



Lifetimes of demolished buildings in US and European cities

RESEARCH

JULIANA BERGLUND-BROWN

ISAAC DOBIE

JORDAINA HEWITT

CATHERINE DE WOLF

JOHN OCHSENDORF

**Author affiliations can be found in the back matter of this article*

ubiquity press

ABSTRACT

Building lifetime is a useful metric that serves as an input for many analyses, including property valuation, life-cycle assessment, material flow analysis and building stock analysis. Additionally, building lifetime is essential for the adoption of circular economy principles and retrofitting in construction, which ultimately will help reduce greenhouse gas emissions in the built environment. Yet, limited end-of-life building data and a focus on the design lifetimes of buildings means estimates for actual building lifetimes are outdated, not empirically based or else not compared across regions. By first sourcing and cleaning an extensive dataset of approximately 15,000 demolished buildings, this paper conducts a statistical analysis to: empirically estimate average building lifetimes in nine US and four European cities; analyse trends in building lifetimes across a number of design variables; and understand building obsolescence by applying techniques from survival analysis to buildings. An average lifetime of 71 years was found across all buildings, with a standard deviation (SD) of 28. Significant differences in lifetimes of use types were identified, with residential buildings lasting the longest. Age of the city did not appear to influence the survivorship of demolished buildings, but current and past demolition trends could.

PRACTICE RELEVANCE

Buildings are often demolished before the end of their technical lifetime. Building demolition occurs for difficult-to-predict reasons such as economic viability, owner preference and unfavourable architectural characteristics, making actual lifetime hard to estimate. Additionally, sparse data pertaining to demolition have a limited understanding of empirical building age in many US and European cities. In practice, knowing building age is important because it is a metric used in scores of engineering analyses, and it can help in the estimation of the environmental and economic impacts of buildings and cities. This research estimates average building lifetime in nine US and four European cities across building characteristics in order to increase literacy about the demolished building stock, identifying what types of buildings are deemed obsolete.

CORRESPONDING AUTHOR:

Juliana Berglund-Brown

Department of Architecture,
Massachusetts Institute of
Technology, 77 Massachusetts
Ave, Cambridge, MA 02139, US
jbbrown@mit.edu

KEYWORDS:

demolition; demolition rate;
obsolescence; building data;
building lifespan; survival
analysis; building longevity;
building stock

TO CITE THIS ARTICLE:

Berglund-Brown, J., Dobie, I.,
Hewitt, J., De Wolf, C., &
Ochsendorf, J. (2025). Lifetimes
of demolished buildings in US
and European cities. *Buildings
and Cities*, 6(1), pp. 1099–1116.
DOI: [https://doi.org/10.5334/
bc.588](https://doi.org/10.5334/bc.588)

1. INTRODUCTION

How long do typical buildings last? This seemingly simple question has elicited a wide array of responses. Discussions first appeared in the literature in 1922, in response to the increasingly short lives (15–30 years) of US office buildings (Burton 1933; Shultz 1922). In the 1980s, data entered the discourse, with literature illustrating the lack of knowledge about rate of loss from the housing inventory in the US; a small dataset from the American Housing Survey (AHS) on residential building lifespan was subsequently developed (Gleeson 1985). Data from the AHS have also been analysed more frequently, estimating an average life of 61 years (Aktas & Bilec 2012) and 102–130 years (Ianchenko et al. 2020). Building lifetime estimates in the literature fluctuate based on material and location, with studies of buildings in Zurich, Switzerland, producing lifetime estimates of 70–200 years (Aksözen et al. 2017). A 2004 study of 204 US buildings found the majority of demolished wood buildings were older than 75 years, while over half of all demolished concrete buildings fell into the 26–50-year category (O'Connor 2004). A study of demolished buildings in South Korea indicates that wood buildings typically last approximately 53 years, whereas steel buildings only live approximately 11 years (Ji et al. 2021). While these estimates are based on real data, building demolition has not been assessed with empirical data on a national scale in the US, and US demolition data have not been evaluated alongside European demolition data.

A further complication is the distinction between *design* life and *actual* life. Design life (how long the building can be technically guaranteed by an engineer) and actual life (how long a building physically stands before it is torn down) mirror another polarity: deterioration- versus decision-based obsolescence (Ianchenko et al. 2020). Obsolescence, defined here as *going out of use*, does not necessarily connote the condition of the building. In fact, myriad factors beyond condition influence demolition decisions, including: owner desire (Kohler & Hassler 2002), economic viability, layout, use type, floor plans and ceiling height (Baker et al. 2023). According to guidance provided by Eurocode EN 1990: ‘The basis of structural design’, the design working life of most buildings is 50 years; for monumental civil structures, it is 100 years (Eurocode EN 1990). With proper maintenance, assessment and repair, however, buildings could last nearly indefinitely (Huuhka et al. 2023). Nonetheless, many structurally viable buildings were deemed obsolete before their intended lifetime: the American Folk Art Museum in New York City, US—named the best cultural building of 2001—lasted 11 years; the National Hockey Stadium in Milton Keynes, UK, 12 years; and the Maupoleum in Amsterdam, the Netherlands, 23 years.

These buildings demonstrate the extremes of a ubiquitous practice: demolition of structures before the end of their functional life—or *premature demolition*. In the UK, 50,000 buildings were demolished in 2021 (Hurst 2021). The largest share of waste in Switzerland is caused by construction activity (FOEN 2018), while in China, construction waste comprises 40% of municipal solid waste (Hao et al. 2010). In the US in 2018, 600 million US tons of construction and demolition (C&D) waste was produced (US EPA 2018). This volume of C&D waste is not without consequences—C&D waste directly correlates with greenhouse gas (GHG) emissions attributable to the built environment. The embodied carbon of the built environment includes demolition processes, transport to end-of-life facilities, waste processing and disposal of waste (Adams et al. 2019). Embodied emissions from building material production currently account for 23% of the 37% of global process-related GHG emissions in the built environment (UNEP & Yale Center for Ecosystems + Architecture 2023). A study of cradle-to-grave embodied GHG emissions of UK masonry buildings found that end-of-life activities account for 21% of the buildings’ lifetime embodied emissions (Moncaster & Symons 2013). Given demolition’s contribution to building GHG emissions, widespread decision-based obsolescence (to say nothing of premature demolition) causes greater demolition quantity, and therefore higher embodied impacts.

Beyond embodied emissions, building age is necessary to characterise operational energy use in building stocks, and to provide projections on the quantity of material stocks for circular practices (Cao et al. 2019). Historically, building lifetime estimates were used to set mortgage loans and predict depreciation schedules (Burton 1933; Gleeson 1981). More recently, it has been used for life-cycle assessment (Aktas & Bilec 2012), and uncertainties about service life of materials affect

environmental impact estimates (Galimshina et al. 2024). Longer residential building lifetimes and slow building stock turnover—i.e. how frequently buildings are demolished and replaced—may have implications for operational energy efficiency (Berrill & Hertwich 2021). Moreover, lifetime is a crucial parameter for circular economy implementation in the built environment. Circular economy employs several resource strategies, including extending product lifetime (Çetin et al. 2021). Prolonging product lifetime in buildings has been linked to better environmental performance (Mequignon et al. 2013).

Lifetime is also important to material flow analyses of building stocks and urban mining, for age directly correlates to loss rates in building stock modeling (Berrill & Hertwich 2021) and provides an insight into which materials could become available—and when (Schebek et al. 2017). In a literature review of 60 dynamic material flow analyses, most authors quantified outflows through the assignment of a lifetime distribution function to products or end-use sectors dependent on available lifetime data (Müller et al. 2014). Many authors also found their models to be most sensitive to mean lifetime value, rather than distribution (Müller et al. 2014) or standard deviation (SD), hence why mean lifetime is an object of this study. While some of the literature has started analysing categorical design and material trends in the existing building stock, few have examined how building characteristics influence building lifetime generally in the US and Europe. In Europe, existing studies highlight typological trends in building lifetimes (Andersen & Negendahl 2023; Huuhka & Lahdensivu 2016), but none has been statistically evaluated or assessed in comparison with the US.

In some studies, obsolescence has not been explicitly identified, but demolition was found not to relate necessarily to building age (Huuhka & Lahdensivu 2016), and newer buildings were seen to have shorter-than-average lifespans across all construction periods (Andersen & Negendahl 2023). In these studies, obsolescence was not quantified. Many have explored changes in the building stock with a view to developing predictive models for building lifetimes (Cai et al. 2015; Cao et al. 2019; Kayo & Tonosaki 2022; Zhou et al. 2019), rather than using data about demolitions to draw conclusions about building lifetime and obsolescence. While certain national studies employ data about demolished building stocks to emphasise the obsolescence of new buildings, as well as trends in their demolition (Andersen & Negendahl 2023; Huuhka & Lahdensivu 2016), the present paper's regional and municipal scope, together with its analysis of trends, is unique.

While the importance of building lifetime is clear, many questions still remain for understanding the demolished building stock beyond outdated, highly localised or projection-based studies. Additionally, the influence of design aspects on lifetime has not been widely analysed. This paper first aims to estimate how long buildings last, via a statistical analysis of an empirical dataset of 14,879 demolished buildings from nine US and four European cities. Next, it identifies demolition trends across a number of attributes, including city, use, style and material types, and determines which differences in building averages are significant. Finally, it offers some conclusions about building obsolescence in US and European cities, first by analysing limited condition data, and then through a quantitative analysis, evaluating survivorship probabilities of demolished buildings in each region.

2. METHODS

A city's building stock has long been a research object (Kohler & Hassler 2002), but there are few analyses of demolished building stocks. The data in this paper originate from 13 cities across several states and countries, and were collated by an iterative process, cleaned and analysed using processes detailed in this section.

2.1 DATA PREPARATION

Perhaps the most intensive aspect of this methodology was data preparation, which involved dataset characterisation, selection, collation and cleaning. Unique to this paper is its approach to aggregating demolition data, described in Figure 1.

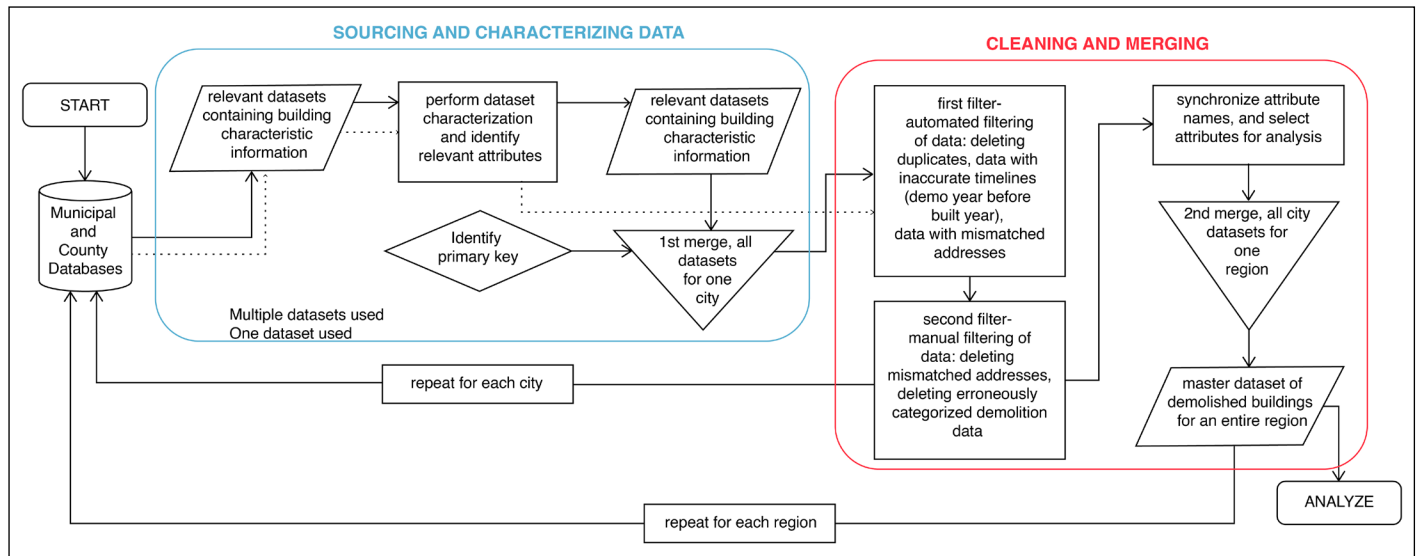


Figure 1: Data preparation methodology flowchart.

2.1.1 Data methods and sources in the literature

Data inaccessibility and scarcity have previously posed problems for understanding building lifespan (Bradley & Kohler 2007). In the US, public data from the AHS have been used solely for analysis of dwellings (Aktas & Bilec 2012; Ianchenko *et al.* 2020). A small study of approximately 200 demolished buildings analysed more than just residential building lifetimes in the US, but at the time of publication is 20 years old. Some research has evaluated building demolitions on the national scale, examining 126,000 demolished buildings in Denmark (Anderson & Moncaster 2020) and 1.8 million demolished buildings in South Korea (Ji *et al.* 2021). These analyses utilise national building registers for demolished building data. Additional work has analysed building lifetime on a municipal scale, including a study in Zurich, Switzerland, that analysed 18,000 buildings demolished over a 180-year period (Aksözen *et al.* 2017). This dataset was compiled from several sources provided by the city and included multimodal and multi-structural datasets. One study compared demolition trends in different cities, evaluating two Japanese cities against one in the UK, using geospatial data capture to evaluate changes in the building stock (Tanikawa & Hashimoto 2009). Building demolition—residential buildings aside—has not been assessed with empirical data on the national scale in the US, and US demolition data have not been evaluated alongside European demolition data. Additionally, data on municipal demolition permits have not been used to make lifetime comparisons.

2.1.2 Data sources and attributes used in this paper

Table 1: Metadata of municipal datasets: year range, size, source and attributes.

CITY	PERIOD OF DEMOLITION DATA COLLECTION	DATASETS MERGED	NUMBER OF BUILDINGS BEFORE THE SECOND MERGE	NUMBER OF BUILDINGS IN THE FINAL ANALYSIS	SOURCE	ATTRIBUTES
Boulder, CO	1997–2024	‘Ownership Parcels’; ‘Construction Permits’	300	122	City of Boulder Open Data Hub (City of Boulder Open Data n.d.)	Core attributes, use
Cambridge, MA	2000–16	‘Cambridge Property Database’; ‘Demolition Permits’	111	84	City of Cambridge Open Data Portal (n.d.)	Condition, Core attributes Geographical coordinates Land and property value Material type Number of floors Roof type Zoning, style, use
Los Angeles, CA	2013–23	‘Assessor Parcel Data’; ‘Demolition Permits’	2,029	818	County of Los Angeles Open Data (n.d.)	Core attributes Geographical coordinates Land and property value Number of floors Zoning, use

(Contd.)

CITY	PERIOD OF DEMOLITION DATA COLLECTION	DATASETS MERGED	NUMBER OF BUILDINGS BEFORE THE SECOND MERGE	NUMBER OF BUILDINGS IN THE FINAL ANALYSIS	SOURCE	ATTRIBUTES
Lynchburg, VA	2000–24	‘Parcels’	139	103	City of Lynchburg GIS Portal (City of Lynchburg Open Data n.d.)	Core attributes Geographical coordinates Land and property value, use
Minneapolis, MN	2016–24	‘Assessing Parcel Data’; ‘Construction Code Permits’	174	171	Open Data Minneapolis (OpenDataMPLS n.d.)	Core attributes Geographical coordinates Land and property value Material type Number of floors Roof type Zoning, use
New York City, NY	2000–24	‘Property Valuation and Assessment Data Tax Classes 1 2 3 4’; ‘DOB Job Application Filings’	4,103	2,356	NYC Open Data (City of New York Data n.d.)	Building height Core attributes Geographical coordinates Land and property value Number of floors Zoning, use
Pittsburgh, PA	2019–24	‘PLI Permits’; ‘Assessor’	73	49	Western Pennsylvania Regional Data Center (Dataset—CKAN n.d.)	Condition Core attributes Number of floors Roof type, style, use
Raleigh, NC	2018–24	‘Parcels’; ‘Building Permits’	208	132	Raleigh Open Data (Open Data Raleigh n.d.)	Core attributes Geographical coordinates Land and property value Material type Number of floors, style, use
Seattle, WA	2005–24	‘Parcels 1’; ‘Building Permits’	1,501	1,470	Seattle Open Data Portal (Seattle GeoData n.d.)	Core attributes Geographical coordinates Zoning, use
Amsterdam	2010–24	‘BAG’ (not able to share)	3,378	2,776	Data Amsterdam (Data en informatie n.d.)	Core attributes Number of floors, use
Copenhagen	2017–24	‘BBRBygning’	1,383	696	Datafordeleren (Datafordeler.dk n.d.)	Core attributes Geographical coordinates Roof type, exterior wall type, use
Zurich	2008–24	‘Gebäude- und Wohnungsregister der Stadt Zürich (GWZ)’	5,326	4,057	Open Data Stadt Zürich —City of Zurich (n.d.)	Core attributes Geographical coordinates Number of floors, use
Helsinki	1974–2024	Specialised dataset (not able to share)	2,753	2,045	City Survey Services (City Survey Services Helsinki n.d.)	Core attributes Geographical coordinates, use

Sources of data on demolished buildings vary based on region. All US demolition data are publicly available at the municipal building level, while European data are available at both the national and municipal levels (depending on location). In the US, municipal data are often accessible via open data portals and can be retrieved on the website or via an Application Program Interface (API) key. The availability of these data varies enormously by city, which serves as a limiting factor for which municipalities ended up in the analysis. In Europe, many cities have similar municipal data portals, but serve the primary function of displaying data, either via maps or catalogues, and an enquiry is required to acquire the raw data. Some European cities and countries have open data portals where data can also be accessed via direct download or API.

The process of city selection involved several iterative steps, including establishing criteria regarding which cities should be included; identifying open data portals regionally; and characterising said city and data by demographics and attributes. The initial criteria for data selection included the robustness of the data, ease of access and maintaining the diversity of the city types utilised. City-wide characteristics used to ensure a representative sample size were: population, density,

and socio-economic and racial demographics. ‘Robustness of data’ referred to the inclusion of the following attributes: year constructed, square footage, material type specified, cost of project, number of stories, location indicators, use/function of building, and whether or not they included demolition data. Datasets with year constructed, year demolished and use type were included in the analysis (with the exception of Amsterdam, which does not have a use type). Sometimes, these characteristics could only be found across several datasets, as was the case for most US cities, and so a merging and cleaning process (detailed in Section 2.1.3) was employed.

Data from Boulder, Cambridge, Los Angeles, Lynchburg, Minneapolis, New York City, Pittsburgh, Raleigh and Seattle were included from the US; from Europe, Copenhagen, Amsterdam, Zurich and Helsinki. [Table 1](#) details each city’s metadata. The majority of data in the US were in demolition or construction permit datasets, and parcel or property valuation datasets. European data were largely found in building registers, with records indicating if the building had been demolished.

2.1.3 Merging and cleaning

As detailed in [Table 1](#), the majority of US building information was found in multiple datasets per city. These datasets were merged via differing primary keys, sometimes in the form of a consistent identifier, parcel number, address or coordinates. In some cases, a dataset’s primary identifier needed to be formulated by conglomerating three separate identity attributes in order to merge. Because this did not always allow for a precise merge, a series of steps to clean the datasets was taken. In Europe, Amsterdam was the only city with multiple datasets.

All cities in this study underwent the first cleaning stage, which included: (1) filtering out buildings where the demolition year was earlier than the year built; (2) filtering out buildings where the demolition year was equal to the year built; (3) deleting duplicates; and for all merged datasets: (4) filtering out all values where the addresses of the merged datasets did not match. There was an additional level of cleaning for some cities. For datasets with demolition permits, permits that had expired or were not granted were removed from the dataset. Human error persists in some of the datasets provided by European cities, with two errors in those for Amsterdam and Zurich. In the Amsterdam error, the wrong ‘status label’ was assigned to buildings, which meant that over 150 buildings indicated demolition after one year. Employees in the data team in Zurich also indicated there was potential for a small amount of data inconsistency. Similar uncertainty arose with merged datasets in the US, where the demolition permit was processed or time stamped after the next building was built. This also meant several buildings indicated being demolished after a year. To avoid the most egregious errors during this transition time period from one building to another, all buildings indicating they had been demolished after fewer than five years of age were filtered out.

2.2 DATA ANALYSIS

2.2.1 Building lifetimes

Statistically, the lifetime of a single building can be defined by one value: time until a specified event, or in this case, time until demolition, t_d . Four functions can characterise the distribution of t_d : a survival function, hazard rate, probability density functions (PDFs) and mean residual life ([Klein & Moeschberger 2006](#)). This paper focuses on PDFs to estimate lifetimes. In this analysis, t_d , described as *age upon demolition*, also known as building lifetime, is calculated using: $t_d = y_d - y_c$, where y_c is construction year and y_d is year demolished.

There has been some debate in the literature over which PDFs to apply to building lifespans. In 1981, the Gompertz human mortality curve was applied to buildings ([Gleeson 1981](#)). Numerous distributions have been used to calculate lifespan, including Weibull, log-normal and gamma ([Miatto et al. 2017](#)). Historically, Weibull has been used to assess material lifespans ([Klein & Moeschberger 2006](#)). One study found Weibull to provide the best fit for buildings ([Aktas & Bilec 2012](#)). Another compared different distributions and posited that best-fit distributions are highly variable based on building type ([Miatto et al. 2017](#)). Most PDFs are parameterised, and parameters vary based on the selected distribution and are determined by a specific dataset. For example, the parameters of a normal distribution are mean and SD (variance). For three analysed PDFs—normal,

log-normal and Weibull—and their respective calculated parameters see Section 3.1. PDFs were developed using the MASS package in R (Venables 2002).

Various methods for establishing a ‘best-fit’ distribution have also been used in the literature, including the chi-squared test (Aktas & Bilec 2012) and the Bayesian information criteria (BIC) evaluation method (Ianchenko et al. 2020). BIC, which pairs parametric functions with the likelihoods achieved from fitting the function to data (Ianchenko et al. 2020), was briefly used in this analysis to compare the three distributions in Figure 3. After Ianchenko et al. (2020), the *flexsurv* package in R (Jackson 2016) was used for this calculation.

In general, mean lifetimes across US and European data were also compared. Power analysis can help assess the probability that a statistical test will adequately detect an effect (Bulus 2025). In order to ensure that the sample size of this data is adequate to make statistical comparisons between the US and Europe, the Welch’s *T*-test function in the R package *pwrss* was used (Bulus & Jentschke 2025). For this assessment, the smallest effect size—Cohen’s $d = 0.2$ —a significance level of 0.05 and 0.8 power were assumed. Additionally, the ratio of variance and number ratio were calculated from the two datasets. As a result, there is a required sample size of 500 and 277 demolished buildings for European and US buildings, respectively. The sizes of the actual datasets, as detailed in Section 3, far exceed the sample sizes needed to have statistical power.

2.2.2 Demolition trends

Lifetime values often have numerous covariates, *i.e.* other factors that influence when a building will be demolished (Eye & Wiedermann 2023). Beyond regional building lifetime values described in Figure 3, this analysis was also interested in how lifetimes vary across cities (Figure 4). This analysis additionally examines several building-specific characteristics that could influence building lifetime, starting with the function—or use—of a building. While specific use categories typically fluctuate based on location, all cities have buildings that can fall into four categories: residential, commercial, industrial and institutional. *Institutional* buildings encapsulate university buildings, governmental and cultural buildings, and assembly buildings. This was done to maintain synchronicity across datasets due to variation in how institutional buildings are classified in some cities. This classification is influenced by land-based systems which, in the US, are dictated by function, activity, structure, site and ownership (White 2005). Some institutional buildings can be challenging to classify, as there could be multiple use types that are accurate. For example, a college sports stadium is an assembly structure, yet also occupied by an institution, hence the categorisation used in this analysis. Use types not included in this analysis are garage or temporary structures. All cities have data about function. While the relationship between average building lifetimes across cities and use types has been analysed for specific geographies, the statistical significance of variance has not yet been evaluated.

This study uses the common statistical model, analysis of variance (ANOVA) to assess whether or not the differences between cities and use type are significant. ANOVA is often used to test differences in the mean of categorical variables, in this case, cities and use type. It tests both within- and between-group variances to produce a *F*-statistic and *p*-value, for which the results are described in Section 3. A $p < 0.05$ indicates the differences across variants are significant. ANOVA relies on several assumptions, including independence, normality and equality of variances. Because all analysed data points have what is considered a significant sample size ($n > 30$), it can be assumed on the basis of the central limit theorem that the sample of demolished buildings is well approximated by a normal distribution (ANOVA in R n.d.). The variances, however, are not equal, and therefore the Welch ANOVA test was used, which is similar in principle to ANOVA but does not require equality of variances. The base *r* functions for one-way ANOVA were used for this assessment.

Several other building attributes present in the data do not occur in every municipality. These include structural construction types, which exist in data from Raleigh, Minneapolis, and Cambridge. All three of these cities also have data about roof type. In Europe, Copenhagen has data about exterior wall construction and roof type. Cambridge, Los Angeles, Minneapolis, Pittsburgh, New York City, Zurich, Copenhagen and Amsterdam have data about the number of floors in each building.

2.2.3 Obsolescence

While establishing the reason for building demolition of all regions is out of scope of this analysis, a few US cities—Pittsburgh and Raleigh especially—reveal that the majority of demolished structures are in average, good or excellent conditions upon demolition. While this is discussed more thoroughly in the results section, the reason for this is that the obsolescence of buildings is caused by more factors than purely technical degradation and can therefore be difficult—some say impossible (Abramson 2016)—to quantify. Early attempts to quantify obsolescence took an exclusively economic approach, assessing depreciation rate per year (Burton 1933). Later, mortality rate and understanding building ‘survivorship’ were assessed, and a life table was constructed (Gleeson 1985). More recently, analyses have evaluated how construction periods influence how long buildings last, but have not been explained through the lens of obsolescence. Survival analysis in the 21st century has been applied to building stock analysis in order to make building stock predictions in the future (Bradley & Kohler 2007).

Given that obsolescence has been previously defined as *going out of use*, the method for quantifying obsolescence in this paper estimates the probability of obsolescence during each year of a building’s life, considering a dataset of demolished buildings. While there are parametric methods to calculate this value, this paper employs a non-parametric statistical approach—the Kaplan–Meier curve—which is typically used to interpret species loss or in medical applications. The Kaplan–Meier estimator approximates a likelihood, $S(t)$, a building will survive to a certain age, as a function of the number of demolitions, d_i , at time t_i , and the number of buildings, n_i , that have survived to that point within the sample. Together,

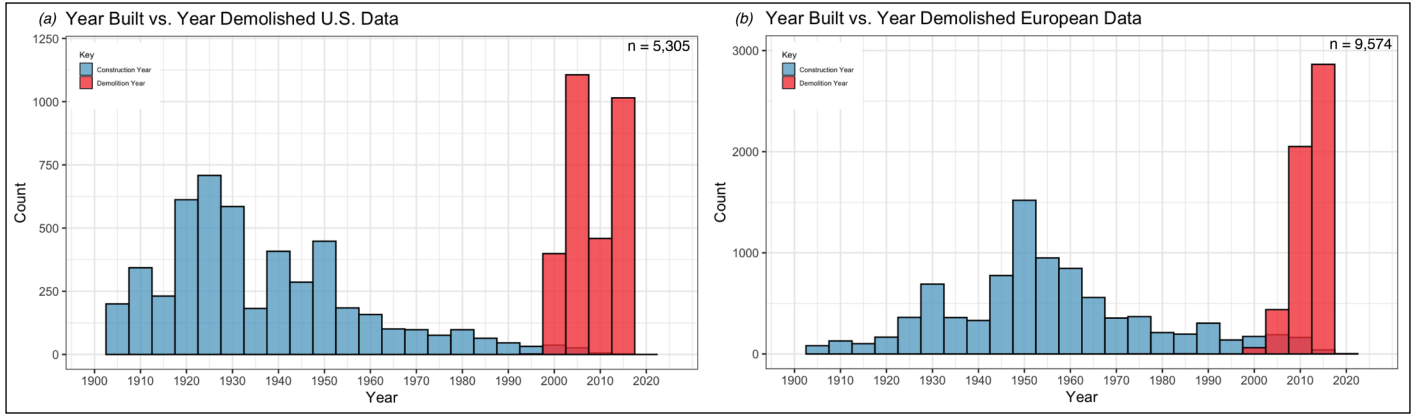
$$S(t) = \prod_{t_i \leq t} \left(1 - \frac{d_i}{n_i} \right).$$

The application of the Kaplan–Meier estimator in this paper is not intended to be utilised to understand the overall longevity of existing building stocks; the lack of censored data means there is too much bias to do so accurately. Typically, the estimator includes censored data, which are data about the population that did not experience the event (in this case, demolition). Applied to an analysis of the entire building stock, the inclusion of censored data would require information from all existing buildings. Comprehensive data about large existing building stock can be difficult to integrate with demolished building stock information, and previous work has employed random sampling methods to do so (Bradley & Kohler 2007). Survival curves have also been used to study small building ‘populations’ with specific typologies, such as an analysis of all (American) football and baseball stadiums in the United States (Wang-Xu et al. 2025). Considering the scope of this study was to explicitly study demolished buildings, censored data are not used, because of: data availability constraints; challenges reconciling dates from the demolished building information with a reasonable time baseline for the existing building stock analysis; and censored data making it difficult to identify trends in demolished buildings because of the large sample of existing buildings compared with demolished ones.

Therefore, what the Kaplan–Meier estimator reveals in Section 3 is a distribution of building obsolescence (death in population analysis) that can be helpful in understanding actual service lifetime, event rate among the subjected population and comparing demolition distribution across attribute groups. Because none of the groups includes censored data, they all experience the same bias and therefore it does not influence observations from their comparison.

3. RESULTS AND DISCUSSION

The results presented in this paper arise from a sample of 9574 demolished European buildings and 5305 demolished US buildings. Considering this paper is not a building stock analysis, the scope is restricted to understanding building demolition data, rather than evaluating and characterising the current building stock of each city. Still, the demolished buildings selected for this analysis have a range of construction years (Figure 2). In the US, the majority of buildings were constructed between 1920 and 1950, whereas in the European data, the majority of buildings were built between 1950 and 1970. Due to data availability, the demolition years for both regions are confined to the 21st century.



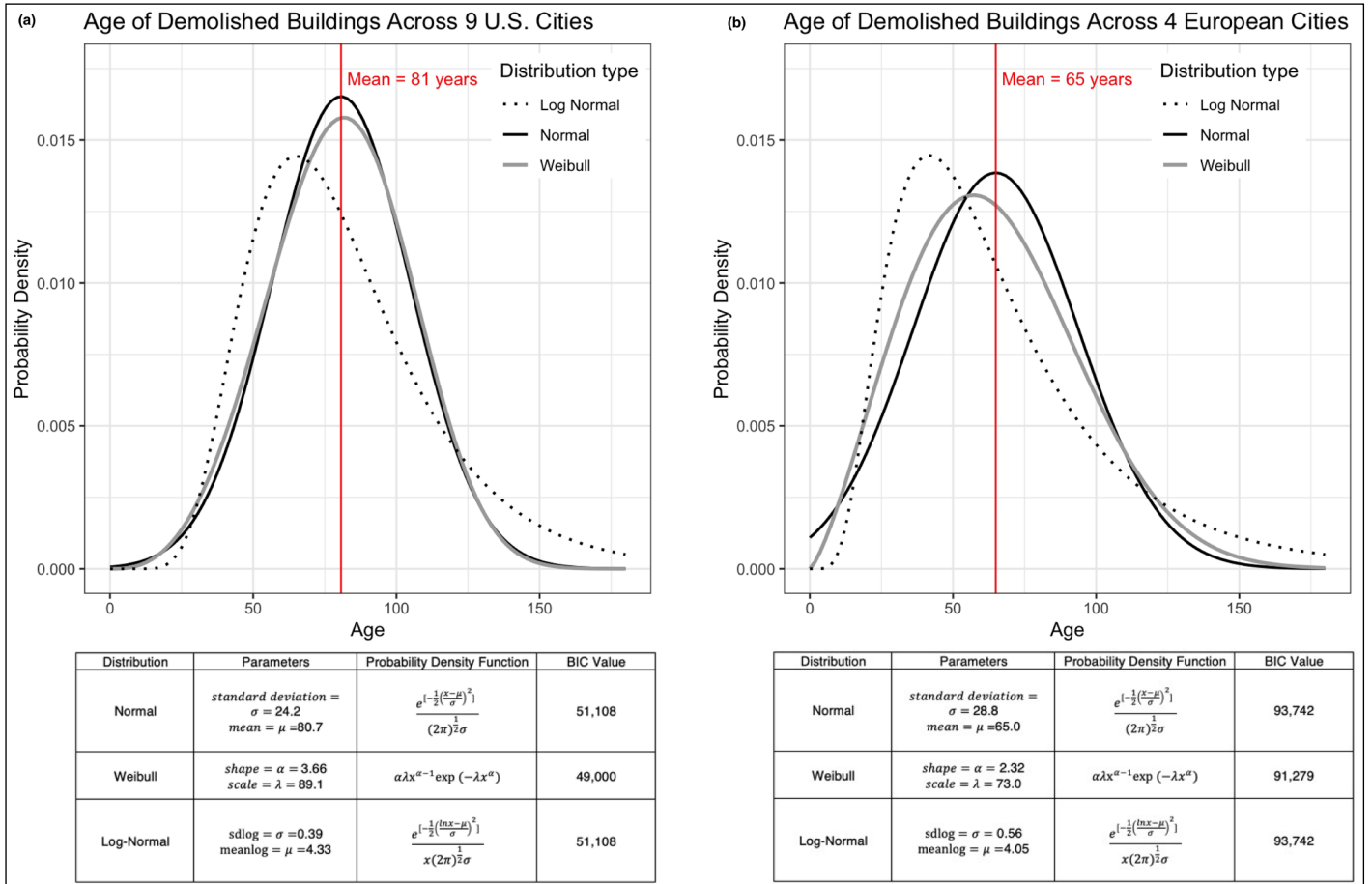
3.1 BUILDING LIFETIMES

In this paper, the lifetime of a single building is defined by one value: the age at which the building is demolished. While the debate over which PDF most adequately models lifetime was discussed in Section 2.1, three parameterised distributions are shown in Figure 3 for US and European cities. Additionally, all distributions for the US appear to be near zero at the start of the x-axis, whereas for European buildings the normal curve has a higher probability at zero because of its larger SD. BIC was used to weigh differences in these distributions; the Weibull distribution is the best fit, considering the lowest BIC value is in practice the best fitting distribution (Ianchenko et al. 2020). Despite the Weibull distribution demonstrating the best fit, the normal distribution is ultimately used for the remainder of this paper. This is largely due to ease of interpretation—and because the impact on final building stock model numbers of choosing certain PDFs is negligible (Miatto et al. 2017).

As Figure 3 demonstrates, the data for US cities have a mean and a median of 81 years, while European cities have a mean of 65 years and a median of 64 years. It is notable that, on average, European buildings have similar if not lower lifetimes than US buildings. This will be further explored below, but it reveals that there is not a direct correlation between the age of the city and the age

Figure 2: Count of demolished buildings in each construction and demolition period for (a) US and (b) European data.

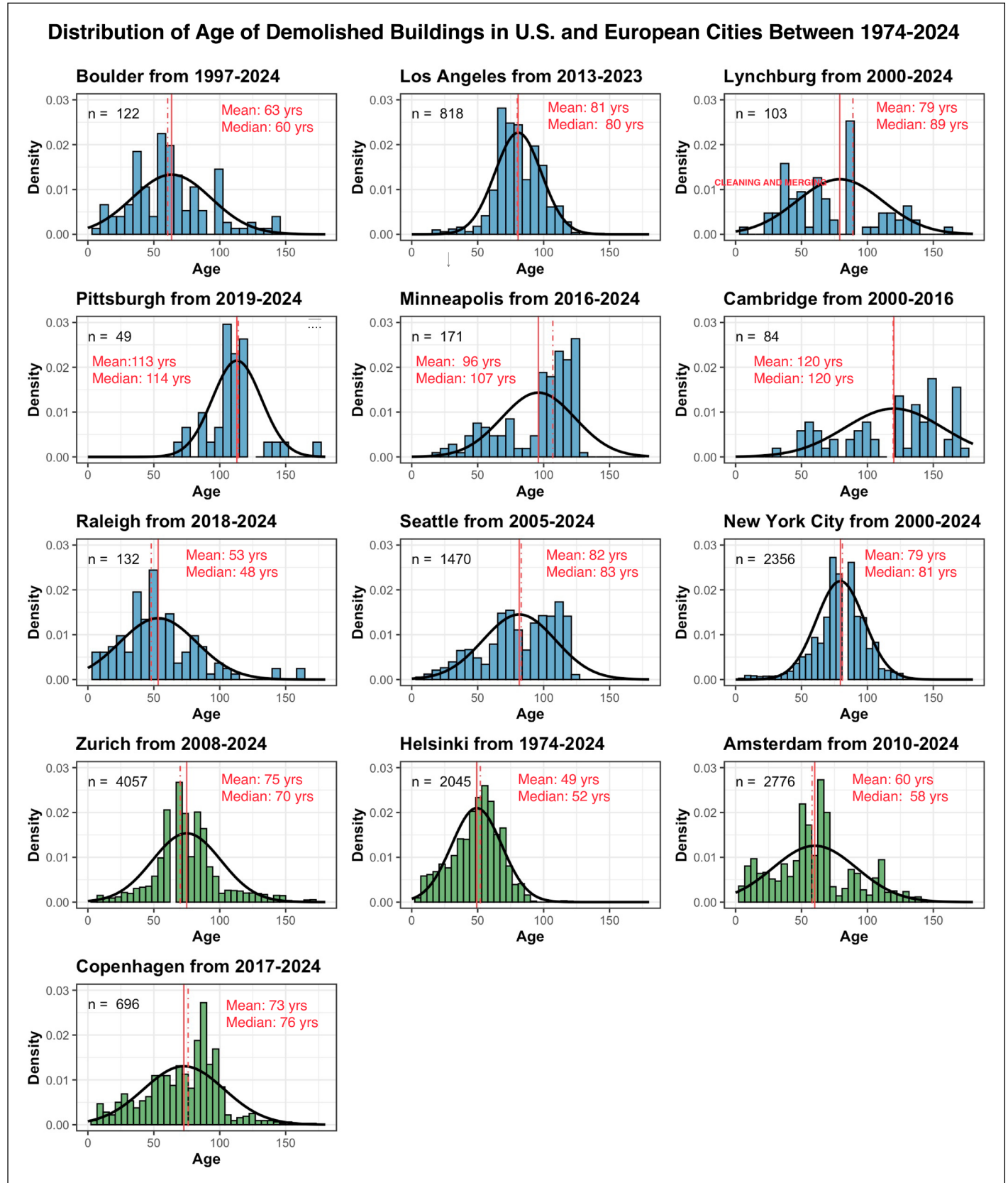
Figure 3: Parameterised lifetime distribution functions for (a) US and (b) European cities.



of demolished buildings. Figure 3 also tabulates the parameters (shape and scale for Weibull as opposed to mean and SD for normal) to utilise these distributions in future analyses. Additionally, the US data have been published openly alongside this paper to be used for any future building lifetime applications. The European data are largely not open source and were delivered directly by municipalities, and so the data cannot be shared.

Figure 4 delineates building lifetime by city. Across the US, the greatest average age is 120 years, in the city of Cambridge, followed by Pittsburgh, which has an average lifetime of 113 years. The

Figure 4: Normal distribution of building lifetimes by cities in the US and Europe, 1974–2024.



lowest average lifetimes per city are Raleigh, with 53 years, and Boulder, with 63 years. Los Angeles, Lynchburg, New York City and Seattle all have averages between 79 and 82 years; Minneapolis has an average of 96 years. For Europe, Zurich had a maximum average of 75 years, followed by Copenhagen and Amsterdam with 73 and 60 years, respectively, and Helsinki, has the lowest at 49 years. It is noteworthy that Helsinki, founded in 1550, and Raleigh, founded two centuries later, have comparable average building lifetimes. Amsterdam also has a lower average building lifetime than all analysed cities, save for Boulder and Raleigh. Therefore, it is clear that the age of a city is not proportional to the age of demolished buildings in that city. Age of a city, however, is not congruent with the age of its current building stock.

While it was not within the scope of this paper to assess the age of the standing building stock (primarily because of inaccessibility of data, in the US especially), some statistical information can help one understand the building stock make up in some cities. A 2021 analysis of New York City estimated that 11% of buildings were built after 1980 (Koursaros 2021). In Zurich, 39% of buildings were built in the last 40 years (Federal Statistical Office 2023). As of 2020, 30% of Finland's dwellings were built in the 1970s and 1980s (Statistics Finland 2021), and the literature on demolished buildings in all Finland found that the majority of demolished buildings were built in the 1960s and 1970s (Huuhka & Lahdensivu 2016). Short building lifetimes in Helsinki can be further explained by anecdotal evidence regarding demolition trends; news outlets have reported that Helsinki is rapidly demolishing buildings from the 1970s and 1980s (YLE News 2024). Given the demolition period in this analysis is concentrated in the last 10 years, the average lifetime of these buildings is consistent with this trend. Differences in the construction year of US versus European buildings is additionally reflected in Figure 2, where the construction year is on average later in European cities. These results are consistent with the findings of Andersen & Negendahl (2023), where expected lifespan was shown to be much lower for new buildings than for older ones.

Another takeaway from Figure 4 is that there appears to be immense variability between cities, which will be statistically evaluated in Section 2.2. Several factors could influence general demolition trends city to city, including growth factors, construction trends, economic or population growth, density and planning considerations, and/or land value and property value. A limitation of this study is that it does not conduct a statistical analysis of these factors across cities because of the limited sample size of cities (more cities would be needed for statistical significance) and limited data. Another notable limitation is the number of datapoints for US cities. While all are considered statistically significant ($n > 30$), it would be interesting to see if a larger sample of demolished buildings in Pittsburgh or Cambridge would yield shorter lifetimes.

3.2 TRENDS IN DEMOLITION ACROSS BUILDING CHARACTERISTICS

Figure 5 demonstrates the differences between age and use type. In Europe, institutional buildings have the shortest average lifetime, followed by commercial buildings, industrial buildings and, finally, residential. In the US, commercial and industrial averages were only one year apart, but there was a substantial lead by residential for the largest average lifetime. In the US, institutional buildings also have the lowest average lifetimes at 55 years. Notably, in Europe, commercial buildings had the lowest on average lifetimes at 43 years. Section 2.2.2. details how use types were classified. Institutional encompasses education, art and culture, and recreation, but this speaks to a limitation of this analysis: the lack of differentiation between assembly, educational and institutional buildings. Future research could further examine the difference in lifetime between these building types. Figure 5 does not display buildings classified as mixed use or 'other'. This was because there was no way of verifying the demolished structure was a building for 'other' building classifications. The Welch ANOVA test demonstrated a p -value $< 2.2e-16$ for both cities and use types. This indicates that at least one difference between cities (and one between uses) was significant, meaning the between-group variance is significantly larger than the within-group variance.

Figure 6 demonstrates the average age of demolition across design variables for three US cities. Figure 6a demonstrates average lifetime by use type; lifetime is the shortest for concrete and steel buildings, which have an average of 67 years, followed by wood frame (91 years) and brick buildings (110 years). The range for wood-frame buildings is the largest. These results are on a

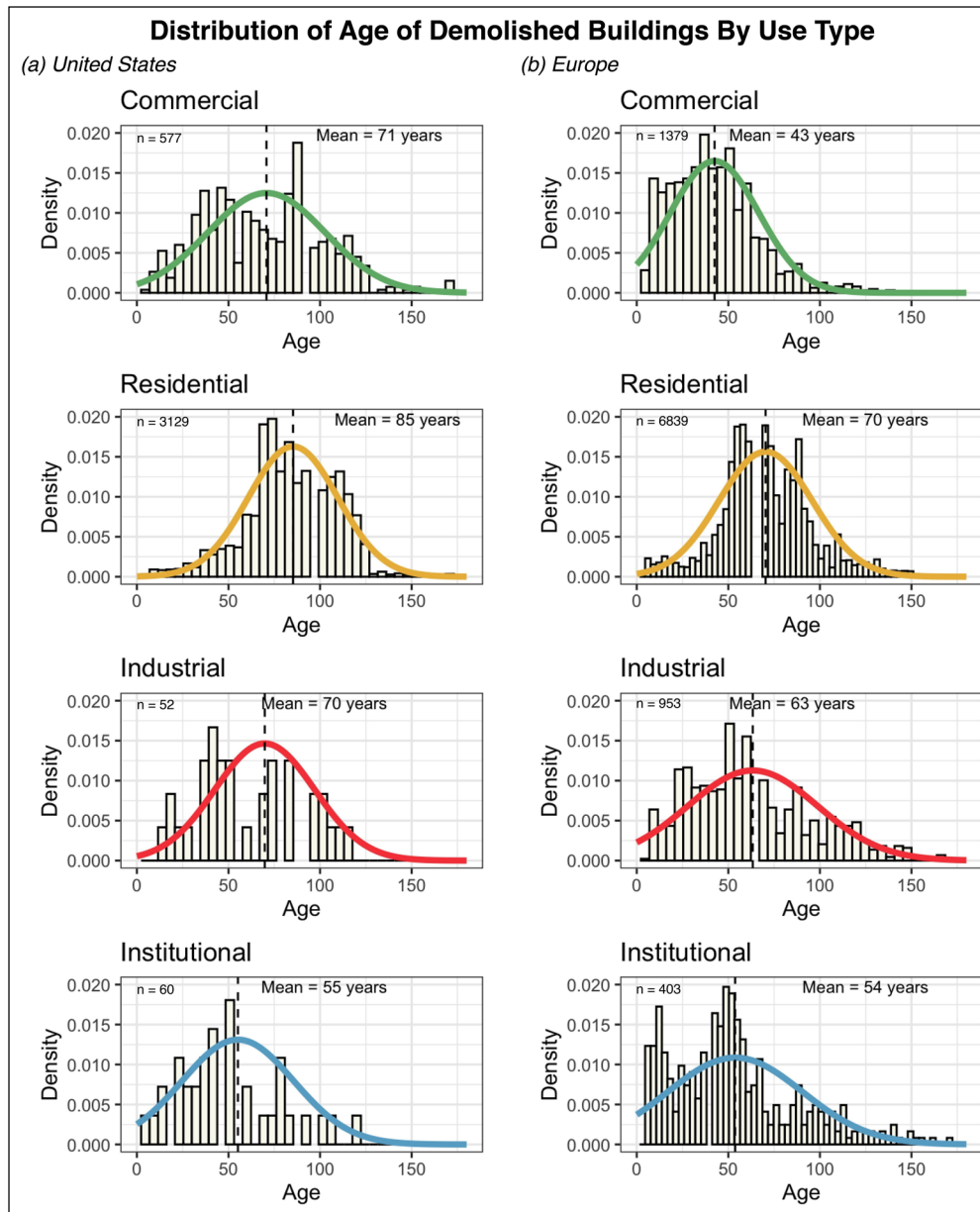


Figure 5: Distribution of building lifetimes by use type in (a) the US and (b) Europe.

par with use type trends. In the US, residential buildings are often made of wood. Additionally, in the US commercial buildings are made of concrete and steel, reflecting the trends in use type, where commercial buildings typically have shorter lives than residential buildings. Similarly, in [Figure 6b](#) flat roofs have the lowest average lifespan (85 years, SD = 38), and are more often made of concrete and steel. Gables, hip roofs and shingles have similar averages—the same typological trends with materials versus use type are mirrored with flat and commercial buildings. The only analysed city with construction material data in Europe was Copenhagen, which had a data attribute for external wall construction material. The averages across age are demonstrated in [Figure 6c](#): buildings with metal exterior construction and exterior construction with concrete or cement had average lifetimes of 30 and 59 years, respectively. When analysing the number of stories across 6948 demolished buildings in the US and Europe that had that attribute, low-rise (one to four stories) and mid-rise (five to nine stories) building lifetimes ranged from six to 356 years, whereas high-rise building (10–14 stories) lifetimes ranged from 13 to 56 years.

In order to evaluate these differences statistically, a Welch ANOVA test was conducted for the data points in [Figures 5a](#) and [b](#). Both evaluations of the two sets of categorical variables ('groups') yielded p -values < 0.05, and that there is at least one significant difference between groups for each set. The non-significant sample size of 14 metal exterior construction buildings in [Figure 6c](#) meant it was ineligible for the Welch ANOVA test.

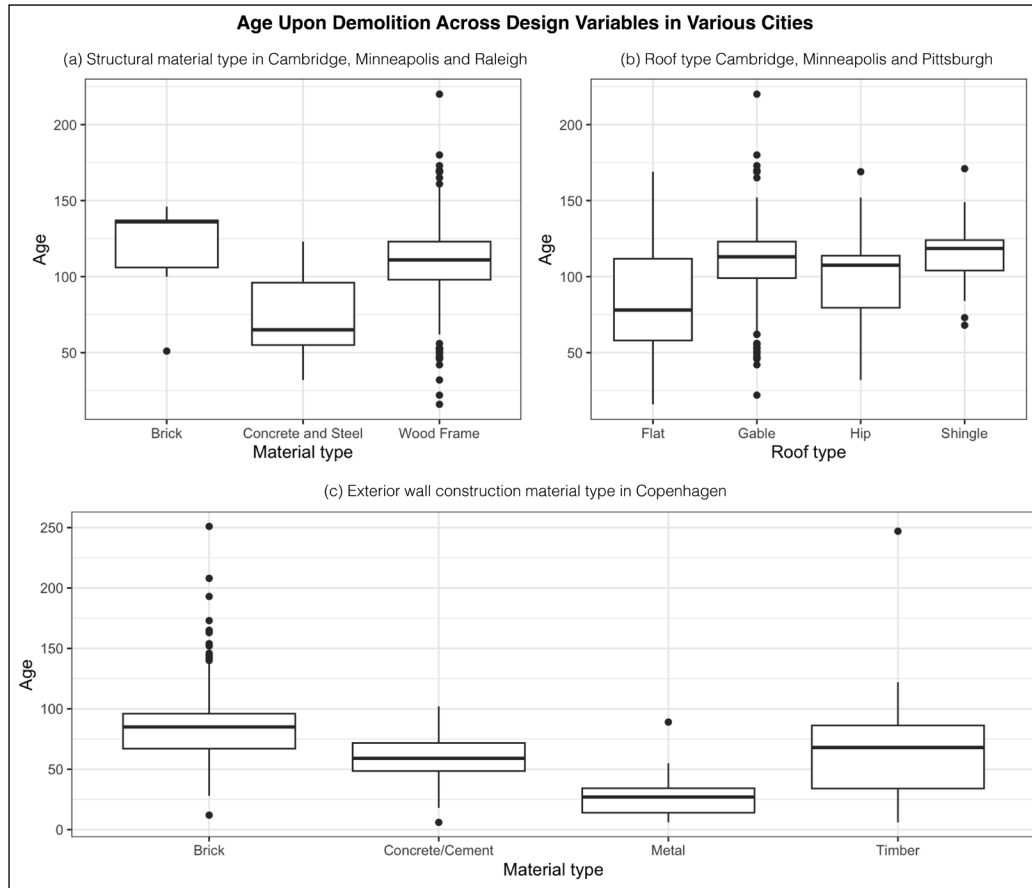


Figure 6: Age upon demolition across several design variables in various cities including: **(a)** structural material, **(b)** roof type and **(c)** exterior wall construction material.

3.3 OBSOLESCENCE

This paper began by distinguishing between deterioration- and decision-based obsolescence. Deterioration implies there is technical failure, or else the building is of poor quality, whereas decision-based obsolescence implies there are reasons outside of technical failure for buildings being demolished. This paper approaches the concept of obsolescence in two ways. The first is by understanding the condition of a building upon demolition. This analysis is constrained by the availability of condition data, which only exist in two cities: Pittsburgh and Raleigh. Of 133 buildings analysed, the breakdown of condition is as follows: 5% were rated excellent, 18% were considered in very good condition and 77% were of average or better condition. This means that the majority of buildings were of average or higher condition when they were demolished, indicating decision-based obsolescence was a larger factor in this small subset of data. Considering this is an extremely limited sample of available data, the authors employed a second lens through which to view obsolescence holistically—not broken down by type of obsolescence, but instead through the general definition of *going out of use*.

The second approach applies techniques from survival analysis to a demolished building stock. The Kaplan–Meier curve, typically applied in medical and ecological settings, is applied to a stock of demolished buildings in Figure 7. Several aspects of a Kaplan–Meier curve provide insights about the analysed population: its steepness (where the steeper portion is equal to a higher event rate); the median survival rate (where 50% of a population is likely to be left); and its shape (which can indicate when there will be increased rates of an event throughout a building’s life). In this analysis, the *incident* refers to a building’s demolition, or obsolescence. With regard to steepness, Figure 7a shows for the US that steepness peaks between 80 and 120 years. In Europe, it first spikes between 50 and 60 years, and is at maximum steepness between 60 and 75 years. In general, the Europe data are steeper than the US data at the beginning of the curve, meaning the incident rate is higher in the first 40 years for European data. Conversely, the incident rate slows much more dramatically in European cities at 90 years, whereas the rate remains relatively

constant from 75 to 125 years in the US. This is indicative of a lower incident likelihood after 90 years in European cities. The same is true when breaking down use types. All use types have a period of increased incident rate that slows around 80–90 years.

When further examining use type breakdowns in Figure 7b and c, industrial and institutional buildings in the US appear more stepped because they have smaller sample sizes. The median survival curve for all samples mirrors the trends in average lifetimes between use types. Institutional buildings in the US exhibit three periods of increased steepness, and commercial, institutional and industrial have much higher incident rates in the first 30 years of life than residential. The same is true for European data, but commercial buildings most quickly reach peak steepness between 20 and 40 years, and incident rates of commercial buildings dramatically decrease at around 70 years.

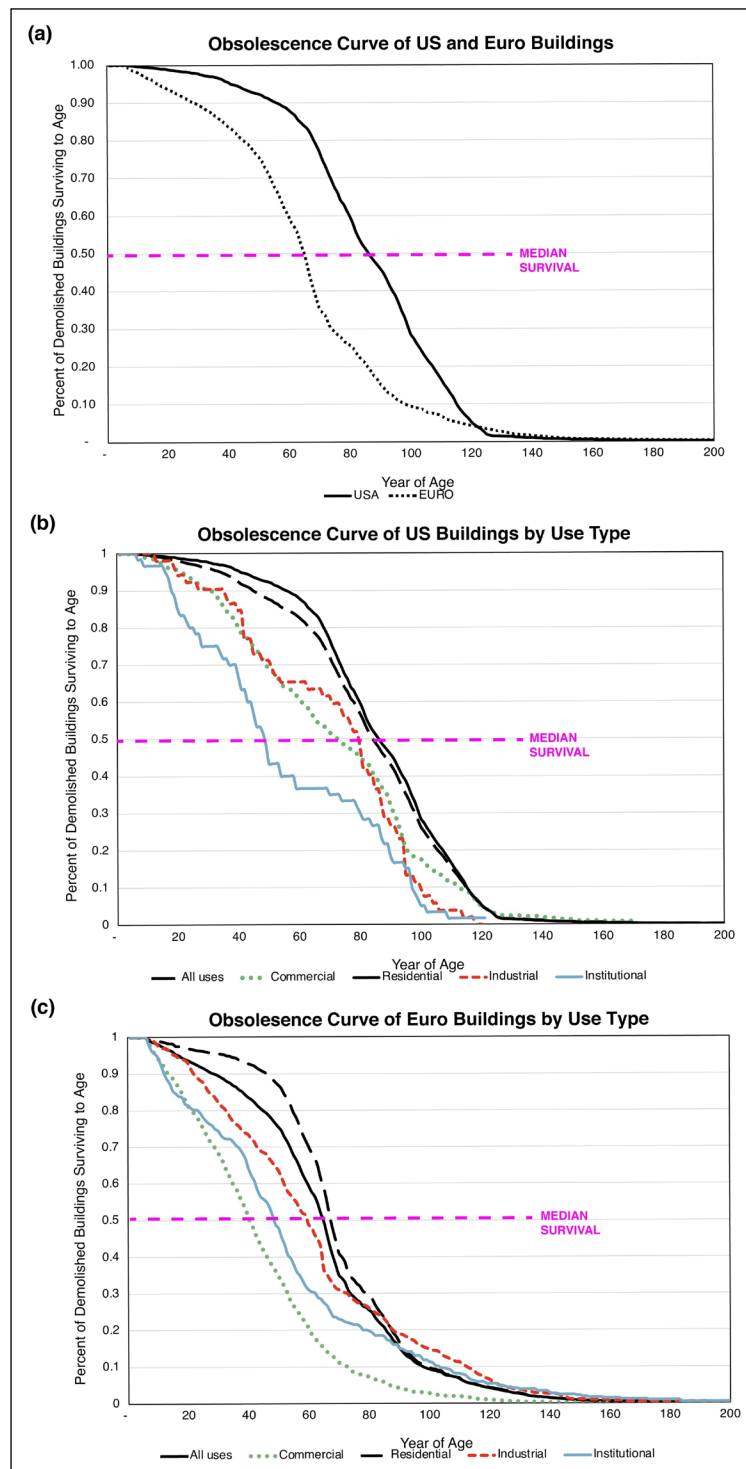


Figure 7: Obsolescence curve of demolished buildings via a survivorship analysis of demolished buildings in the US and Europe broken down by (a) region, (b) use type in the US and (c) use type in Europe.

These findings are backed by Andersen & Negendahl (2023), who indicate that older remaining buildings likely have historical, cultural or technical characteristics that reduce the risk of deconstruction and lead to a longer lifespan; they also suggest older buildings at risk for demolition earlier could have already been demolished. In general, this could reflect a phenomenon described as the value of age in America:

the older a building gets, the more we have respect and affection for its evident maturity

(Brand 1994: 25)

Because all buildings have been demolished in the sample, Figure 7 shows uncensored data, explained in Section 2.2.3. This is another limitation, as not including censored data can introduce bias into the building curve. Because of this bias, conclusions cannot be drawn about overall survival of urban building stocks, but instead can be used to compare probabilities of even rates across the analysed attributes. For this analysis, it was important to be able to understand exclusively the obsolescence of demolished buildings, as opposed to buildings that comprise the existing building stock.

4. KEY TAKEAWAYS AND FUTURE WORK

Average building lifetime estimates for US buildings have not previously been assessed with actual data across several use types. Additionally, they have not been compared with European cities. This paper is the first to assess building lifetimes of all building types based on empirical data across US cities and is the first to compare US building lifetimes with those of European cities. While this paper's contributions and limitations have been described in Section 3, there are several key takeaways and future opportunities for research.

In general, building lifetime estimates vary significantly between cities and use types and do not directly correlate with age of the city. Commercial, industrial and institutional buildings were found to have shorter lifetimes than residential buildings. Buildings made of concrete and steel have shorter lifetimes than brick and wood buildings, as do flat-roofed buildings compared with their multidimensional counterparts. With regard to obsolescence, there is a period during a demolished building's life where demolition is most likely to occur, and deterioration is not an exclusive demolition indicator.

Future analyses are needed to assess the age of the remaining building stock in combination with demolished buildings stocks, in addition to assessing which factors contribute most significantly to demolition trends in cities.

The building data collated in this analysis can increase literacy about the demolished building stock in US and European cities. They could also be used as an input into various building stock analyses, property valuation and life-cycle assessments.

ACKNOWLEDGEMENTS

The authors thank those responsible for managing the open data portals in each analysed city, and specifically Dirk Graas in Amsterdam and Suvi Uotila in Helsinki.

AUTHOR AFFILIATIONS

Juliana Berglund-Brown  orcid.org/0000-0003-1943-8144

Department of Architecture, Massachusetts Institute of Technology, Cambridge, MA, US

Isaac Dobie  orcid.org/0009-0007-4706-9223

Department of Architecture, Massachusetts Institute of Technology, Cambridge, MA, US

Jordaina Hewitt  orcid.org/0000-0002-3260-3995

Department of Civil and Environmental Engineering, Stanford University, Stanford, CA, US

Catherine De Wolf  orcid.org/0000-0003-2130-0590

Institute of Construction & Infrastructure Management, ETH Zürich, Zurich, CH

John Ochsendorf  orcid.org/0000-0002-6235-1995

Department of Architecture, Massachusetts Institute of Technology, Cambridge, MA, US

The authors have no competing interests to declare.

DATA ACCESSIBILITY

All US data in this analysis are attached as a supplemental data online file and are open source. European data are limited due to specific sharing requests by cities, but some may become available from the corresponding author upon request.

FUNDING

This work was made possible by the National Science Foundation Graduate Research Fellowship Program (grant number DGE-2141064) and ETH Zürich UP2030 (grant number 23.00060).

SUPPLEMENTAL DATA

Supplemental data for this article can be accessed at: <https://doi.org/10.5334/bc.588.s1>

REFERENCES

- Abramson, D. M. (2016). *Obsolescence: An architectural history*. University of Chicago Press. <https://doi.org/10.7208/9780226313597>
- Adams, M., Burrows, V., & Richardson, S. (2019, September). *Bringing embodied carbon upfront*. World Green Building Council. <https://worldgbc.org/article/bringing-embodied-carbon-upfront/>
- Aksözen, M., Hassler, U., Rivallain, M., & Kohler, N. (2017). Mortality analysis of an urban building stock. *Building Research & Information*, 45(3), 259–277. <https://doi.org/10.1080/09613218.2016.1152531>
- Aktas, C. B., & Bilec, M. M. (2012). Impact of lifetime on US residential building LCA results. *International Journal of Life Cycle Assessment*, 17(3), 337–349. <https://doi.org/10.1007/s11367-011-0363-x>
- Andersen, R., & Negendahl, K. (2023). Lifespan prediction of existing building typologies. *Journal of Building Engineering*, 65, 105696. <https://doi.org/10.1016/j.jobbe.2022.105696>
- Anderson, J., & Moncaster, A. (2020). Embodied carbon of concrete in buildings, Part 1: Analysis of published EPD. *Buildings & Cities*, 1(1), article 1. <https://doi.org/10.5334/bc.59>
- ANOVA in R. (n.d.). Stats and R. <https://statsandr.com/blog/anova-in-r/>
- Baker, H., Moncaster, A., Wilkinson, S. J., & Remøy, H. (2023). Demolition or retention of buildings: Drivers at the masterplan scale. *Buildings & Cities*, 4(1). <https://doi.org/10.5334/bc.308>
- Berrill, P., & Hertwich, E. G. (2021). Material flows and GHG emissions from housing stock evolution in US counties, 2020–60. *Buildings & Cities*, 2(1). <https://doi.org/10.5334/bc.126>
- Bradley, P., & Kohler, N. (2007). Methodology for the survival analysis of urban building stocks. *Building Research & Information*, 35(5), 529–542. <https://doi.org/10.1080/09613210701266939>
- Brand, S. (1994). *How buildings learn: What happens after they're built*. Viking.
- Bulus, M. (2025, September 16). *Practical power analysis in R*. https://cran.r-project.org/web/packages/pwrss/vignettes/examples.html#1_Generic
- Bulus, M., & Jentschke, S. (2025). *pwrss: Statistical power and sample size calculation tools (Version 1.0.0)* [Software]. <https://cran.r-project.org/web/packages/pwrss/index.html>
- Burton, J. E. (1933). Building obsolescence and the assessor. *Journal of Land & Public Utility Economics*, 9(2), 109–120. <https://doi.org/10.2307/3139079>
- Cai, W., Wan, L., Jiang, Y., Wang, C., & Lin, L. (2015). Short-lived buildings in China: Impacts on water, energy, and carbon emissions. *Environmental Science & Technology*, 49(24), 13921–13928. <https://doi.org/10.1021/acs.est.5b02333>
- Cao, Z., Liu, G., Duan, H., Xi, F., Liu, G., & Yang, W. (2019). Unravelling the mystery of Chinese building lifetime: A calibration and verification based on dynamic material flow analysis. *Applied Energy*, 238, 442–452. <https://doi.org/10.1016/j.apenergy.2019.01.106>
- Çetin, S., De Wolf, C., & Bocken, N. (2021). Circular digital built environment: An emerging framework. *Sustainability*, 13(11), article 11. <https://doi.org/10.3390/su13116348>
- City of Boulder Open Data. (n.d.). <https://open-data.bouldercolorado.gov/>
- City of Lynchburg Open Data. (n.d.). <https://data-cityoflynchburg.opendata.arcgis.com/>

- City of New York Data.** (n.d.). NYC Open Data. <https://opendata.cityofnewyork.us/>
- City Survey Services Helsinki.** (n.d.). *Historical buildings* [Dataset].
- County of Los Angeles Open Data.** (n.d.). <https://data.lacounty.gov/datasets>
- Data en informatie.** (n.d.). Data Amsterdam. <https://data.amsterdam.nl/>
- Datafordeler.dk.** (n.d.). <https://datafordeler.dk/>
- Dataset—CKAN.** (n.d.). Western Pennsylvania Regional Data Center. <https://data.wprdc.org/dataset/>
- Eurocode EN.** (1990). *The basis of structural design: Eurocode EN 1990 | Eurocodes: Building the future.* <https://eurocodes.jrc.ec.europa.eu/events/basis-structural-design-eurocode-en-1990>
- Eye, A. von, & Wiedermann, W.** (2023). *The general linear model: A primer.* Cambridge University Press.
- Federal Statistical Office.** (2023, December 13). *Buildings by period of construction.* <https://datawrapper.dwdn.net/aa806785c5ae09c9b2f57ae39882d8777/>
- FOEN.** (2018, November 3). *Raw materials, waste and the circular economy: In brief.* Federal Office for the Environment (FOEN). <https://www.bafu.admin.ch/bafu/en/home/themen/thema-abfall/abfall--das-wichtigste-in-kuerze.html>
- Galimshina, A., Moustapha, M., Hollberg, A., Lasvaux, S., Sudret, B., & Habert, G.** (2024). Strategies for robust renovation of residential buildings in Switzerland. *Nature Communications*, 15(1), 2227. <https://doi.org/10.1038/s41467-024-46305-9>
- Gleeson, M. E.** (1981). Estimating housing mortality. *Journal of the American Planning Association*, 47(2), 185–194. <https://doi.org/10.1080/01944368108977104>
- Gleeson, M. E.** (1985). Estimating housing mortality from loss records. *Environment and Planning A: Economy and Space*, 17(5), 647–659. <https://doi.org/10.1068/a170647>
- Hao, J. L., Tam, V. W., Yuan, H. P., Wang, J. Y., & Li, J. R.** (2010). Dynamic modeling of construction and demolition waste management processes: An empirical study in Shenzhen, China. *Engineering, Construction, and Architectural Management*, 17(5), 476–492. <https://doi.org/10.1108/09699981011074574>
- Hurst, W.** (2021, June 27). *Demolishing 50,000 buildings a year is a national disgrace.* <https://www.thetimes.com/uk/politics/article/demolishing-50-000-buildings-a-year-is-a-national-disgrace-wbrf09952>
- Huuhka, S., & Lahdensivu, J.** (2016). Statistical and geographical study on demolished buildings. *Building Research & Information*, 44(1), 73–96. <https://doi.org/10.1080/09613218.2014.980101>
- Huuhka, S., Moisio, M., Salmio, E., Köliö, A., & Lahdensivu, J.** (2023). Renovate or replace? Consequential replacement LCA framework for buildings. *Buildings & Cities*, 4(1). <https://doi.org/10.5334/bc.309>
- Ianchenko, A., Simonen, K., & Barnes, C.** (2020). Residential building lifespan and community turnover. *Journal of Architectural Engineering*, 26(3), 04020026. [https://doi.org/10.1061/\(ASCE\)AE.1943-5568.0000401](https://doi.org/10.1061/(ASCE)AE.1943-5568.0000401)
- Jackson, C.** (2016). Flexsurv: A Platform for Parametric Survival Modeling in R. *Journal of Statistical Software*, 70(8), 1–33. <https://doi.org/10.18637/jss.v070.i08>
- Ji, S., Lee, B., & Yi, M. Y.** (2021). Building life-span prediction for life cycle assessment and life cycle cost using machine learning: A big data approach. *Building and Environment*, 205, 108267. <https://doi.org/10.1016/j.buildenv.2021.108267>
- Kayo, C., & Tonosaki, M.** (2022). Lifetimes of buildings in Japan. *Resources, Conservation and Recycling*, 185, 106504. <https://doi.org/10.1016/j.resconrec.2022.106504>
- Klein, J. P., & Moeschberger, M. L.** (2006). *Survival analysis: Techniques for censored and truncated data.* Springer Science & Business Media.
- Kohler, N., & Hassler, U.** (2002). The building stock as a research object. *Building Research & Information*, 30(4), 226–236. <https://doi.org/10.1080/09613210110102238>
- Koursaros, G.** (2021, May 29). *How old are buildings in New York City?* | Tableau Public. https://public.tableau.com/app/profile/george.koursaros/viz/NYCBuildings_16222929546320/NYCBuildings
- Mequignon, M., Ait Haddou, H., Thellier, F., & Bonhomme, M.** (2013). Greenhouse gases and building lifetimes. *Building and Environment*, 68, 77–86. <https://doi.org/10.1016/j.buildenv.2013.05.017>
- Miatto, A., Schandl, H., & Tanikawa, H.** (2017). How important are realistic building lifespan assumptions for material stock and demolition waste accounts? *Resources, Conservation and Recycling*, 122, 143–154. <https://doi.org/10.1016/j.resconrec.2017.01.015>
- Moncaster, A. M., & Symons, K. E.** (2013). A method and tool for ‘cradle to grave’ embodied carbon and energy impacts of UK buildings in compliance with the new TC350 standards. *Energy and Buildings*, 66, 514–523. <https://doi.org/10.1016/j.enbuild.2013.07.046>
- Müller, E., Hilty, L. M., Widmer, R., Schluep, M., & Faulstich, M.** (2014). Modeling metal stocks and flows: A review of dynamic material flow analysis methods. *Environmental Science & Technology*, 48(4), 2102–2113. <https://doi.org/10.1021/es403506a>

- O'Connor, J.** (2004). Survey on actual service lives for North American buildings. Paper presented at Wood frame Housing Durability and Disaster Issues conference, Las Vegas, NV, US, October 2004. https://cwc.ca/wp-content/uploads/2013/12/DurabilityService_Life_E.pdf
- Open Data Portal.** (n.d.). City of Cambridge. <https://data.cambridgema.gov/browse>
- Open Data Raleigh.** (n.d.). <https://data-ral.opendata.arcgis.com/>
- Open Data Stadt Zürich.** (n.d.). Open Data Stadt Zürich—City of Zurich. <https://data.stadt-zuerich.ch/>
- OpenDataMPLS.** (n.d.). <https://opendata.minneapolis.gov/>
- Schebek, L., Schnitzer, B., Blesinger, D., Köhn, A., Miekley, B., Linke, H. J., Lohmann, A., Motzko, C., & Seemann, A.** (2017). Material stocks of the non-residential building sector: The case of the Rhine-Main area. *Resources, Conservation and Recycling*, 123, 24–36. <https://doi.org/10.1016/j.resconrec.2016.06.001>
- Seattle GeoData.** (n.d.). <https://data-seattlecitygis.opendata.arcgis.com/>
- Shultz, E.** (1922). The effect of obsolescence on the useful and profitable life of office buildings. Paper presented at the Convention of the Ohio Association of Building Owners and Managers, 27 April 1922. Historical Collections Department, Baker Library, Harvard.
- Statistics Finland.** (2021). *Dwellings and housing conditions*. https://stat.fi/til/asas/2020/01/asas_2020_01_2021-10-14_en.pdf
- Tanikawa, H., & Hashimoto, S.** (2009). Urban stock over time: Spatial material stock analysis using 4d-GIS. *Building Research & Information*, 37(5–6), 483–502. <https://doi.org/10.1080/09613210903169394>
- UNEP & Yale Center for Ecosystems + Architecture.** (2023). *Building materials and the climate: Constructing a new future*. United Nations Environment Programme (UNEP). <https://wedocs.unep.org/xmlui/handle/20.500.11822/43293>
- US EPA.** (2018). *Construction and demolition waste*. US Environmental Protection Agency (US EPA). https://environment.ec.europa.eu/topics/waste-and-recycling/construction-and-demolition-waste_en
- Venables, W. N.** (2002). *Modern applied statistics with S*. Springer.
- Wang-Xu, M., Berglund-Brown, J., Clifford, B., & Ochsendorf, J.** (2025). Levelling the playing field: Lifetimes of North American sports stadiums. *Proceedings of IASS Annual Symposia*, Volume 2025. International Association for Shell and Spatial Structures (IASS).
- White, S. M.** (2005, September). *Classifying and defining uses and building forms: Land-use coding for zoning regulations* (Zoning Practice No. 9). American Planning Association. <https://planning-org-uploaded-media.s3.amazonaws.com/document/Zoning-Practice-2005-09.pdf>
- YLE News.** (2024, May 15). News: Why is Finland demolishing rather than renovating older buildings? YLE News. <https://yle.fi/a/74-20088784>
- Zhou, W., Moncaster, A., Reiner, D. M., & Guthrie, P.** (2019). Estimating lifetimes and stock turnover dynamics of urban residential buildings in China. *Sustainability*, 11(13), article 13. <https://doi.org/10.3390/su11133720>

TO CITE THIS ARTICLE:

Berglund-Brown, J., Dobie, I., Hewitt, J., De Wolf, C., & Ochsendorf, J. (2025). Lifetimes of demolished buildings in US and European cities. *Buildings and Cities*, 6(1), pp. 1099–1116. DOI: <https://doi.org/10.5334/bc.588>

Submitted: 30 March 2025

Accepted: 10 November 2025

Published: 16 December 2025

COPYRIGHT:

© 2025 The Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC-BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited. See <http://creativecommons.org/licenses/by/4.0/>.

Buildings and Cities is a peer-reviewed open access journal published by Ubiquity Press.