. doi: 10.1111/risa.12806. URL https://onlinelibrary.wiley.com/doi/10.1111/risa.12806.

Jidong Wu, Mengqi Ye, Xu Wang, and Elco Koks. Building Asset Value Mapping in Support of Flood Risk Assessments: A Case Study of Shanghai, China. *Sustainability*, 11(4):971, February 2019. ISSN 2071-1050. doi: 10.3390/su11040971. URL http://www.mdpi.com/2071-1050/11/4/971.

Anja Wünsch, Ulrich Herrmann, Heidi Kreibich, and Annegret H. Thieken. The Role of Disaggregation of Asset Values in Flood Loss Estimation: A Comparison of Different Modeling Approaches at the Mulde River, Germany. *Environmental Management*, 44(3):524–541, September 2009. ISSN 0364-152X, 1432-1009. doi: 10.1007/s00267-009-9335-3. URL http://link.springer.com/10.1007/s00267-009-9335-3.

Stanley Zionts. A multiple criteria method for choosing among discrete alternatives. *European Journal of Operational Research*, 7(2):143–147, June 1981. ISSN 03772217. doi: 10.1016/0377-2217(81)90275-7. URL https://linkinghub.elsevier.com/retrieve/pii/0377221781902757.

Hannes Zschiesche. DIN 277:2021-08, Grundflächen und Rauminhalte im Hochbau. Norm, DIN Media GmbH, August 2021. URL https://www.dinmedia.de/de/norm/din-277/342217323.