

Building-level exposure asset value modelling for Germany: an Ahrweiler case study

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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~~Verified, harmonised, 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~~exposure data are essential for next-generation risk assessments, risk management, and impact-based 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 are~~ not readily available or not compiled in one dataset. To address this gap, we present an evaluation of potential exposure ~~modelling frameworks utilizing model workflows employing~~ 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~~one flood-affected region in Germany and a weighted scoring model, we evaluate the ability of ~~candidates each workflow~~ 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~~model workflow disaggregating national accounts onto cadastre-derived building footprints slightly ~~out performs other candidates~~out performs the other workflows owing mainly to its transparency and adaptability. However, we conclude that all but the ~~land-use derived candidate are defensible exposure modelling frameworks~~land-use derived workflow are defensible for object-level exposure modelling — ~~so long as some relevant validation is performed. The frameworks presented here when validated. While these findings are limited to one specific region, the workflows developed here provide the basis for broader evaluation across regions with different building stocks, economic structures, and data quality. Workflows like these 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 et al., 2007, Merz and Thieken, 2004]. These models typically ~~conceptualize~~ conceptualise 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~~ vulnerability 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., in Germany 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 See Section 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 needs, DC or NAV for asset accounting and compensation-oriented analyses, and insured value for insurance or reinsurance applications~~ [Daniell, 2014]. 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 can be useful for real-estate, relocation, or recovery-planning questions, but appears less often in natural hazard studies [Merz et al., 2010, Gerl et al., 2016]. [Merz et al., 2010, Gerl et al., 2016, Molinari et al., 2020]. For floods, most exposure models still use whole-building asset values, even when the expected damage mechanism is concentrated on the ground or first floor [Gerl et al., 2016, Molinari et al., 2020, Molinari and Scorzini, 2017]. 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~~ community-, block-, or grid-level units [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, Wunsch et al. [2009] and Molinari and Scorzini [2017] show that, although the procedure for estimating exposed assets (e.g., binary vs regression-based asset value disaggregation) 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~~ utilised open building data and census data to disaggregate ~~residential~~ floor area onto a 50 m gridded exposure model to show that coarse exposure models ~~over-estimate~~ overestimate losses. 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~~ overestimate. Although these and most related studies focus on loss modelling rather than exposure modelling alone, many of their findings translate directly because not only is exposure modelling embedded within the broader loss-modelling workflow, it is also a precondition for it.

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., €/m² or €/m³) to obtain asset value (€). For example, Paprotny et al. [2020b] disaggregated national gross fixed asset values of dwellings for 22 ~~EU~~ European Union (EU) countries to derive national €/m² 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-~~type~~ replacement costs from country-wide unit costs (€/m²) (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~~ the European High-Resolution Exposure (EHRE) model, which assigns probabilistic ESRM20 building classes to OpenStreetMap (OSM) [OpenStreetMap contributors, 2017] building footprints, while retaining the ESRM20 ~~per-building per-asset-type~~ 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~~ exposure model workflows 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~~ workflows, and quantitatively ~~and transparently evaluate these~~ evaluate these while deliberately retaining their different source cost bases (RC, DC, and NAV) for transparency, to identify a robust, reproducible ~~model~~ workflow for multi-sector risk analysis and impact forecasting.

2 Methods

Our study first developed and processed candidate *sector classification* and *asset value* ~~models~~ workflows, fundamental components of ~~most~~ exposure models. These ~~candidate models~~ workflows 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 Fig. 1). In July 2021, the region experienced a severe flood event that caused significant economic losses and fatalities [Lehmkuhl et al., 2022] (see Figure Fig. 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].

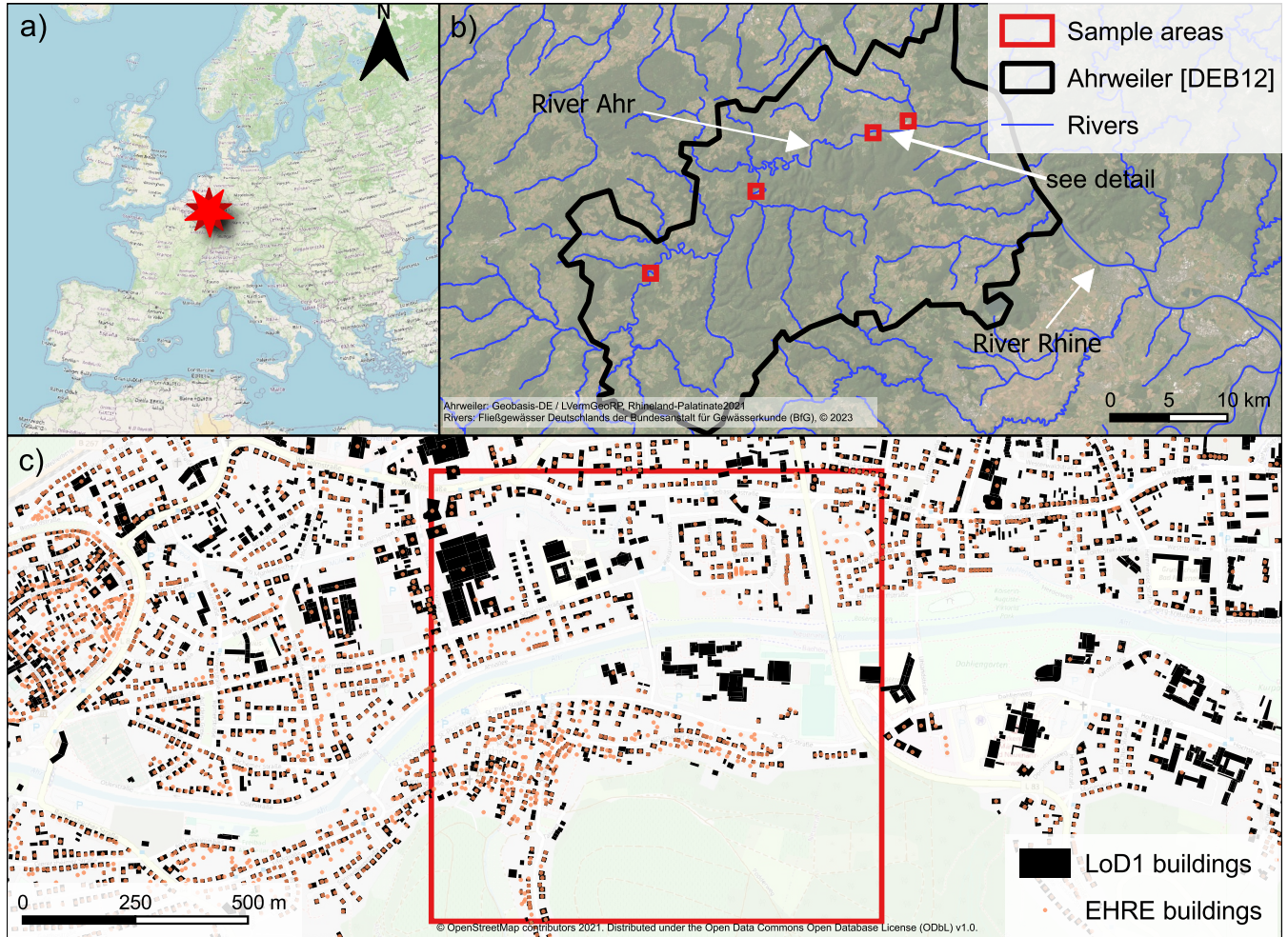


Figure 1: Study area maps showing: a) study location; b) study boundary ([NUTS-3 Nomenclature of Territorial Units for Statistics level 3 \[NUTS 3\]](#) name [and code]); and c) typical detail of village area with building locations from datasets discussed in the text. Map data from OpenStreetMap, [licensed under the Open Database License \(ODbL\)](#) — [openstreetmap.org/copyright](#).

The service sector ~~in Ahrweiler~~ constitutes the most important economic sector with a share of ~~dominates Ahrweiler’s economy, accounting for~~ 70.9% of ~~the GDP;~~ gross domestic product (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].



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

2.2 Data

To develop and process our candidate ~~models, we first gathered~~ exposure model workflows, we began by searching for freely available building-exposure and asset-value datasets, with a focus on building fixed asset values ~~, that is, considering the~~ (i.e., values for structural and non-structural architectural components of the buildings ~~, but not their rather than~~ movable contents/equipment). A systematic search using Google [Google, 2025a] and Google Scholar [Google, 2025b] yielded the datasets ~~summarized~~ summarised in Table S2, from which we then selected those datasets listed in Table 1 for further analysis (see ~~Seet~~ Section S2 for details). The three asset value candidate datasets considered here are the Basic European AssetsMap (BEAM), ~~the European High Resolution Exposure (EHRE) model~~ EHRE, 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~~ gross value added.

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 <i>Other buildings and structures</i>	10 sector groups	free access	2018	Eurostat [2025a]
Insee Capital Stocks		tabular (national)	gross fixed capital € for <i>Other buildings and structures</i> and <i>Buildings other than dwellings</i>	10 sector groups	free access	2018	Insee [2022]
Paprotny [2022]		tabular (national)	RC €/m ² <u>per residential floor area</u> for dwellings and household contents (2000–2020)	Residential only	free access	2022	Paprotny [2022]
BEAM		polygon	DC or NAV €/m ² <u>per land-use polygon area</u> (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 <u>land-use</u> types	35 landuse <u>land-use</u> types	free access	2024	OpenStreetMap contributors [2017]
CORINE		polygon	landuse <u>land-use</u> types	19 landuse <u>land-use</u> 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 <u>new-construction unit costs</u> €/m ³ <u>by gross building volume</u> , <u>regionalisation</u> 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~~ harmonised 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~~ state statistical

offices collect these data, and “Statistisches Bundesamt (Destatis)” (Federal Statistical Office) who provide the data organises the national submission to Eurostat [Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder, 2021]. Prior to 2025, data were usually organized-organised using the Statistical Classification of Economic Activities in the European Community (NACE Rev. 2), a hierarchical scheme distinguishing 21 level-one-level-one categories or sectors [European Commission, 2008]. For example, the ~~Gross value added (GVA)~~ at basic prices by ~~NUTS3-NUTS 3~~ 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 [European Commission. Statistical Office of the European Union, 2013]. This table provides GVA estimates per year for ~~Nomenclature of Territorial Units for Statistics (NUTS)~~ NUTS 3 regions (roughly 400 in Germany) for six economic sector groups (see Table S3). Providing a more refined ~~discretization~~ discretisation 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 lumps together many assets not of interest to exposure modelling of non-residential building assets (e.g., railways), and generally requires 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~~ BEAM was developed to “estimate, evaluate and compare real and potential damages caused by natural disasters all across Europe” and provides ~~€/m² 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]. ~~These values are provided as NUTS 2-level €/m² averages per land-use area, not per building area, then mapped to land-use polygons so that obtaining per-building asset values requires aggregating polygon totals and redistributing them to individual buildings.~~ 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)~~ DC by multiplying €/m² construction costs by a depreciation rate, before disaggregating to ~~land-use~~ 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~~ land-use polygons using employee counts and density factors. While the BEAM data product is freely available and ~~their~~ its methods are (briefly) ~~summarized~~ summarised in IABG mbH and geomer GmbH [2020], all factors mentioned above and the software pipeline are unpublished and proprietary. ~~Here we use the 2020 “Germany BEAM update”; however, a new version was released in late 2025 while this article was in review [IABG mbH and geomer GmbH, 2025].~~

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~~ High-Resolution Exposure (EHRE) model

The ~~European High-Resolution Exposure (EHRE)~~ 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 [~~GFZ, 2024, Schorlemmer et al., 2020~~, later developed and enriched with other datasets by Oostwegel et al., 2025], 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”~~ remainder estimates, which are represented on a $\approx 100\text{m}$ grid. EHRE inherits all the occupancy cases, structural classes (~~GEM~~ Global Earthquake Model [GEM] Building Taxonomy v3.0 [Silva et al., 2022]), number of building occupants, and ~~replacement costs per building per asset type replacement costs~~ 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)~~ RC, referenced to 2020, ~~are~~ is obtained by applying country- and occupancy-specific reconstruction costs ($\text{€}/\text{m}^2$, 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 the 53 GEM Taxonomy occupancy types, and (iii) a final rule-based selection. EHRE then groups these 53 GEM occupancy types into three modelled occupancy cases – residential (14 types), commercial (6 types), and industrial (6 types) – and treats the remaining 27 as other types outside the ESRM20 building-class set, with no replacement value assigned. EHRE’s consolidation requires deterministic allocation of some mixed-use (MIX) categories to modelled occupancy cases; for clarity, the full mapping is reproduced in Supplementary Data Table 1. 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~~ analysis below, geometries with non-building functions (e.g. stadiums, water tanks, bridges) were discarded.

Another source we use for building data is ~~OpenStreetMap (OSM)~~ 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~~ land-use polygons, providing 35 ~~land-use~~ land-use classes in our study area. Further ~~land-use~~ 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-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) (“Con-

struction costs for new buildings 2021”) [BKI, 2021]. BKI [2021] provides construction cost values of 75 different building use types as €/m³ (see Table S9), based on a database of several thousand invoiced projects for new buildings collected by architectural associations in Germany. ~~The~~ These unit costs refer to gross building volume (Bruttorauminhalt, BRI), which is derived from gross floor area by storey, measured to the outside of external walls, and the vertical distance between floor or ceiling reference surfaces, with roof volumes treated according to roof geometry [Zschiesche, 2021]. This BKI [2021] 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 and building contractors.

2.3 Candidate ~~Models~~ Workflows

In ~~loss-modelling~~ natural hazards research, 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 the~~ workflows for assigning sector labels to building assets, ~~the results of which are evaluated shown in Table 3, and evaluate these~~ against our hand-labelled benchmark dataset. From these, the three ~~best-performing~~ best-performing workflows are further developed into ~~candidate asset value models formulated on the~~ asset value workflows formulated on BEAM, Eurostat, and EHRE datasets as described below. All resulting derived datasets are provided in Buhrmann [2025b] and Buhrmann [2025a].

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:

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

where $RC_{r,s,y,AN.1121}$ is the *Buildings other than dwellings* (AN.1121; Table S4) RC for a NUTS 3 region r in sector s for year y ; $RC_{n,s,y,AN.112}$ 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 $GFC_{n,s,y,AN.112}$ and $GFC_{n,s,y,AN.1121}$ 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, 2025]. Values for each variable are provided per-sector group in Table S5 and [Table S6](#). Within our NUTS 3 region, these values were finally distributed to individual buildings proportional to building volume (m³), computed by multiplying LoD1 footprint area by height attributes.

For residential buildings, asset values were calculated ~~by multiplying LoD1 footprint area as usable floor area multiplied~~ by the national value of 2.478 €/m² taken from Paprotny [2022] who calculated this value replacement cost of 2.478 €/m² from Paprotny [2022]. Paprotny et al. [2020b] derived this unit cost by dividing the national

gross replacement cost of the dwelling stock, ~~derived-estimated~~ from Eurostat national accounts and ~~perpetual inventory method estimates from 2018~~ ~~perpetual-inventory estimates~~, by the total residential floor area in Germany [Paprotny et al., 2020b]. Usable floor area was estimated by multiplying LoD1 footprint area by storey count and a 0.7 usable-area coefficient, with storeys inferred from LoD1 height using 3.3 m for the ground floor and 2.4 m for each additional storey [Figueiredo and Martina, 2016, Paprotny et al., 2020b]. The resulting footprint-to-usable-area relation for all residential buildings is shown in Fig. S3.

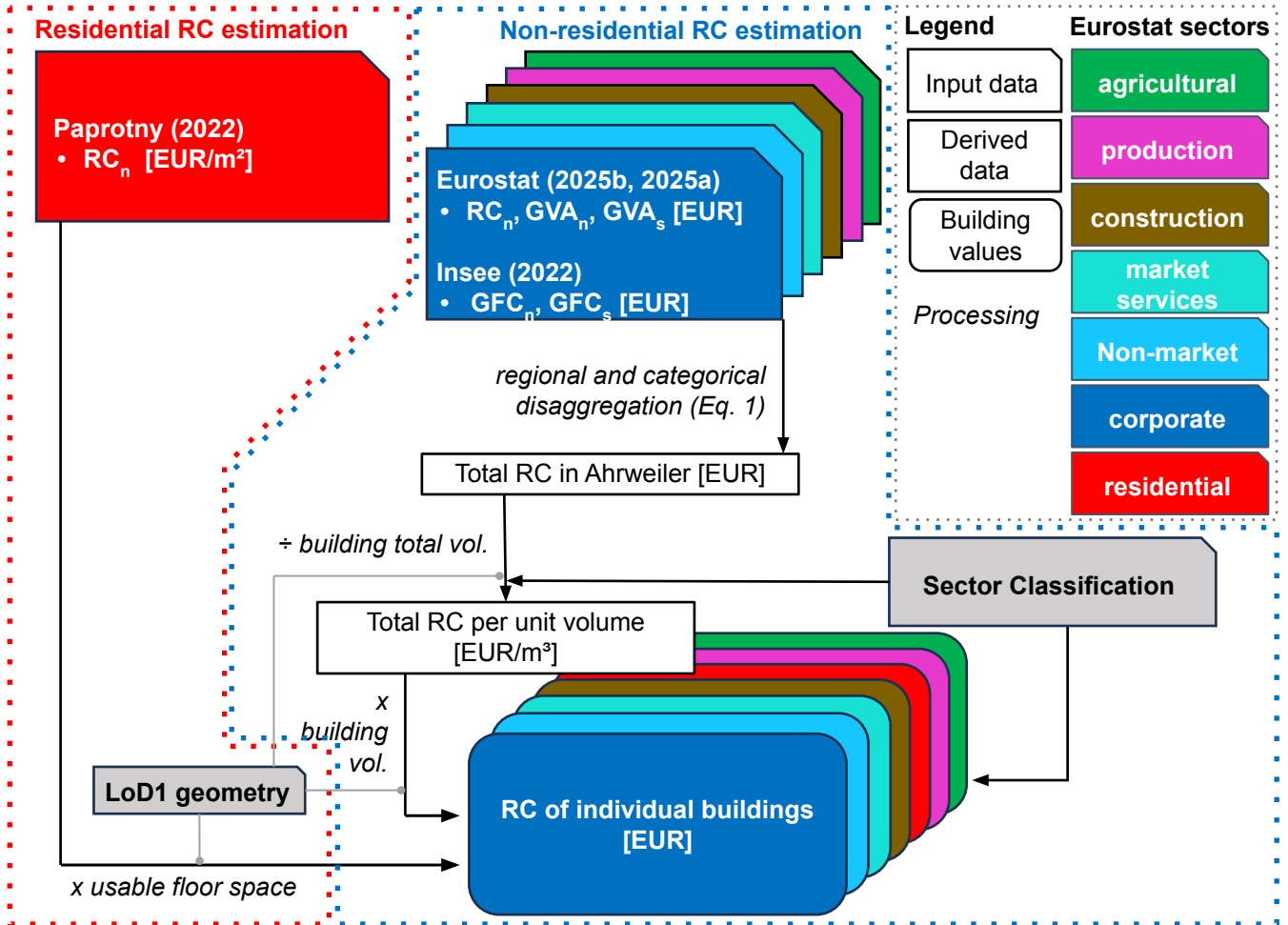


Figure 3: LoD1+Eurostat asset value model workflow adapted from Paprotny et al. [2020a,b] showing the residential (red) and non-residential (blue) RC calculation.

Table 3: Method summary of study exposure model workflows and benchmark dataset

<u>Name (ref.)</u>	<u>Per-asset geometry source</u>	<u>Classification</u>	<u>Per-asset values</u>	<u>Regional total asset values</u>
<u>LoD1 + Eurostat (Fig. 3)</u>	<u>LoD1</u>	<u>LoD1 function mapped to Eurostat sector group</u>	<u>Non-residential: regional sector totals estimated from national Eurostat capital-stock values using regional GVA and gross fixed-capital ratios [Paprotny et al., 2020a], then distributed to LoD1 buildings by volume; residential: LoD1-derived usable floor area times national residential replacement-cost-per-m² value [Paprotny et al., 2020b].</u>	<u>Sum per-asset values.</u>
<u>LoD1 + BEAM (Fig. 4)</u>	<u>LoD1</u>	<u>LoD1 function mapped to BEAM sector group</u>	<u>Regional sector totals from BEAM polygon values times polygon area, adjusted to the building-value component where required, then distributed to LoD1 buildings by volume [Copernicus, 2020].</u>	<u>Sum per-asset values.</u>
<u>EHRE (Fig. 5)</u>	<u>EHRE, from OSM</u>	<u>EHRE, from ESRM20 and OBM</u>	<u>EHRE object-level replacement values, inherited from ESRM20 and assigned to OSM/OBM buildings; stochastic structural-class values collapsed to deterministic replacement value and multiplied by structural and non-structural composition factors, excluding contents [Nievas et al., 2023].</u>	<u>Sum per-asset values, including remainder buildings where OSM is incomplete.</u>
<u>OSM land-use (Fig. 6)</u>	<u>LoD1</u>	<u>OSM and CORINE land-use polygons spatially joined to LoD1 buildings</u>	<u>N/A</u>	<u>N/A</u>
<u>Benchmark dataset (Fig. S1)</u>	<u>LoD1</u>	<u>Hand-labelled to BKI types</u>	<u>BKI new-construction unit costs times regional cost factor and LoD1 building volume [BKI, 2021].</u>	<u>N/A</u>

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 using disaggregated BEAM data for~~ 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-land-use~~ polygon scale $\text{€}/\text{m}^2$ asset value, ~~we and here we focus on per-asset values, we~~ opted to back-calculate a regional aggregate € , then re-distribute this to individual buildings by volume for each sector. ~~To For all non-residential sectors it was necessary to~~ subtract the equipment values included in BEAM from our building value estimate, ~~for which~~ per-sector multipliers adapted from ~~[Arbeitskreis Volkswirtschaftliche Gesamtrechnungen der Länder, 2023]~~ ~~Arbeitskreis Volkswirtschaftliche Gesamtrechnungen~~ and shown in Table S7 were used. See Fig. 4 for a ~~visualization~~ ~~visualisation~~ of the workflow.

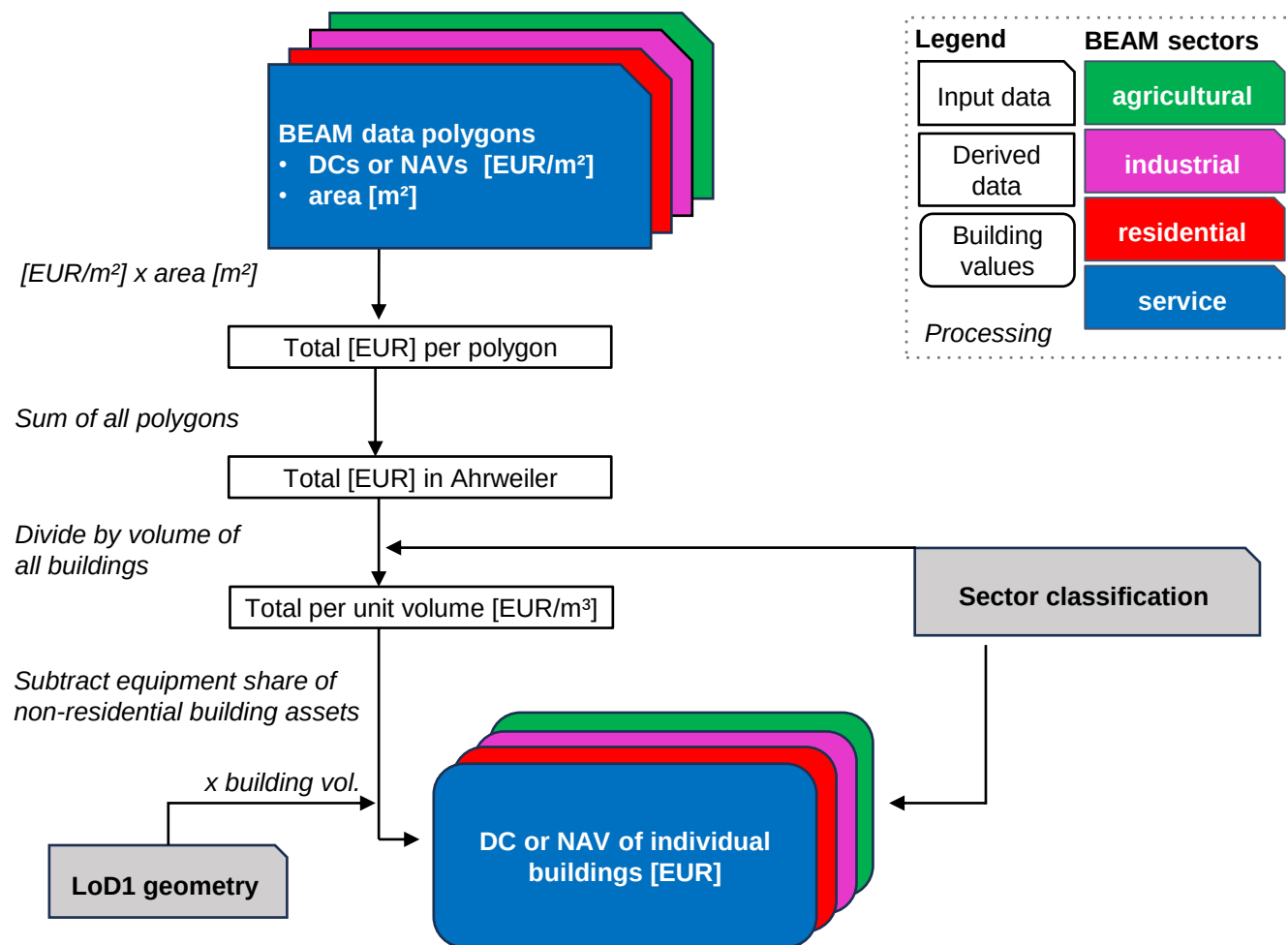


Figure 4: LoD1+BEAM asset value model workflow.

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 links each footprint to stochastic structural classes and replacement values for each building ESRM20 per-asset-type replacement values. To obtain a single deterministic building asset value for comparison against the other models workflows, we sum and collapse these classes to a single weighted-mean replacement value, then multiply by the structural and non-structural factors shown in Table S8 (effectively excluding the “contents” component). The workflow is visualized EHRE workflow is visualised in Fig. 5 and the source EHRE data extract is provided in Nievas [2025].

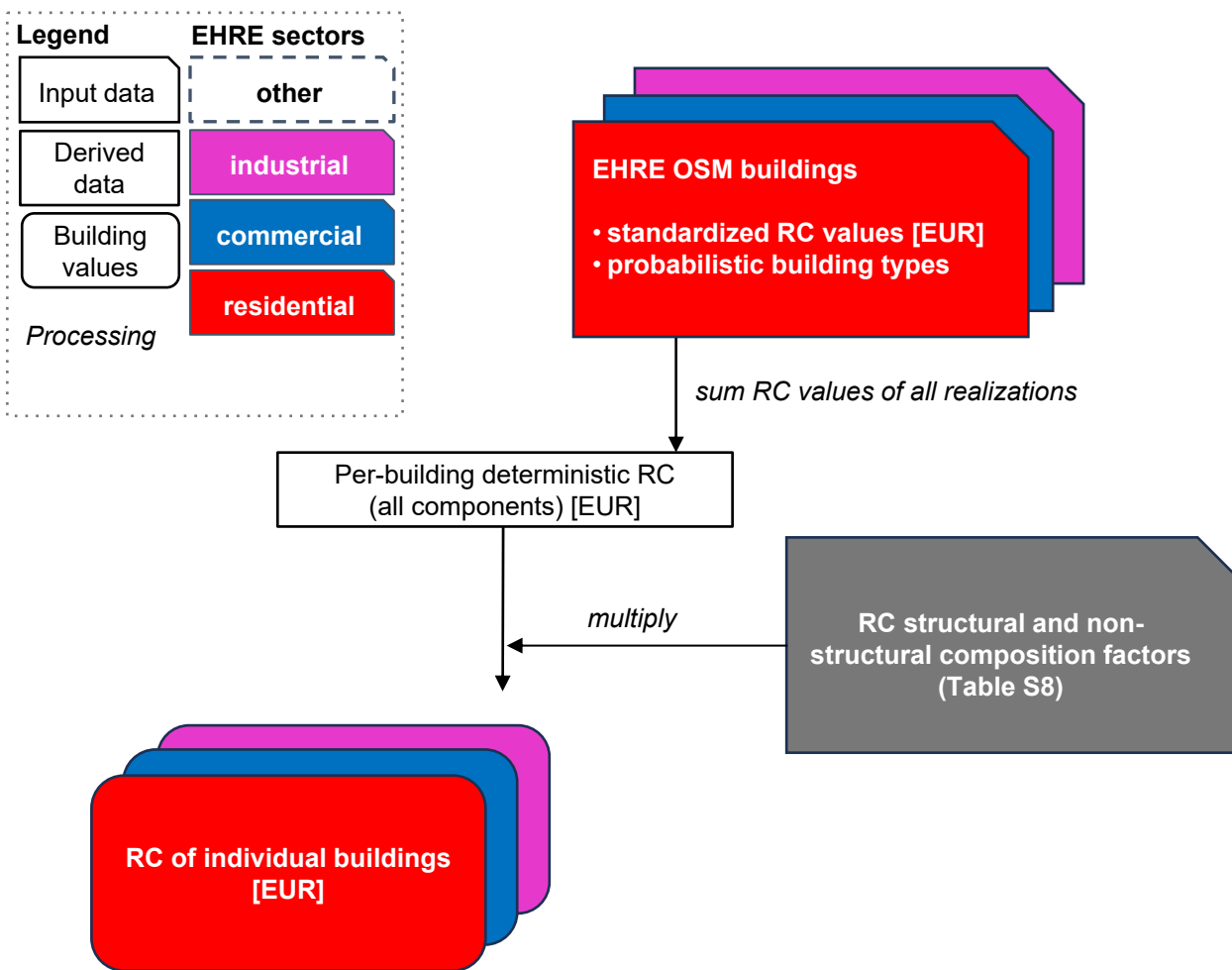


Figure 5: EHRE asset value model workflow adapted from Nievas et al. [2023]. Note other category assets do not contain asset values and are therefore omitted from value calculations.

2.3.4 OSM land-use 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, hierarchically prioritising the more granular OSM polygons over 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 \(96.73%\)](#) [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](#) [land-use-based](#) workflow is shown in [Figure Fig. 6](#).

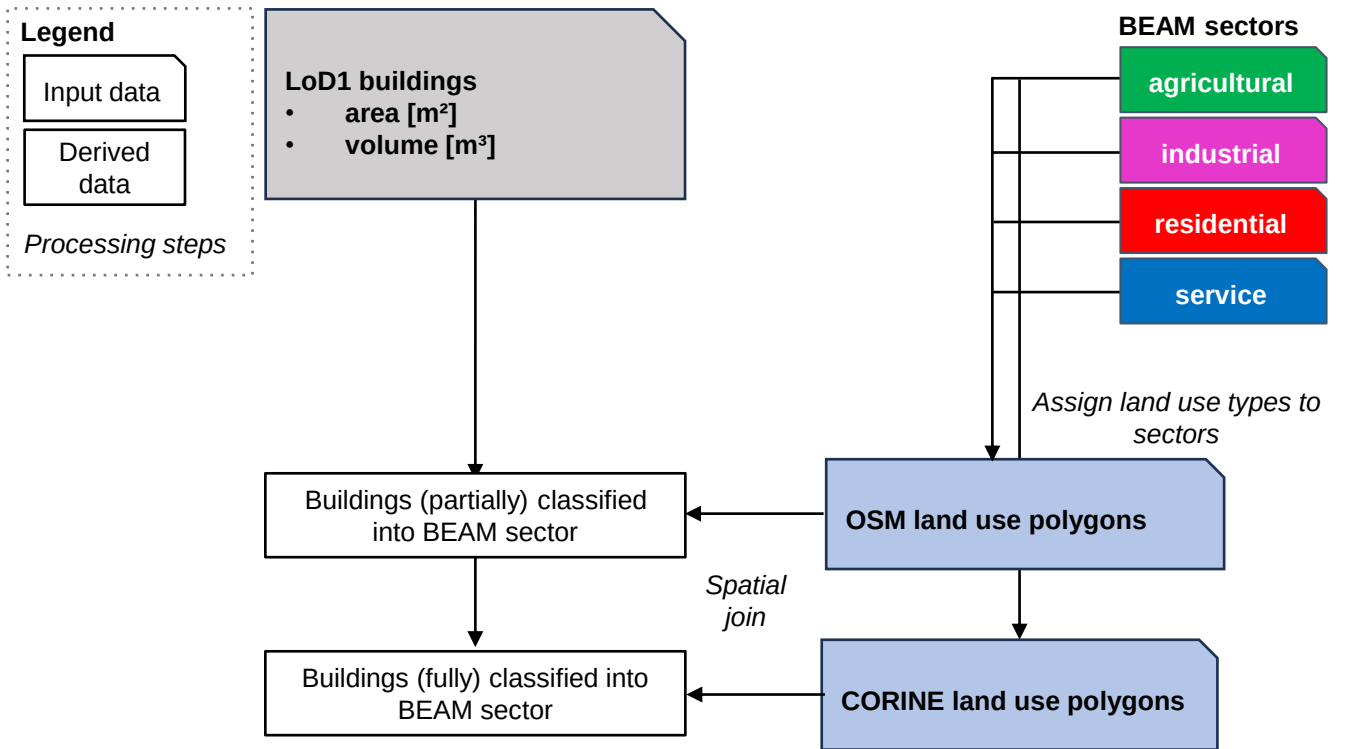


Figure 6: OSM [land-use](#) [land-use sector](#) classification model workflow.

2.4 Benchmark Dataset

To develop our benchmark dataset, we selected four representative study plots based on knowledge of the region ([Figure Fig. 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](#) [categorised](#) 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”, “[Warehouse/storage building, single-use](#)”) whose sector assignment [is ambiguous](#) [does not neatly fit into the three basic sectors](#) (see Supplementary Data Table 1 [for complete specification of the sector label mapping](#)). 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 [Section S4](#) for details). [Unit construction costs from BKI \[2021\] ranged from 370–495 €/m³ for](#)

330 *residential*, 210–290 €/m³ for *industrial*, 215–545 €/m³ for *service*, and 160–495 €/m³ for *ambiguous* building
331 use types (Table S9). New construction costs per-asset were then calculated by multiplying ~~unit construction costs~~
332 ~~from BKI [2021] (see Table S9)~~ the relevant unit construction cost, the regional cost factor for Ahrweiler county
333 (0.986; also provided in BKI [2021]), and individual building volumes from LoD1. The ~~workflow is summarized in~~
334 ~~Fig~~ benchmark dataset creation is summarised in Fig. S1.

3 Results & Discussion

This section presents and discusses ~~the evaluation results of the candidate sector classification and asset value models~~ first the sector-classification results, then the asset-value results.

3.1 Sector Classification

To quantify the classification performance, we first calculated one-vs-rest confusion counts and derived precision, recall, and F_1 for each benchmark dataset sector and each workflow (Section S5). The differences in classification results between the four ~~classification-models-workflows~~ against the four sectors of the benchmark dataset for the 844 sample buildings are ~~summarized~~ summarised in Fig. 7 with per-label performance metrics provided in Table S11 and mean values for each ~~model-workflow~~ in Table S12.

~~Examining performance across all four models shows~~ Across the four workflows, precision ranges from 0.50–0.66, recall from 0.57–0.78, and the F_1 score (F_1) from 0.45–0.71 (Table S12), with LoD1+Eurostat (Fig. 7a) and LoD1+BEAM (Fig. 7b) performing best ($F_1 = 0.71$; Table S12). Both these ~~models-workflows~~ are in perfect agreement with each other (assuming equivalence of all Eurostat “~~services~~” 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~~” market services and service in the Eurostat and BEAM ~~models-workflows~~ respectively. However, our manual classification of these buildings in the benchmark dataset describes many as *industrial* ($n=66$) or *ambiguous* ($n=68$). In other words, while some rare buildings with specific uses are well classified in LoD1 (e.g., ~~Schools, Churches, Fire Departments~~ schools, churches, fire departments), there is insufficient resolution (i.e., label groups are too broad) to differentiate between the more numerous industrial and service buildings. Beyond this, the two additional categories in the Eurostat ~~model-workflow~~ compared to the BEAM workflow (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 dataset service classification. However, because we opted for a simple ~~four-category benchmark~~ four-category benchmark dataset, this advantage is not reflected in the performance metrics of Table S12.

The OSM ~~land-use model~~ land-use workflow (Fig. 7d) performs the worst of all ~~models-workflows~~ ($F_1 = 0.45$), chiefly by over-assigning buildings to the *residential* sector. For example, about 90% of ~~benchmark~~ buildings labelled as *service* in the benchmark dataset are misclassified as *residential* by this ~~model-workflow~~. This bias arises from the application of coarse ~~land-use~~ 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~~ EHRE (Fig. 7c), which is ~~OSM geometry indexed~~ indexed to OSM geometry, it was necessary to spatially join ~~these the EHRE~~ records to the LoD1-based benchmark dataset (see Section S5). Because LoD1 is designed for 3D building representation, some objects that are single-part in EHRE are multi-part in LoD1. ~~To~~ to provide a fair comparison, we merged these LoD1 building ~~part geometries were merged in these cases~~. ~~Further, we slightly parts~~ (see label “c” in Fig. S2). We also manually shifted $< 1\%$ of LoD1 features to match EHRE geometry in obvious (and rare) cases in obvious near-match cases, but left benchmark dataset records without a plausible EHRE counterpart unmatched. 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 dataset records, which are likely attributable to differences in data vintage because they exist in 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 but not in OSM (see label “b” in Fig. S2). Conversely, EHRE records not present in the benchmark dataset were discarded (see label “d” in Fig. S2).~~ Considering these disparate geometries, EHRE had comparable performance to the other ~~non-land-use based models~~ non-land-use based workflows in the residential ($F_1 \approx 0.92$) ~~sector~~. The sector

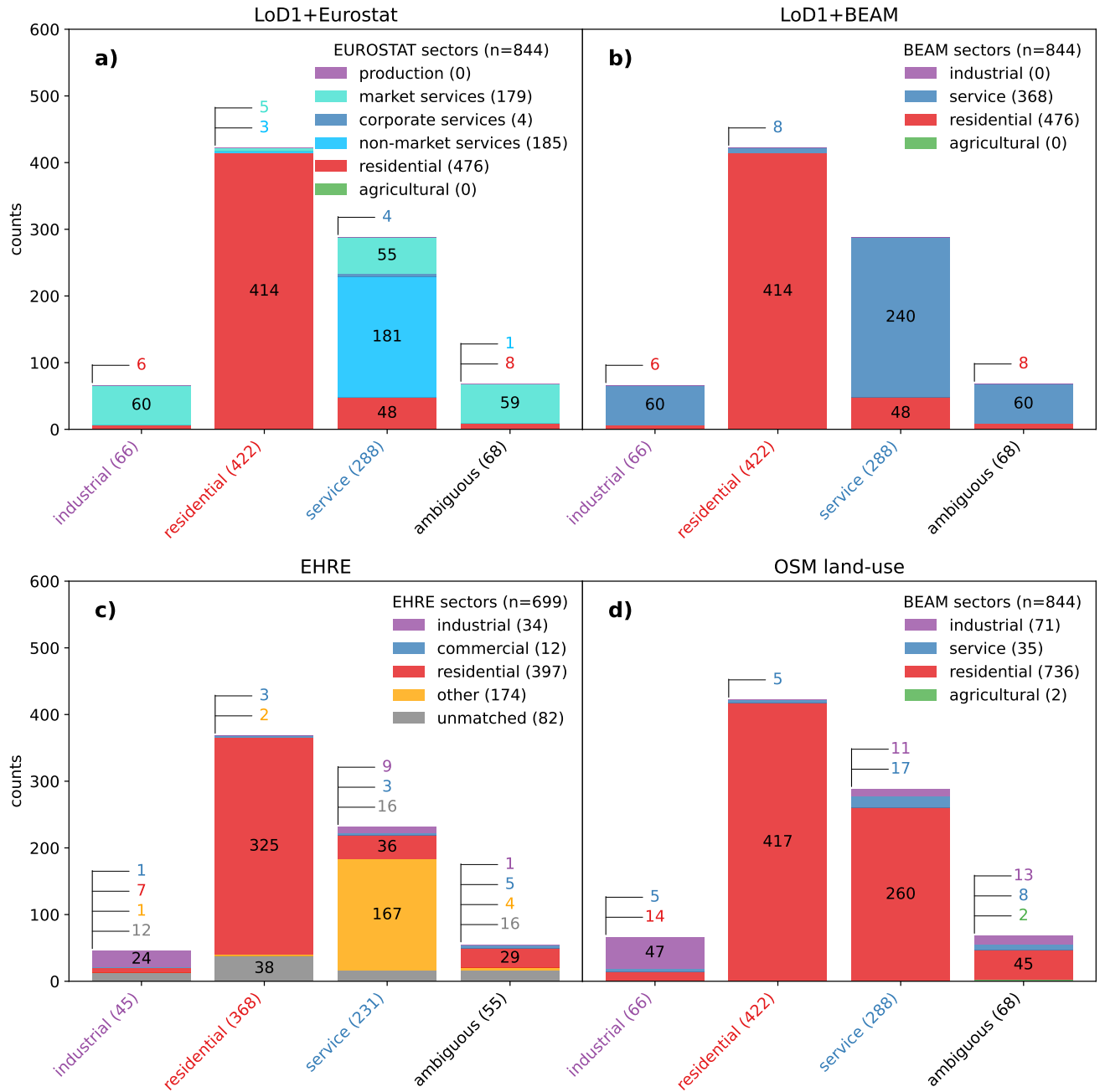


Figure 7: Sample building sector classification results against the benchmark dataset for four candidate model workflows. Bars labelled by building count and grouped by the three economic sectors of the benchmark dataset plus a fourth *ambiguous* category. Bars are coloured by the sector classification of each candidate model workflow. Note that no Eurostat production and no BEAM industrial features are among the 844 sample buildings (unlike in the whole case study area). Also note that EHRE (panel c) is natively OSM-indexed (unlike the others which are LoD1 indexed), leading to unmatched records (n=82); other panels had no unmatched records as they share the geometry indexing of the benchmark dataset. EHRE also treats some benchmark dataset building collections as single-part, leading to the anomalous total building count (n=699) (see text for details).

($F_1 = 0.89$). However, EHRE generally assigned the service sector benchmark labels however EHRE generally assigned dataset labels 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). We treat EHRE's application of these *other* labels ~~we consider as omission errors~~, because replacement values are omitted from these assets) ~~rather than~~, rather than as *commission errors*, which would imply an active assertion of the wrong label (see label "e" in Fig. S2). 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~~ ($F_1 \approx 0.72$) ~~workflows~~ ($F_1 = 0.85$). 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 the EHRE model~~ (Table 4).

Looking at the ~~The~~ three classification sectors of the benchmark dataset (industrial, residential, and service), ~~shows the variability in~~ ~~show variable~~ performance across the four ~~candidate models~~ ~~workflows~~. The highest classification agreement was observed for residential buildings, with all ~~four models~~ ~~workflows~~ classifying nearly all sample buildings consistently (recall ≥ 0.98); ~~over-estimation over-assignment of residential labels~~ was more challenging, especially for OSM ~~land-use~~ ~~land-use~~ (Fig. 7d; precision $\approx 0.57 = 0.57$) as discussed above. For the service sector, the LoD1 function-based ~~models~~ ~~workflows~~ (Fig. 7a,b) had reasonable true positive capture (recall $\approx 0.83 = 0.83$), but over-classified *industrial* and *ambiguous* buildings as *service* (precision $\approx 0.65 = 0.65$). For industrial assets, ~~the OSM land-use model EHRE~~ performed best ($F_1 \approx 0.68$), ~~$F_1 = 0.72$~~ , with the OSM ~~land-use workflow~~ close behind ($F_1 = 0.69$), 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~~ ~~workflows~~ failed to map any industrial assets owing to the lack of any such labels ~~in the dataset (see Supplementary Data Table 1 within our sample building set (see Fig. 7).~~

The final benchmark ~~dataset~~ category *ambiguous* was used as a catch-all for unclear or mixed building use in our hand labelling. As the two LoD1-based ~~models~~ ~~workflows~~ (Fig. 7a,b) do not have any mixed or ambiguous categories, these benchmark ~~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 dataset buildings were forced into standard LoD1 labels Building for business or trade. EHRE on the other hand does have a function classes.~~ For example, the benchmark dataset *ambiguous* class includes labels such as "Commercial buildings, with apartments", "Warehouse/storage building, single-use", and "Single, multiple and multi-storey garages", whereas LoD1 represents buildings through ordinary function labels such as "Building for business or trade", "Garage", or "Parking garage" rather than a mixed or ambiguous class. Similarly, EHRE does not have an ~~mixed ambiguous~~ category; ~~however, most these assets (n=46) we found to be clearly~~ because it deterministically maps *MIX* occupancy types to *residential*, *industrial* or *service* in our benchmark (rather than *ambiguous*), or *other* categories (see Supplementary Data Table 1). If these EHRE mixed (*MIX*) assets were instead mapped to the benchmark *ambiguous* category, EHRE would yield fewer false positives (precision increasing from 0.56 to 0.60), but with a small loss in recall (0.57 to 0.55) and therefore a negligible improvement overall (F1 increasing from 0.53 to 0.54).

In summary, the LoD1 function-based ~~models~~ ~~workflows~~ (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 ~~ambiguous~~ ~~ambiguous~~ buildings. The open-source object-based EHRE also performed well (Fig. 7c), especially if the *other* category ~~is were~~ considered *service* and the *MIX* category were considered *ambiguous*. Lastly, the open-source hierarchical imputation OSM ~~land-use based model land-use based workflow~~ (Fig. 7d) performed the worst against our benchmark ~~dataset~~, primarily through the over-assignment of *residential* labels; therefore, we exclude this ~~model workflow~~ from the subsequent sections. ~~Including it in the regional-total and per-asset value comparisons would require joining the OSM labels to an asset-value source such as Eurostat, producing an OSM+Eurostat hybrid that would mix label performance with the same Eurostat value basis already represented by LoD1+Eurostat. This would add redundancy and confusion rather than new asset-value information, while EHRE already provides an OSM-based asset estimate.~~

3.2 Regional Total Asset Values

We next extended three of the above sector classification label sets by joining sector classification schemes above with asset values from regional datasets. Table 4 provides a summary of resulting asset values aggregated to the Ahrweiler District. Table 4 summarises the resulting district-scale asset values for Ahrweiler.

Table 4: Building asset value model Asset-value workflow results per sector for Ahrweiler (DEB12; Fig. 1). Sectors with no buildings are omitted. See text for model workflow descriptions. Remainder buildings are a special category provided by the EHRE model that impute missing OSM data which can result in decimal values. NAV: net asset values; RC: replacement costs; DC: depreciated (construction) costs.

LoD1+Eurostat (RC)

sector	building count	aggregate €M€	unit value
residential	44,819	11,384,811,080.126,3 25,906.3	2,478.05 €/m ² 2,478 €/m ²
production	19	552,506,523.363,537 552.5	52,517.024,021,700,1 €/m ³ 52,517 €/m ³
market services	14,905	489,525,994.666,568 489.5	21,479,952,616,382 €/m ³ 21 €/m ³
corporate services	94	547,607,960.112,811 547.6	2,391.013,442,045,81 €/m ³ 2,391 €/m ³
non-market services	1,919	1,353,996,889.450,93 1,354.0	251.007,959,029,079 €/m ³ 251 €/m ³
TOTAL	61,756	14,328,448,447.720,1 28,850.0	

LoD1+BEAM

sector	building count	aggregate €M€	unit value (€/m ³)
residential (DC)	44,819	5,331,570,129.091,11 5,331.6	117.50 118
service (NAV)	16,918	7,638,566,436.173,9 7,638.6	294.78 295
industrial (NAV)	19	477,635,393.202,383 477.6	104,033.80 104,034
TOTAL	61,756	13,447,771,958.467,4 13,447.8	

EHRE (RC)

sector	building count	aggregate €M€	
residential	53,077	12,316,135,045 12,316.1	
commercial	813	1,676,279,987 1,676.3	
industrial	600	565,948,012.4 565.9	
residential (remainder)	10,202.2	2,363,409,469 2,363.4	
commercial (remainder)	364.72 364.7	748,354,884.4 748.4	
TOTAL	65,056.92 65,056.9	17,670,127,398 17,670.1	

Comparing across models Looking first at the building counts, the two LoD1-based workflows share the same inventory of 61,756 buildings, whereas EHRE includes 54,490 explicit buildings and 65,056.9 buildings when its remainder layers are included (Table 4). Next, this table highlights the different cost bases used by the workflows: LoD1+Eurostat and EHRE report RC, while LoD1+BEAM reports DC for residential buildings and NAV for non-residential buildings. Comparing across workflows, we find large variations in estimated asset value district-wide aggregates. This echoes the findings of [Röthlisberger et al., 2018] Röthlisberger et al. [2018], who showed that model estimates can diverge by factors up to 50–200 at 10 km² aggregation in Switzerland. Comparing our findings for the residential sector residential sector for the two LoD1 function-based models workflows with identical assets (LoD1+BEAM and LoD1+Eurostat), we find the Eurostat-based RC estimate more than double that of is nearly five times BEAM’s DC. Computationally, this arises primarily from disaggregating with LoD1+BEAM’s 117.50 €/m³ DC vs. 118 €/m³ DC versus Paprotny [2022]’s 2,478 €/m² RC 2,478 €/m² RC applied to estimated

usable floor area (Table 4); which, and is unsurprising considering BEAM includes depreciation whereas [Paprotny, 2022] Paprotny [2022] does not. More surprising, considering these different cost-bases, the Although LoD1+Eurostat estimates lower non-residential sectors counterbalance the residential differences, such that the total (totals than LoD1+BEAM, its larger residential RC dominates the aggregate result, making its all-sector) sums of the two LoD1-based models happen to fall within $\approx 7\%$ total about 2.1 times larger. Looking at the unit costs, both LoD1-based models workflows produced some implausible values as a result of disaggregating regional values onto sectors poorly represented by LoD1. For example, the 19 production/industrial buildings (which are exclusively LoD1 “substations”): LoD1+Eurostat’s production unit cost is and LoD1+BEAM’s industrial unit costs are both roughly two orders of magnitude beyond any of the comparable BKI unit costs (Table S9) while LoD1+BEAM’s industrial sector, with only 19 buildings, is three orders of magnitude beyond. Similarly. Conversely, LoD1+Eurostat’s market services unit cost is roughly an order of magnitude lower than any of the BKI values. This suggests the BKI service unit costs because the 489.5 M€ sector total is distributed across about 23 million m³ of mapped LoD1 building volume for this sector, yielding only 21 €/m³. Together, these extreme values suggest 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 EHRE estimates a lower residential RC than LoD1+Eurostat, with 12.3 B€ in explicit buildings and 14.7 B€ when the residential remainder is included, despite its higher building count (Table 4). By contrast, EHRE and LoD1+Eurostat estimate similar non-residential building stock in EHRE is the smallest of all models (3.0 B€) totals (3.0 B€ and 2.9 B€, respectively), both less than half the LoD1+BEAM estimate (8.1 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.

3.3 Per-Asset Values

Comparing asset-to-asset, ~~Figure~~Fig. 8 presents the two LoD1-geometry distributed asset value ~~models-model workflows~~ against the BKI [2021] construction-cost benchmark ~~dataset~~ (also LoD1-geometry distributed). ~~This figure~~ Because this benchmark dataset is drawn from a single, predominantly residential region, it is likely not representative of areas where industrial and service buildings are more prevalent. This Fig. 8 shows a near-linear relationship between modelled and benchmark ~~dataset~~ asset values for all sectors, which is intuitive if we consider that both the ~~models-workflows~~ and the benchmark ~~dataset~~ are geometry-based; ~~i.e.~~, they differ mainly in the unit cost multipliers applied to the building area or volume (see Table 4 and Table S9 for unit costs). Setting aside the sectors with implausible disaggregated unit rates (e.g., *market services* and *corporate services*), ~~all-most non-residential~~ assets in the LoD1+Eurostat ~~model-workflow~~ underestimate the benchmark ~~dataset~~. This can also be seen ~~(partially)~~ by comparing the *non-market services* unit cost (~~348 €/m³~~251 €/m³) to the BKI service unit costs (Table S9); ~~;~~ nearly all of which are higher. This ~~underestimation in our LoD1+Eurostat model non-residential underestimation~~ likely arises from ~~its~~ LoD1+Eurostat’s reliance on stock-average values [Paprotny et al., 2020a], in contrast to the new-build construction cost averages reported by BKI. ~~Similarly, Surprisingly, we find that the Eurostat residential asset values do not follow the same pattern and are generally higher than the benchmark dataset. This over estimate is likely influenced by the method we used to calculate the usable floor area, which multiplies the LoD1 footprint area by a height-derived storey count and a 0.7 usable-area coefficient after Paprotny et al. [2020b]. Fig. S4 shows the lack of precision of the storey counts estimated in this way; which generally exceed the observed benchmark dataset counts, in some cases by three storeys, inflating usable floor area and therefore residential RC at the object level. Further, sensitivity to the area multiplier is substantial. For example, using LoD1 footprint area directly gives a residential RC roughly 14.5 B€ (56 %) lower than the usable floor area estimates used here. Conversely, all residential BEAM assets underestimate their BKI counterparts, with a unit cost of 118 €/m³, lower than any reported by BKI. While this is unsurprising considering BEAM includes a depreciation factor, the modest residential over-assignment of residential labels discussed earlier, or inaccurate building volumes (62 false positives; Table S11) could also influence the discrepancy. In contrast, the LoD1+BEAM service assets are less biased, with the 295 €/m³ falling within BKI’s wide range (Table S9); however, this results in higher variance than the other sectors. Thus, these differences should be read primarily as conceptual alignment with stock-average or depreciated values rather than inherent model deficiency; with the available data, we cannot isolate the specific mechanisms driving each discrepancy.~~

Unlike the LoD1-based ~~models-workflows~~ and the benchmark ~~dataset~~, 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 workflows~~ 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). ~~Even the relatively similar aggregate inventories in Table 4 (LoD1: 61,756 buildings; EHRE with remainder: 65,056.9, 5.3 % higher) mask important differences in object definition and sector composition, so total count agreement should not be interpreted as asset-level comparability across LoD1 and EHRE. Our early attempts at this to address this evaluation challenge 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 commercial and industrial comparisons are more difficult to interpret because of small sample sizes and object-matching ambiguity.~~ 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’s average per-asset-type replacement costs (which are based on average building areas).

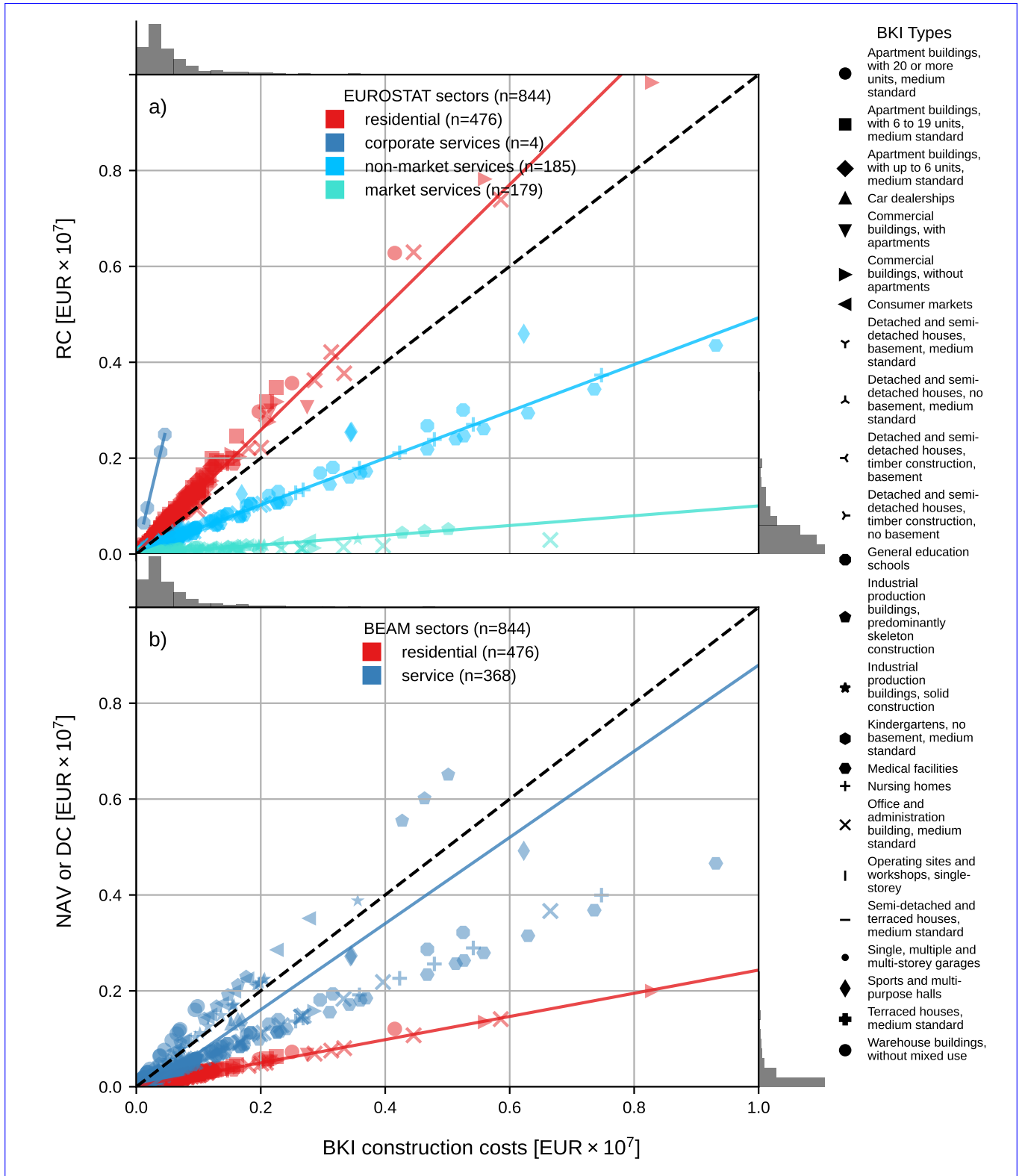


Figure 8: Asset values for (a) LoD1+Eurostat (RC) and (b) LoD1+BEAM (residential is DC while non-residential is NAV) models against the benchmark dataset. Data markers represent the BKI [2021] type and colours represent the model-assigned sector. Solid lines provide the linear trend of the respective 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.

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~~ exposure model workflows presented above. Derived from the multiple-criteria decision-making mathematical framework, this technique is widely used to ~~prioritize~~ prioritise 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 5, each ~~model is subjectively~~ workflow is scored on a scale of 0–10 for each criterion before scores are multiplied by their respective weights then summed. The benchmark dataset classification score was calculated from Table S12, while the criterion weights and remaining workflow scores were assigned through iterative discussion among the authors until consensus was reached on a final set of values.

Table 5: Scores and weights for the asset value ~~models~~ model workflows. See Table S13 for a description of each criterion.

Criteria	Weight	LoD1+Eurostat	LoD1+BEAM	EHRE
Benchmark classification	0.15	7	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	6.8	6	6.3

~~Translating the sector and asset value benchmark comparisons from above to the WSM, the~~ In the WSM, LoD1+Eurostat ~~model slightly outperforms the other candidates~~ slightly outperforms the other workflows owing mainly to ~~the benchmark~~ its benchmark dataset 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~~ licence (commonly provided for free to public bodies and research institutes under specific agreements), while commercial users typically obtain fee-based licences. Of the ~~three asset value model~~ 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,~~ 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~~ workflows, 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~~ workflow is described by Fig. 3 and Eq. 1. EHRE is the only ~~model~~ workflow to explicitly consider uncertainty, both through the incorporation of probabilistic building types and the use of “~~remainder~~” remainder layers and the “~~other~~” 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~~ workflow for their context.

3.5 Limitations and recommendations

With this study, we provide the first per-asset evaluation of asset value ~~models~~ model workflows for exposure modelling. Although extending these workflows to other regions in Germany would be straightforward, the need for a labour-intensive hand-labelled benchmark dataset restricted our evaluation to a single region, meaning the findings are only transferable 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 dataset 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. Further, these additional variables are rarely ingested by loss models, and therefore their inclusion in our evaluation would be of limited use to most readers.

The ~~dependency~~ dependence of our benchmark dataset 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~~ disaster-affected buildings; however, this information is notoriously difficult to collect and plagued with uncertainty when self-reported [Rözer et al., 2019]. For the LoD1+Eurostat residential estimate in particular, the reliance on inferred rather than observed usable floor area introduces uncertainty and complexity: future work should improve this conversion. Similarly, because we opted to provide a broad evaluation, we include asset value model workflows with different cost ~~basis~~ bases (RC, DC, NAV) and years (2018, 2020, and 2022), making our findings less conclusive. Aligning cost bases or developing ~~standardized~~ standardised conversion approaches could improve the ~~appearance~~ comparability 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~~ machine-learning and remote-sensing-based methods, especially for asset classification. For example, ~~Gouveia et al. [2024]~~ Gouveia et al. [2024] and 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~~ privacy-protected under the EU’s General Data Protection Regulation [Union, 2016]. While many benefits arise from such protections, ~~policy-makers~~ policymakers 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~~ model workflows 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~~ model workflows and evaluated these with our hand-labelled benchmark dataset.

From this, we found that the ~~cadaster-derived~~ cadastre-derived LoD1-based ~~models~~ workflows performed best overall against the benchmark dataset at labelling a building’s sector ($F_1 = 0.71$), but lacked the resolution necessary to identify industrial uses. This contrast between strong residential performance and near-complete failure for industrial assets indicates a limitation of cadastral function categories rather than a modelling error. It also cautions against the uncritical use of authoritative building function data for economic sector classification. Aggregate,

600 region-wide values diverged between the candidate ~~models~~ workflows (up to an order-of-magnitude at the sector
601 level), suggesting an under-appreciated level of uncertainty — comparable to uncertainties reported in other aspects
602 of risk modelling, like vulnerability — and ~~emphasizing~~ emphasising the need for local validation. Similarly, we
603 found implausible unit rates when disaggregating regional sector totals onto LoD1 functions that poorly represent
604 our local sector mix (e.g., unit costs ~~three-orders-of-magnitude~~ hundreds of times beyond comparable published val-
605 ues), signalling the importance of aligning regional data with building-level data. Setting these implausible unit rates
606 aside, we found ~~both Eurostat and BEAM-based models generally~~ BEAM and most non-residential LoD1+Eurostat
607 values underestimate the new construction costs reported by our benchmark ~~— This dataset, while LoD1+Eurostat~~
608 residential values are generally higher. This likely reflects, respectively, ~~Eurostat's~~ BEAM's inclusion of depreciation,
609 Eurostat's reliance on stock-average replacement costs rather than new-build price lists, and ~~BEAM's inclusion of~~
610 ~~depreciation in construction costs~~ the sensitivity of residential estimates to usable-floor-area assumptions. Extending
611 this evaluation using a scoring model to examine less-quantitative factors important for exposure modelling like sus-
612 tainability, transparency, and adaptability, we find all candidate ~~models~~ workflows (except the ~~land-use-based model~~)
613 ~~score similarly~~ land-use-based workflow obtain similar total scores. However, the ~~LoD1- and Eurostat-based model~~
614 LoD1+Eurostat workflow performs slightly better, mainly due to its ease of adaptation across regions and time
615 periods, and the relative simplicity of maintaining and updating it.

616 These findings suggest that, other than the land-use-based ~~model~~ workflow, any of the three ~~workflows considered~~
617 ~~here~~ asset value model workflows can provide a defensible asset-level exposure model in Germany, albeit with
618 different cost ~~basis~~ bases. Modellers should select the workflow that aligns with their sustainability, adaptability,
619 sophistication, and cost-basis needs and perform local validation. In summary, we find transparent, maintainable
620 workflows, not coarse ~~land-use~~ land-use proxies, yield the most reliable object-level exposure when grounded in
621 local validation.

622 **Code/Data Availability**

623 Source datasets used for the analysis are listed in Table 1 and are freely available at the web links provided; with
624 the exception of the EHRE data extract which is provided in Nievas [2025] [and the BKI book](#). All sector mappings
625 we employ are provided in Supplementary Data Table 1. Results for the three ~~candidate-asset-value-models-asset~~
626 [value model workflows](#) (and their corresponding sector classifications) are openly provided in Buhrmann [2025b]
627 with geometry provided in Buhrmann [2025a] (upon request to preserve privacy). Software to ~~develop-the-models~~
628 [implement the workflows](#) and perform the analysis is provided in Buhrmann [2025c].

629 **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~~

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

630 **Competing interests**

631 Some authors are members of the editorial board of journal NHESS.

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