

# Advanced spatio-temporal source–demand matching for practical waste heat utilization in district heating<sup>☆</sup>

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## ABSTRACT

Waste heat is widely recognized as a key lever for advancing climate neutrality in urban heating systems. While recent policy regulations have significantly improved the transparency of waste heat potentials, the gap between reported theoretical potentials and their practical usability remains insufficiently explored. This study develops a novel residual-aware, guided source–demand allocation approach, leveraging officially reported, technically detailed waste heat source information and high-resolution building typology data to reveal key insights into spatial and technical utilization potentials and limitations. The results also derive key distributional and operational source characteristics, combined with spatial and typological building patterns, considering three refurbishment scenarios. The proposed methodology provides a transparent and policy-relevant tool for translating reported waste heat potentials into actionable planning insights. The results indicate that the utilizable share of the reported waste heat potential is reduced to approximately 35 % due to techno-spatial constraints, decreasing further to approximately 24 % when temporal source–demand coincidence is additionally considered. Depending on building refurbishment progress, the number of potentially supplied buildings ranges from 1.8 to 5.7 million. Overall, these findings demonstrate that coordinated spatio-temporal planning, combined with efficiency measures, is essential to unlock the significant, yet primarily spatially constrained, waste heat potential.

## 1. Introduction

The transition to a climate-neutral energy system demands a widespread and coordinated use of renewable energy and waste heat sources [1] in the context of smart energy [2] or multi-energy [3] systems to exploit synergies through sector integration [4]. In Europe, the final energy demand for heating in buildings and industrial processes accounts for roughly half of total final energy consumption [5] and remains predominantly fossil-based (57 %) [6], accounting for about one-third of energy-related greenhouse gas emissions [5,7]. Achieving climate neutrality therefore requires a comprehensive transformation, combining improvements in energy efficiency and the adoption of CO<sub>2</sub>-neutral energy carriers [5,8].

Waste heat (often termed excess heat [5,9]) represents a promising and largely untapped resource, considered a significant “technology wedge” [10], that can play a key role in supporting Positive Energy Districts within the framework of the European Strategic Energy Technology Plan (SET-Plan) [1,11]. Waste heat applications are highly

flexible and can be adapted to a wide range of situations [12] through various utilization pathways, including on-site recovery (especially in energy-intensive sectors [13]), temperature upgrading via heat pumps, conversion to electricity or cooling, and off-site supply [14], with District Heating (DH) emerging as a key enabler for large-scale integration. DH networks allow the utilization of waste heat at sustainable costs [15], often demonstrated as the most cost-effective heating option in techno-economic studies [6]. The implementation of 4th-generation DH networks with large-scale heat pumps can further increase utilizable potentials [16,17], while contributing to primary energy savings through fuel substitution and improved system efficiency [18]. This becomes crucial given that most existing European DH systems are fossil-based, with 35 % of combined heat and power plants fired by coal, 39 % by gas, and only 11 % by renewable sources [19]. Estimates suggest that 20–50 % of industrial energy input is lost as waste heat [20], with global recovery potentials of 6–12 % (theoretical) and 6–9 % (economic) [21]. For the EU [16,22], total waste heat potentials are estimated at 267–300 TWh/a, of which around 46 % is located

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### Nomenclature

|        |                                                             |
|--------|-------------------------------------------------------------|
| ADV    | Advanced Case                                               |
| CV     | Coefficient of Variation                                    |
| DBSCAN | Density Based Spatial Clustering of Applications with Noise |
| DH     | District Heating                                            |
| OSM    | OpenStreetMap                                               |
| PAR    | Peak-to-Average Ratio                                       |
| PfA    | Platform for Waste Heat                                     |
| REF    | Reference Case                                              |
| SCR    | Spatial Coverage Ratio                                      |
| SLP    | Standard Load Profiles                                      |
| SMR    | Spatial Matching Ratio                                      |
| STCR   | Spatio-Temporal Coverage Ratio                              |
| STD    | Standard Case                                               |
| STMR   | Spatio-Temporal Matching Ratio                              |
| TCR    | Temporal Coverage Ratio                                     |
| TMR    | Temporal Matching Ratio                                     |
| WHS    | Waste Heat Source                                           |

near demand centers [18]. However, the estimated contribution to DH varies widely, ranging from 1–8 % depending on DH coverage, temperature levels, and future waste heat availability assumptions [5] up to 78 % under favorable conditions [23]. At the national scale, potentials remain comparatively limited, e.g. around 5 % of district heating demand in Denmark [24]. Case studies report absolute potentials typically in the range of 30–40 TWh/a (e.g. Italy: 38 TWh/a for district heating [25]; Switzerland: 37 TWh/a [26]; European non-metallic minerals: 37 TWh/a [27]). These variations are primarily driven by spatial and operational constraints as well as methodological assumptions, including the amount of residual heat, temperature levels, intermittency, temporal distribution, and costs for transport, storage, and energy conversion [12,15,19].

While waste heat is increasingly recognized as a valuable resource, its quantification remains constrained by fragmented and limited data availability [26], necessitating the application of diverse methodological approaches, including top-down, bottom-up, and hybrid methods [28]. These approaches typically rely on different data sources, such as surveys or measurements [14], fuel consumption (e.g. diesel and natural gas) and CO<sub>2</sub> emissions [12], national statistics and literature [29], number of employees [9], or emission data from the European Pollutant Release and Transfer Register (E-PRTR) [18]. As a result, spatial analyses are often based on aggregated or coarse-resolution data, limiting their applicability for district-level planning [7,18]. At the same time, temporal dynamics, such as hourly load profiles and seasonal variations, are frequently simplified or neglected, despite their importance for system integration [6,30]. Only few approaches combine both spatial and temporal dimensions [9]. In addition, many studies focus on isolated aspects, such as specific building segments (e.g. residential buildings [8]), individual demand profiling approaches [7,30,31], or single WHSs, including supermarkets and power plants [32], data centers [33], or electrolyzers [7]. Consequently, a comprehensive representation of building typologies and their interaction with diverse WHSs is often lacking. Thus, methodological approaches for matching heat demand and supply remain one of the central research gaps in large-scale potential assessments [25]. A further limitation has historically been the lack of detailed waste heat data. Meanwhile, recent policy regulations such as the German Energy Efficiency Act (§17(2) sentence 1) require companies exceeding defined thresholds to report detailed technical data to the Platform for Waste Heat (PfA) [34] (see Table 1).

By developing a novel residual-aware, guided source–demand allocation approach, this work aims to translate the reported PfA waste heat potentials into practically usable heat potential under realistic spatial and operational conditions. It investigates, at high spatial and temporal resolution, the distributional and operational characteristics of WHSs, the typological structure of buildings that can potentially be supplied, and the impact of building refurbishment on the utilizable potential. Through this comprehensive and detailed approach, the study bridges the gap in generally spatio-temporal source–demand matching — regardless of energy source and building type — showcasing the evaluation of the practical potential of WHSs for urban heat supply systems.

In the following, the term spatio-temporal matching refers to two complementary dimensions: spatial matching, representing a static (time-aggregated) assessment of utilizable potential under geographic and technical constraints, and temporal matching, capturing hourly supply–demand dynamics (cf. [15,21]).

## 2. Methodology and materials

Our spatio-temporal matching approach comprises three main stages, beginning with the collection and preprocessing of data on WHSs and buildings, including the derivation of key techno-spatial characteristics of the PfA-WHSs and the building stock. This is followed by the application of multiple spatial source–demand matching algorithms to analyze spatial constraints and their effects on achievable waste heat utilization. Finally, temporal source–demand matching is performed based on hourly load profiles to account for temporal variations and to derive key indicators for efficient waste heat utilization. Table 1 summarizes the datasets and their key parameters and attributes used in this analysis.

### 2.1. Waste heat sources

This section describes the datasets and methods used to characterize the WHSs, including their temporal profiles, locations, and process-type classification, providing the basis for the subsequent spatio-temporal matching with buildings.

#### 2.1.1. Source profiling

As listed in Table 1, the reported waste heat potential of each source is not available as an hourly time series. Instead, the dataset provides key figures that allow a reliable reconstruction of temporal profiles. We map the annual waste heat amount [kWh/a] into an hourly profile using the reported average monthly waste heat flow values (kW, January–December) in combination with the operational schedule (days per week, daily operating hours, and weekend availability). For this purpose, a full-year hourly time index (8760 h) is generated. The operational schedule is translated into an hourly availability pattern, where hours outside the declared operating periods are set to zero. Within the active hours, the monthly average waste heat flow values are used to represent seasonal variations. The resulting hourly values are scaled such that the annual integral of the profile equals the reported annual waste heat quantity. This procedure reflects the reported average thermal output during declared operating hours but does not capture unpredictable short-term intra-day fluctuations beyond the defined schedule. For analysis and visualization in the subsequent sections, sources are differentiated according to the pre-defined availability schedule categories provided by the PfA dataset: 5d–24h (5 days/week–24 h/day), 5d–8h (5 days/week–8 h/day), 7d–24h (7 days/week–24 h/day), 7d–8h (7 days/week–8 h/day), and Irregular. The category Irregular comprises sources operating on 5 or 7 days per week with less than 8 or between 9 and 23 operating hours per day.

For transparency and reproducibility, the complete workflow for generating hourly waste heat profiles from the PfA dataset is provided in the Supplementary Material as Python script `wasteheat_profiling.py`.

**Table 1**  
Summary of datasets and key attributes used for spatio-temporal matching.

| Data      | Description                                                                                                                                                                                     | Used attributes                                                                                                                                                                                                                                                                        |
|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| WHSs      | 25 596 reported WHSs with a theoretical potential of ca. 243 TWh, fully available (neither partially nor fully utilized as of 29 July 2025) [35].                                               | Company name and address, process type, annual waste heat quantity [ $\text{kWh/a}$ ], average monthly waste heat flow [kW], availability schedule (days and hours per week), weekend availability (yes/no), average daily availability [h], temperature level [ $^{\circ}\text{C}$ ]. |
|           | Residential: A total of 42 507 505 apartments in 19 116 274 buildings surveyed in the 2022 Census [36], aggregated into 3 141 050 hectare grid cells ( $100\text{m} \times 100\text{m}$ ) [37]. | Total living area, construction year and building type, current energy carrier and heating system, correlated with area-specific heat demand values from [38].                                                                                                                         |
| Buildings | Non-residential: 479 581 building polygons representing 14 heat-demanding building types retrieved from OpenStreetMap (OSM) [39].                                                               | Ground area, building height, number of floors, building type, correlated with area-specific heat demand values from [40].                                                                                                                                                             |
|           | Reported national heat demand [41].                                                                                                                                                             | Space heating, domestic hot water, and process heat for the residential (555 TWh), tertiary (184 TWh), and industrial (447 TWh) sectors, used to scale the high-resolution, building-level estimates.                                                                                  |
|           | SLP heat demand profiling [42].                                                                                                                                                                 | Building type, construction year, correlated with hourly air temperature data for the years 2020–2025 [43].                                                                                                                                                                            |

### 2.1.2. Geocoding

WHSs are reported with heterogeneous address quality, including missing house numbers, inconsistent postal codes, and varying company name formats. To enable reliable geolocation, a multi-stage geocoding procedure is applied. Initial attempts using open-source geocoding services (e.g., Nominatim via the *geopy* Python library) yielded insufficient spatial accuracy, as these services rely primarily on deterministic address matching and offer limited support for handling inconsistent or incomplete address information. To overcome these limitations and improve geolocation quality, a hybrid address-name geocoding approach with candidate ranking is adopted using the Google Places API. The API generates a set of plausible location candidates based on combinations of company name, address fragments, and municipality. In cases of ambiguous input data, this includes: (i) entering an address that corresponds to multiple companies at the same location, or (ii) entering a company name that yields multiple address candidates within the same locality; these candidate locations are subsequently evaluated using fuzzy string matching (*RapidFuzz* in Python), comparing reported company names and address components with the retrieved place metadata. Each candidate is assigned a similarity score, and the highest-ranked candidate is selected as the most accurate geolocation (see Fig. 1a).

### 2.1.3. Source classification

The reported 25 596 WHSs (cf. Table 1) correspond to individual WHSs with measurable waste heat potential rather than distinct companies, as some companies operate multiple WHSs at the same site. For the purpose of spatio-temporal matching with the building stock, WHSs belonging to the same plant and exhibiting technically and temporally similar profiles were aggregated. This reduces the number of plants by approximately 50%, resulting in 12 420 aggregated plants. When further aggregated by operator and site (i.e., physical location) and considering only the annual waste heat quantity, a total of 6392 sites can be geolocated.

Furthermore, process descriptions in the PfA dataset exhibit heterogeneous and non-standardized terminology, complicating the systematic classification of waste heat sources and hindering the derivation of analytical insights and key performance indicators. To address this, an initial exploratory text analysis was performed using the *nlTK* Natural Language Toolkit and the *collections.Counter* class in Python to identify frequently occurring keywords in the process descriptions. Based on these results, a rule-based classification framework was developed employing a domain-specific keyword taxonomy representing concrete plant types (e.g., boilers, furnaces, cooling systems, drying units, and compressed air systems). Generic or context-dependent terms — such as “exhaust air” (638 occurrences), “waste heat” (242), “waste heat

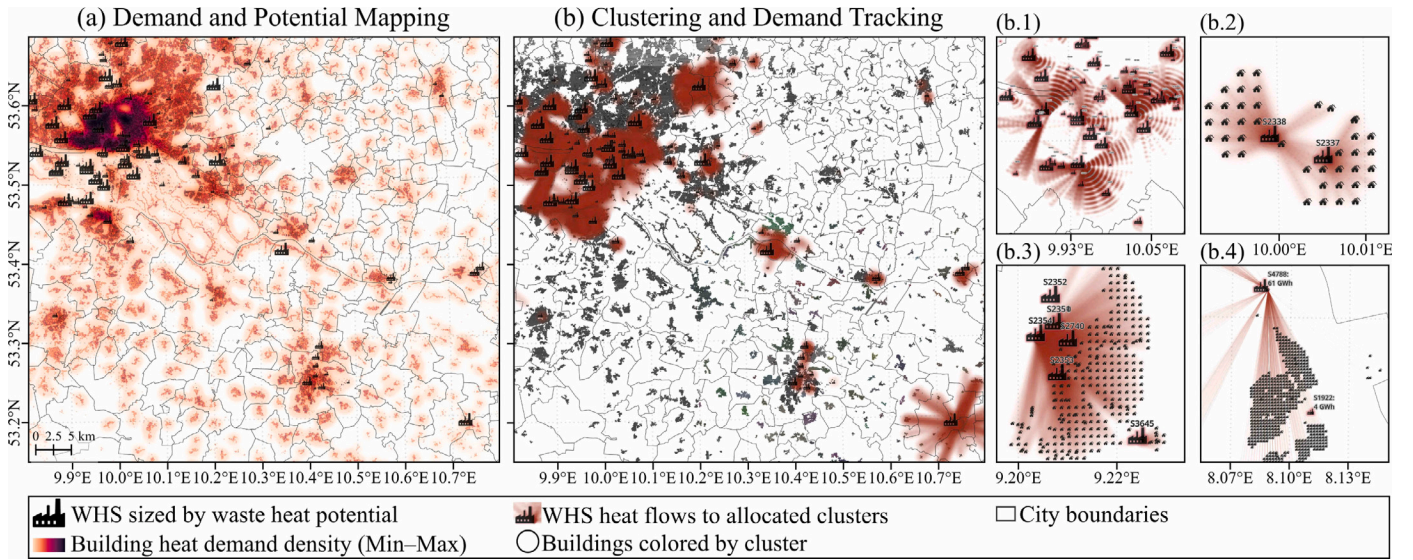
potential” (165), “heating” (133), and “filter” (102) — were intentionally excluded from forced assignment to avoid misclassification. For example, “exhaust air” denotes a medium rather than a system type and can appear in diverse contexts such as paper machines, kitchens, or afterburners, which would violate the system-type assignment logic.

### 2.2. Building data and demand profiling

Based on the typological attributes (cf. Table 1), the annual heat demand for all residential and non-residential buildings (comprising 12 major building types) was estimated for three distinct energy efficiency scenarios following [44]: REF — original construction status without subsequent refurbishment, STD — standard renovation level corresponding to the German minimum standard, and ADV — advanced renovation level approaching passive-house standards. This differentiation allows assessing the influence of building energy efficiency improvements on the practical usability of the WHSs, including the number of buildings that can be supplied and the temporal alignment between supply and demand. To maximize reliability, sector-specific scaling factors were applied to match the annual heat demand reported in Table 1.

Subsequently, hourly demand profiles were generated using the *demandlib* Python library, which implements the SLP methodology [45]. In addition to annual heat demand, the following input parameters are required:

1. SLP-type — defines the applicable load profile (e.g., single-family house, multi-family house, retail) for each considered Census and OSM building type.
2. Building class — applicable only for residential buildings, incorporating the thermal quality based on construction year. Table 2 summarizes the adjustable classes according to the share of pre-1978 buildings in the study area, which are used as a proxy for lower thermal efficiency as they predate the first German thermal insulation ordinance. Consequently, this *demandlib* input parameter primarily characterizes the REF scenario, while the STD and ADV scenarios are represented through adjusted annual heat demand levels reflecting building refurbishment.
3. Public holidays — considered using the Python module *workalendar*.
4. Outdoor air temperature — provided as hourly time series to account for temperature-dependent heating behavior. *demandlib* automatically accounts for thermal inertia through a “geometric series” approach based on a weighted sum of daily mean outdoor temperatures over the current and three preceding days.



**Fig. 1.** Spatial matching process illustrated for an exemplary area. (a) Mapping of building heat demand and WHSs potential. (b) Building clusters (colored areas) after removal of buildings classified as noise (see Section 2.3.1). Red rays indicate heat flows from WHSs to allocated clusters, with line thickness proportional to the flow magnitude. Subpanels show allocation mechanisms: (b.1) guided source–demand allocation, (b.2) controlled spill-over to neighboring clusters to utilize surplus heat, (b.3) multi-source supply of a single cluster, and (b.4) dominant WHS supplying multiple clusters while neighboring WHS remains unused.

**Table 2**

Building classes accepted in *demandlib* for heat demand profiling, based on construction period composition [46].

| Building type   | Share of old buildings ( $\leq 1978$ ) | Class |
|-----------------|----------------------------------------|-------|
| Non-residential | –                                      | 0     |
|                 | 0.86–1.00                              | 1     |
|                 | 0.81–0.86                              | 2     |
|                 | 0.76–0.81                              | 3     |
|                 | 0.71–0.76                              | 4     |
| Residential     | 0.66–0.71                              | 5     |
|                 | 0.61–0.66                              | 6     |
|                 | 0.56–0.61                              | 7     |
|                 | 0.51–0.56                              | 8     |
|                 | 0.46–0.51                              | 9     |
|                 | 0.41–0.46                              | 10    |

Initial attempts to obtain hourly temperature data via dynamic interpolation with the *Meteostat* library yielded reliable results; however, the computational effort was prohibitive for large-scale applications, with data retrieval times of approximately 30 seconds per location. Therefore, hourly temperature data were directly obtained from the Climate Data Center [43] of the German Weather Service for all German weather stations. Each district was assigned the time series of the geographically nearest station with complete hourly records. Finally, the resulting building-level demand profiles constitute an hourly heat load time series [kW] for each building, with an annual integral corresponding to the estimated annual heat demand.

Analogous to the source profiling workflow, the complete workflow for generating hourly building heat demand profiles is provided in the Supplementary Material via the Python script `heat_demand_profiling.py`.

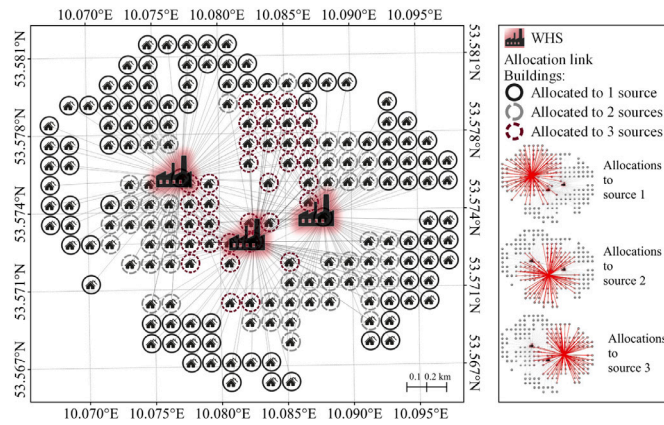
### 2.3. Spatio-temporal matching

This section details the geoprocessing steps used for spatially matching WHSs with buildings, as partially illustrated in Figs. 1 and 2, and introduces the matching metrics employed to evaluate the spatio-temporal feasibility of WHSs.

#### 2.3.1. Geoprocessing

**Spatial clustering and guided source–demand allocation.** To represent spatially coherent demand areas, buildings were grouped into clusters corresponding to districts or neighborhoods (Fig. 1b). These clusters serve as the fundamental spatial units for waste heat allocation and reflect typical structures used in heat planning. Clustering was performed using the *Density Based Spatial Clustering of Applications with Noise (DBSCAN)* algorithm, which is well suited for urban environments characterized by irregular building patterns, heterogeneous densities, and an unknown number of clusters [47]. Unlike partitioning methods such as *k-means*, *DBSCAN* does not require predefining the number of clusters and allows for arbitrary cluster shapes as well as the explicit identification of noise points. This property is particularly important for distinguishing dense urban districts from sparsely built or isolated structures. The algorithm requires specification of two hyperparameters [47,48]:  $\epsilon$ , defining the maximum distance between two points within the same cluster, and *MinPts*, defining the minimum number of points required to form a cluster. As the Census building data are represented by centroids of grid cells (100 m  $\times$  100 m) (cf. Table 1), the choice of an  $\epsilon$ -distance of 150 m ensures direct connectivity between adjacent and diagonally neighboring grid cells. This avoids artificial gaps within individual districts. Smaller distance thresholds would contradict the underlying spatial abstraction of the hectare grid, while larger thresholds would reduce spatial specificity by merging functionally distinct areas. A minimum number of five points (*MinPts* = 5) to prevent isolated or scattered buildings from being treated as independent districts. Given the underlying Census hectare grid, where individual points may represent only a few buildings (e.g., 3 buildings, potentially comprising many dwellings, at lat: 50.9216, lon: 6.9337) or several dozen buildings (e.g., 90 buildings at lat: 53.1100, lon: 8.7649), even the smallest clusters correspond to groups of buildings rather than isolated structures. Buildings not assigned to any cluster were classified by *DBSCAN* as noise.

The resulting clusters form the basis for the guided source–demand allocation, ensuring that waste heat is primarily allocated within spatially coherent demand areas before being distributed across larger distances. This approach follows established practices in spatial energy system analysis and aligns with previous clustering-based heat planning studies [49]. For each WHS, the allocation process begins within its own cluster. Buildings belonging to the same cluster are sorted strictly



**Fig. 2.** Illustration of overlapping source-building allocations in distance-based matching. Buildings located within the overlapping catchment areas of multiple WHSs may be assigned to more than one source, leading to double counting and an overestimation of supplied heat demand.

by increasing distance to the source, ensuring that the nearest buildings are supplied first. This design reflects the practical preference for short transmission distances and prevents buildings from being bypassed in favor of slightly closer buildings in other districts (see Fig. 1b.1).

**Residual demand tracking mechanism.** While the clustering- and distance-based representation provides the initial spatial framework for matching between WHSs and buildings, it remains purely relational and does not account for the fact that each building's heat demand is spatially fixed and can only be satisfied once within a competitive multi-source environment. In particular, the raw distance matrix captures pairwise distances but does not represent the positional relationship of buildings relative to multiple sources, nor does it prevent the same building from appearing in multiple source-target pairs. Fig. 2 illustrates the limitations of a purely distance-based matching approach. In the presence of multiple nearby WHSs, buildings may be assigned to several sources simultaneously, resulting in overlapping allocations and an artificial inflation of covered demand.

To address this limitation, a *residual demand tracking mechanism* is incorporated into the guided source-demand allocation algorithm. Each building is assigned a residual annual heat demand, initialized with its full estimated demand. During allocation, WHSs supply buildings sequentially, and the residual demand is reduced accordingly. Once a building's residual demand reaches zero, it is removed from the active allocation pool. This mechanism represents a methodological extension of proximity-based matching approaches commonly applied in previous studies, where demand exclusivity and spatial competition between multiple sources are typically not enforced.

**Spill-over logic across clusters.** If an WHS retains surplus after all buildings within its allocated cluster have been served, the algorithm permits a controlled spill-over into neighboring clusters, while consistently respecting the residual demand tracking mechanism (see Fig. 1b.2).

**Multi-source coverage.** When the waste heat potential of a single source is insufficient to fully satisfy the residual demand of buildings within its allocated cluster, additional sources may supply the remaining demand. In dense urban areas, this ensures that all available sources are effectively utilized or integrated, even when residual demand is only partially met (see Fig. 1b.3).

**Dominant source rule.** In districts with several large WHSs, the dominant source rule prioritizes the largest source as the primary supplier. This avoids unrealistic stacking effects in which multiple large sources would be partially utilized within the same district, resulting in unnecessary infrastructure expansion (see Fig. 1b.4).

### 2.3.2. Matching metrics

To evaluate the spatio-temporal alignment between waste heat supply and building heat demand, a set of matching indicators is introduced. Let  $\dot{Q}_{s,t}$  and  $\dot{Q}_{d,t}$  denote the aggregated waste heat supply [kW] and building heat demand [kW] at time step  $t$ , respectively, obtained by summing the individual time series  $\dot{q}_{s,i,t}$  and  $\dot{q}_{d,i,t}$  over  $n$  units indexed by  $i$  (WHSs for supply and buildings for demand) using Eq. (1):

$$\dot{Q}_{s,t} = \sum_{i=1}^n \dot{q}_{s,i,t}, \quad \dot{Q}_{d,t} = \sum_{i=1}^n \dot{q}_{d,i,t} \quad (1)$$

The total annual waste heat potential  $Q_s$  and the annual building heat demand  $Q_d$  (both in [kWh]) are obtained by summing over all hourly time steps in a year ( $T = 8760$ ):

$$Q_s = \sum_{t=1}^T \dot{Q}_{s,t}, \quad Q_d = \sum_{t=1}^T \dot{Q}_{d,t} \quad (2)$$

**Matching ratios (Supply-Side).** The supply-side analysis evaluates the fraction of the theoretical waste heat potential that can be utilized under spatial and temporal constraints. Let  $Q_{SM}$  [kWh] denote the spatially utilizable waste heat potential obtained from the allocation procedure described in Section 2.3.1. The spatial feasibility of WHSs is quantified by the SMR:

$$SMR = \frac{Q_{SM}}{Q_s} \quad (3)$$

Since WHSs often exhibit operating profiles that differ from the temporal profile of building heat demand, the temporally utilizable waste heat potential  $Q_{TM}$  [kWh] is determined by aggregating the minimum of supply and demand at each time step over the year:

$$Q_{TM} = \sum_{t=1}^T \min(\dot{Q}_{s,t}, \dot{Q}_{d,t}) \quad (4)$$

The fraction of spatially utilizable waste heat that can be practically utilized considering temporal supply-demand compatibility is defined as the TMR:

$$TMR = \frac{Q_{TM}}{Q_{SM}} \quad (5)$$

Combining spatial and temporal constraints yields the STMR:

$$STMR = \frac{Q_{TM}}{Q_s} = SMR \times TMR \quad (6)$$

**Coverage ratios (Demand-Side).** From the building demand perspective, the share of heat demand that can be supplied by spatially matched waste heat is expressed by the SCR:

$$SCR = \frac{Q_{SM}}{Q_d} \quad (7)$$

Considering both spatial and temporal constraints, the fraction of building heat demand that can be practically covered by waste heat is expressed by the Spatio-Temporal Coverage Ratio (STCR):

$$STCR = \frac{Q_{TM}}{Q_d} = SCR \times TMR \quad (8)$$

Introducing a Temporal Coverage Ratio (TCR) would be mathematically equivalent to TMR, making it semantically redundant.

**Temporal profile characteristics.** Temporal characteristics of waste heat supply and heat demand are further described by structural indicators. The residual heat load  $\dot{Q}_{r,t}$  [kW] is defined as the difference between aggregated heat demand and waste heat supply:

$$\dot{Q}_{r,t} = \dot{Q}_{d,t} - \dot{Q}_{s,t} \quad (9)$$

Negative values represent surplus waste heat that cannot be utilized at the respective time step, while positive values indicate deficit heat that must be supplied by alternative sources or storage. The fraction of time steps without available waste heat is quantified by the

zero-output share  $Z_0$ , capturing structural intermittency and temporal unavailability of the source [30]:

$$Z_0 = \frac{1}{T} \sum_{t=1}^T \mathbf{1}(\dot{Q}_{s,t} = 0) \quad (10)$$

where  $\mathbf{1}(\cdot)$  denotes the indicator function. It should be noted that  $Z_0$  is intended as a source characterization metric and does not account for temporal source–demand coincidence. The temporal variability of load profiles is quantified using the CV, defined as the ratio of the standard deviation  $\sigma$  to the mean  $\mu$  [50,51]:

$$CV = \frac{\sigma}{\mu} \quad (11)$$

Higher CV values indicate stronger seasonal or diurnal fluctuations, highlighting the need for balancing mechanisms within the system. To capture the magnitude of extreme loads, peak intensity is quantified using the PAR, which relates the maximum hourly load to the annual mean and provides a consistent metric for evaluating load peaks. For waste heat supply,  $Z_0$ , CV, and PAR together enable a systematic differentiation between stable base-load and highly intermittent streams. For building demand, CV and PAR similarly support both temporal matching assessment and system dimensioning.

### 3. Results

The results of the spatio-temporal matching include a detailed characterization of the WHSs, analysis of their spatial distribution, building allocation and energy efficiency impacts, as well as multi-scale evaluation of spatial, temporal, and combined matching feasibility.

#### 3.1. Distributional and operational WHSs characteristics

**Distributional characteristics.** Starting with a descriptive analysis of the PfA-WHSs dataset, the results reveal that annual waste heat potentials span a wide range, from approximately 1 kWh to  $7.7 \times 10^9$  kWh. The mean annual waste heat ( $9.5 \times 10^6$  kWh) is roughly twelve times higher than the median ( $8.1 \times 10^5$  kWh), reflecting a strongly right-skewed distribution. This skewness indicates that mean-based statistics are highly sensitive to a few exceptionally large sources, making percentile-based measures, such as the median and interquartile range, more robust descriptors of typical WHSs. Linear-scale visualizations can therefore be misleading, as the largest sources dominate the scale while the majority of small and medium sources collapse near zero. A logarithmic representation ensures scale invariance and allows proportional differences to become interpretable across the entire range of values.

To capture the distributional patterns more effectively, Fig. 3 presents three complementary representations of annual waste heat potential: (a) the density-size distribution highlighting the modal peak and dense core range, (b) the rank-size distribution on a log-log scale illustrating the heavy-tailed structure, and (c) the Lorenz curve showing the cumulative contribution of sources to the total potential.

Fig. 3a shows a dense core range based on kernel density estimation. The modal peak corresponds to a global maximum of 254 kW, while the most frequent WHSs span between 64 kW and 800 kW, with annual potentials from  $1.52 \times 10^5$  kWh to  $4.36 \times 10^6$  kWh. This range encompasses 17 650 WHSs, providing roughly 20 TWh, corresponding to 8 % of the total potential. The distribution is concentrated within roughly one order of magnitude around the modal scale, highlighting a pronounced mid-scale clustering of WHSs.

Visual inspection of Fig. 3b suggests several apparent changes in slope, which might give the impression of distinct structural regimes. However, a rolling local slope analysis in log-log space shows a gradual steepening, with the apparent “kinks” reflecting smooth curvature rather than discrete regimes. The distribution is structurally heterogeneous, with a continuously extending upper tail characterized as heavy-tailed. The pronounced heavy-tail is indicated by the horizontal

line labeled “Heavy Tail Start”. This threshold is estimated using the *powerlaw* Python library [52], following the methodology of Clauset et al. [53], which identifies the optimal cutoff that best fits a power-law distribution. The cutoff occurs at  $1.59 \times 10^7$  kWh, showing that the most extreme values are confined to a very small upper fraction of the distribution.

In Fig. 3c, the Lorenz curve illustrates the cumulative distribution of waste heat potential and reveals strong concentration effects. A comparatively small fraction of high-capacity WHSs (1658, corresponding to the top 6.5 %) accounts for approximately 83 % of the total potential. The concentration is further highlighted by the largest single WHS, which contributes 3.14 % of the total potential, while the four largest WHSs together account for approximately 23 TWh, corresponding to 9.4 % of the total.

In summary, WHSs in the 64–800 kW range are most prevalent (see Fig. 4), whereas heavy-tail WHSs with waste heat flows  $\geq 7000$  kW are particularly important for maximizing the effective utilization of waste heat in buildings and should therefore be prioritized in planning. Fig. 5 maps the spatial distribution of these heavy-tail WHSs across all federal states, showing 1089 sites hosting a total of 1658 WHSs with varying density and spatial patterns. For example, in Rhineland-Palatinate the sites are largely dispersed along the state borders, whereas in North Rhine-Westphalia they are more centrally concentrated.

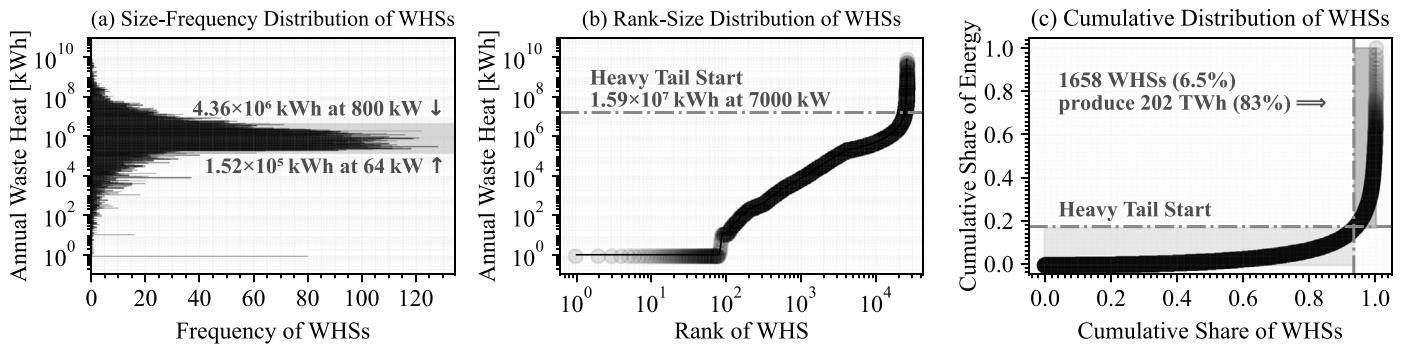
**Operational characteristics.** To further understand the operational characteristics of these sources, the generated hourly waste heat profiles of all reported WHSs are analyzed. Fig. 4 illustrates the median waste heat flow of all reported WHSs over the year, faceted by temperature level (columns) and availability schedule (rows), resulting in 25 temperature-schedule categories. This representation provides both a time-resolved view and a statistical summary of waste heat flows. Across all categories, the highest waste heat potential occurs under continuous operation (7d–24h), primarily from mid-temperature sources (25–60 °C), which contribute approximately 56 % of the total potential, followed by high-temperature sources (60–90 °C) contributing about 10 %. Beyond these aggregate contributions, the temporal profiles reveal systematic differences in magnitude, variability, and intermittency across operational schedules. These dynamics are further quantified using statistical indicators: PAR captures the magnitude of short-term peaks relative to typical waste heat flows, CV describes the temporal stability of WHSs, and  $Z_0$  indicates the fraction of hours without waste heat flow.

First, structural intermittency strongly correlates with the availability schedule. Continuous operation (7d–24h) exhibits very low zero-output periods across all temperature levels ( $Z_0 \approx 2\text{--}5\%$ ), most likely reflecting short maintenance periods. In contrast, restricted schedules — particularly weekday-only operation such as 5d–8h — show substantially higher non-supply periods, reaching up to  $Z_0 = 78\%$ , while maintaining comparable magnitudes across temperature levels within the same schedule class.

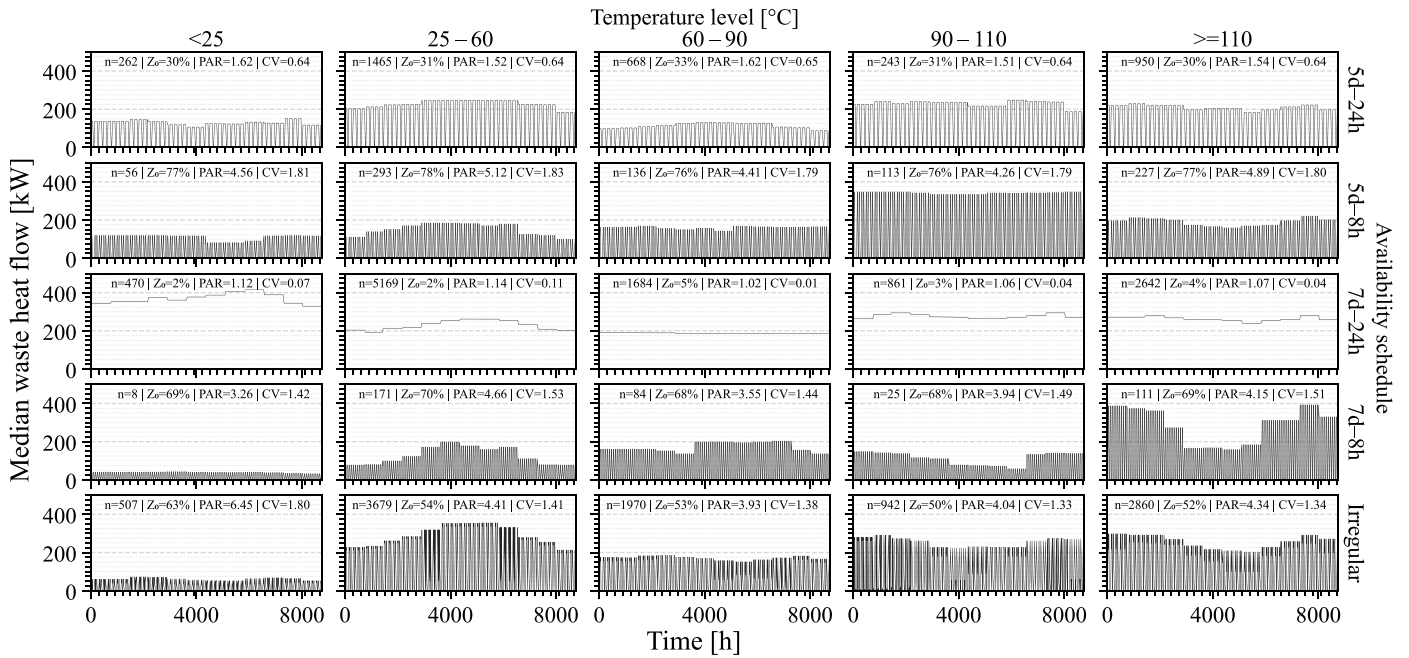
Second, based on CV, the WHSs can be grouped into three main stability categories. Continuous operation (7d–24h) exhibits the most stable profiles with  $CV \approx 0.01\text{--}0.11$ . Sources operating under 5d–24h schedules show moderate variability ( $CV \approx 0.64\text{--}0.65$ ), whereas all remaining schedules display highly variable behavior ( $CV > 1$ ).

In total, 42 % of WHSs, representing 83 % of the total potential, fall into the stable CV category. A further 14 % of sources (3 % of the potential) exhibit moderate variability, while the remaining 44 % of sources account for 14 % of the potential and show highly intermittent supply.

From a system integration perspective, low CV values indicate sources that can be more easily integrated into district heating systems due to their continuous supply and lower storage requirements. Conversely, high CV values reflect pronounced peaks and fluctuations, making utilization more challenging and requiring balancing mechanisms such as thermal storage.



**Fig. 3.** Distributional characteristics of WHSs. (a) Density-size distribution (horizontal histogram with kernel density estimate), highlighting the modal peak and the dense core range. (b) Rank-size distribution on log-log scale, illustrating the heavy-tailed structure and the onset of the heavy tail. (c) Lorenz curve showing the cumulative contribution of WHSs to total waste heat potential.



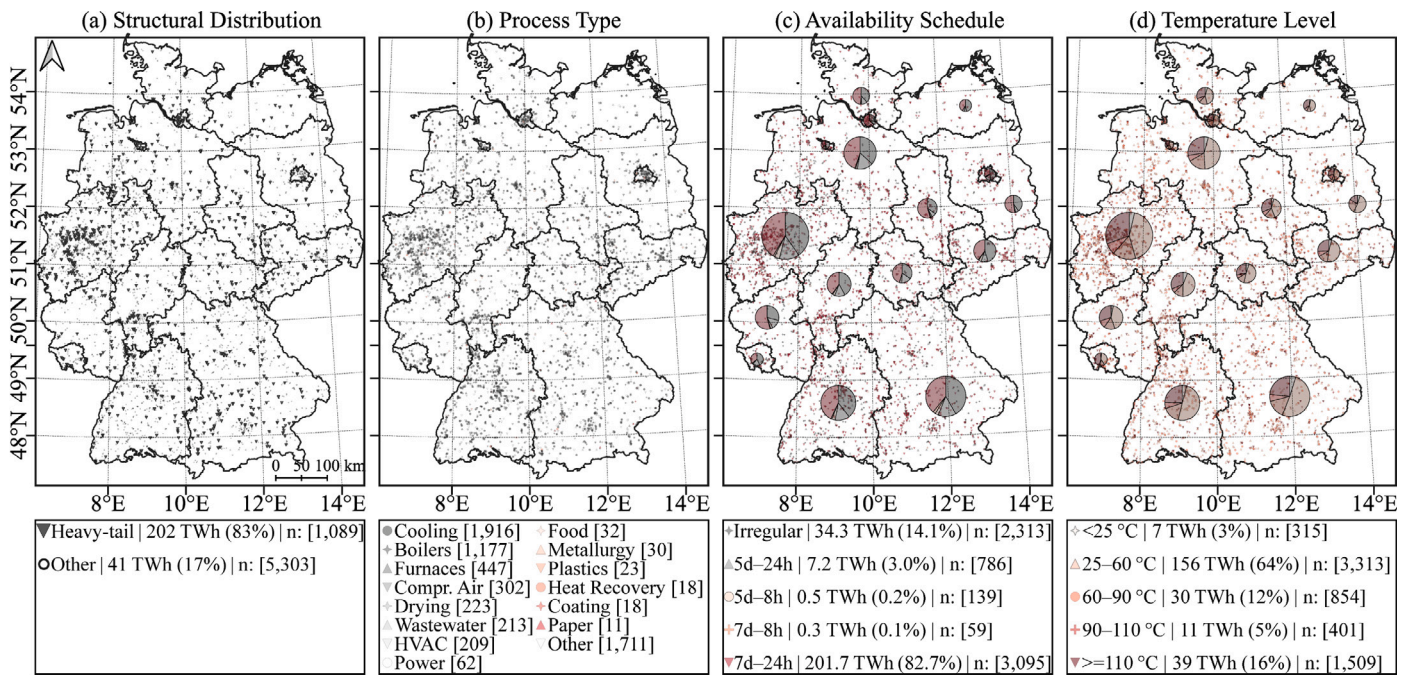
**Fig. 4.** Annual profiles of median waste heat flow, faceted by temperature level (columns) and availability schedule (rows). Each panel reports the number of WHSs ( $n$ ), the zero-output share ( $Z_0$ ), the PAR, and the CV. Continuous profiles occur exclusively in the 7d–24h categories, while other schedules exhibit intermittent, duty-cycle-driven, sawtooth-like patterns due to regular and irregular shutdown periods.

The PAR is largely consistent across temperature levels within the same availability schedule, indicating that temporal availability and temperature level constitute largely independent dimensions of waste heat quality. While availability schedules govern temporal variability and associated balancing requirements, temperature levels primarily determine the technical integration pathway (e.g., direct use versus heat pump integration).

Consistent with this interpretation, continuous sources (7d–24h) not only dominate the dataset and show higher spatial availability — particularly at 25–60 °C ( $n = 5169$ ) and  $\geq 110$  °C ( $n = 2642$ ) — but also provide reliable base-load potential due to low  $Z_0$ , low CV, and moderate PAR. By contrast, irregular sources are characterized by higher non-supply risk (approximately 55% zero-output periods), stronger variability, and pronounced peaks, especially for the widely distributed 25–60 °C category ( $n = 3679$ , PAR = 4.41).

Overall, these results highlight a fundamental trade-off between temporal stability and annual potential: continuous operation at low to moderate temperatures provides the most reliable base-load supply, whereas intermittent schedules require storage, demand flexibility, or process integration to make the waste heat effectively utilizable.

**WHSs classification by process type.** Building upon the analysis of operational profiles, further insights can be gained by classifying WHSs according to their process types. Fig. 5b maps the spatial distribution of the WHSs differentiated by process category. At low temperatures, the previously highlighted continuous 7d–24h operation is dominated by Cooling/Chilling (25–60 °C) with 1974 WHSs across 1916 sites, and by HVAC/Building/Ventilation/IT (25–60 °C) with 370 WHSs. Together, these categories account for 84% of the 2508 WHSs operating 7d–24h at 25–60 °C. This concentration of continuously available, low- to mid-grade heat indicates a substantial, geographically distributed base-load potential suitable for low-lift heat pumps or direct space heating in low-temperature systems. At high temperatures, Boilers/CHP/Exhaust sources ( $\geq 110$  °C) comprise 1208 of 1282 WHSs (94%) across 1177 sites operating 7d–24h, providing highly reliable, high-exergy base-load suitable for direct industrial use, high-temperature district heating, or steam integration with minimal upgrading. For process heat, furnaces ( $\geq 110$  °C) include 521 WHSs operating 7d–24h and 357 WHSs operating 5d–24h (together 57% of WHSs in this category), distributed over 447 sites. The predominance of continuous operation underscores



**Fig. 5.** Spatial patterns and structural distribution of WHSs, illustrated by (a) locations of heavy-tail WHSs, (b) process types, (c) availability schedules, and (d) temperature levels. Markers show individual sources, and pie charts indicate the relative shares per federal state, with pie size reflecting the total number of WHSs. Numbers in square brackets denote the number of plotted sites, while individual sites may include multiple WHSs.

**Table 3**

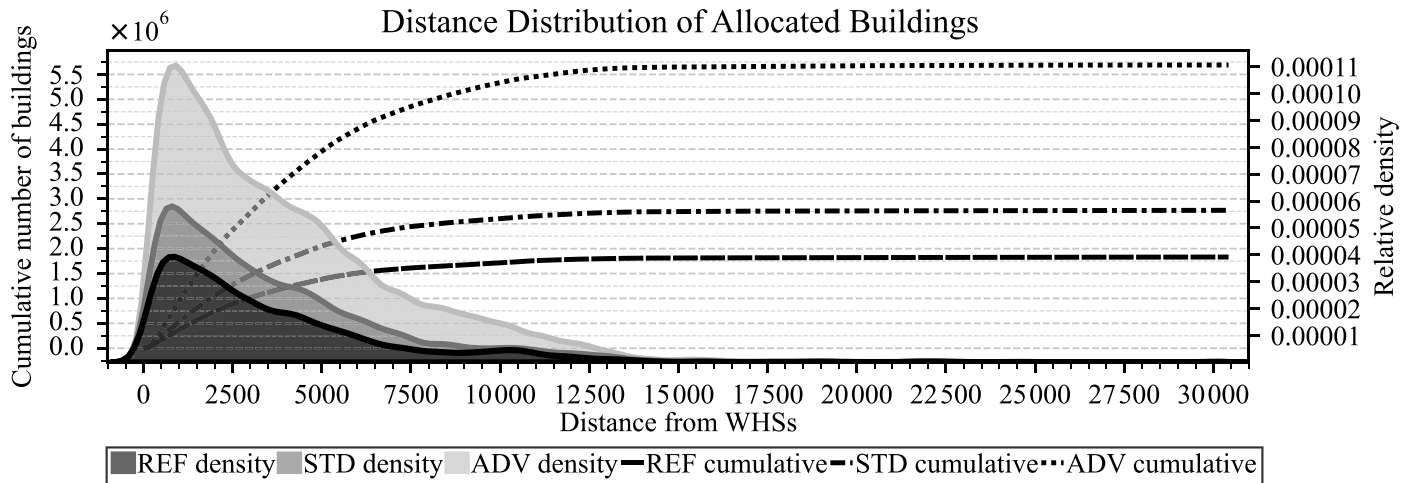
Number of reported WHSs by federal state, availability schedule, and temperature level, sorted by WHS availability 7d–24h.

| Federal state                 | Availability schedule |        |       |       |        | Temperature level |             |             |              |         |
|-------------------------------|-----------------------|--------|-------|-------|--------|-------------------|-------------|-------------|--------------|---------|
|                               | Irregular             | 5d–24h | 5d–8h | 7d–8h | 7d–24h | <25 °C            | 25 °C–60 °C | 60 °C–90 °C | 90 °C–110 °C | ≥110 °C |
| North Rhine-Westphalia        | 2332                  | 799    | 206   | 63    | 2390   | 213               | 2427        | 932         | 448          | 1770    |
| Bavaria                       | 1765                  | 606    | 107   | 92    | 1652   | 205               | 2159        | 630         | 236          | 992     |
| Baden-Wuerttemberg            | 1260                  | 432    | 100   | 32    | 1373   | 132               | 1587        | 509         | 185          | 784     |
| Lower Saxony                  | 1002                  | 435    | 42    | 25    | 1219   | 116               | 1220        | 478         | 159          | 750     |
| Rhineland-Palatinate          | 424                   | 191    | 42    | 15    | 787    | 45                | 608         | 219         | 150          | 437     |
| Hesse                         | 630                   | 210    | 48    | 14    | 600    | 90                | 664         | 195         | 86           | 467     |
| Saxony-Anhalt                 | 346                   | 74     | 21    | 12    | 548    | 42                | 397         | 173         | 76           | 313     |
| Saxony                        | 588                   | 133    | 51    | 12    | 516    | 54                | 622         | 192         | 99           | 333     |
| Thuringia                     | 341                   | 164    | 37    | 4     | 448    | 48                | 487         | 124         | 54           | 281     |
| Brandenburg                   | 315                   | 45     | 9     | 5     | 410    | 38                | 409         | 141         | 67           | 129     |
| Schleswig-Holstein            | 285                   | 82     | 12    | 4     | 363    | 32                | 313         | 116         | 60           | 225     |
| Hamburg                       | 107                   | 32     | 1     | 6     | 241    | 15                | 189         | 77          | 23           | 83      |
| Mecklenburg-Western Pomerania | 181                   | 23     | 20    | 1     | 156    | 13                | 164         | 42          | 30           | 132     |
| Saarland                      | 178                   | 81     | 2     | 11    | 149    | 7                 | 161         | 47          | 16           | 190     |
| Berlin                        | 160                   | 55     | 7     | 6     | 105    | 8                 | 148         | 29          | 49           | 99      |
| Bremen                        | 82                    | 12     | 21    | 0     | 77     | 3                 | 78          | 42          | 8            | 61      |

firm capacity contributions, while the sizable 5d–24h cohort aligns with weekday-focused demands, where diurnal storage can bridge off-hours. In contrast, Compressed Air Systems at 60–90 °C exhibit mixed availability: 308 of 817 WHSs (38 %) are 7d–24h, and another 375 (39 %) are irregular, located across 302 sites.

In Fig. 5c and d, the regional distribution of waste heat sources is further analyzed with respect to temperature levels and availability schedules to assess structural differences across federal states using the standard deviation of relative shares for each category. For both availability schedules and temperature levels, variation across federal states is generally moderate, ranging from 1 to 8 percentage points. Availability schedules display slightly larger regional differences, with weekday-only operations relatively evenly distributed across federal states (5d–8h: 2 percentage points; 5d–24h: 4 percentage points). In contrast, irregular operations exhibit moderate variability (6 percentage points), indicating some spatial clustering, particularly in Berlin and Mecklenburg-Western Pomerania, whereas continuously operating

sources (7d–24h: 8 percentage points) show the highest variability, reflecting a pronounced concentration with the highest relative shares found in Hamburg, Saxony-Anhalt, Rhineland-Palatinate, and Brandenburg; however, in absolute numbers, the largest contributions come from North Rhine-Westphalia, Bavaria, Baden-Württemberg, and Lower Saxony (Table 3). For temperature levels, variation across federal states is slightly smaller, ranging from 1 to 6 percentage points. Very low temperature sources (<25 °C) show the lowest variability (1 percentage point), indicating a relatively homogeneous distribution across Germany. Mid- to high-temperature sources (25–110 °C) exhibit moderate variability (3–4 percentage points), while very high-temperature sources (≥110 °C) show the largest variation (6 percentage points), reflecting a stronger influence of regional industrial structures. The highest relative shares of ≥110 °C WHSs are observed in Saarland and Mecklenburg-Western Pomerania, while absolute numbers correspond to the federal states named for availability schedules.



**Fig. 6.** Distance distribution of buildings allocated to WHSs and the effect of efficiency upgrades (REF, STD, ADV) on the cumulative number of allocated buildings. Shaded areas indicate the density curves of building counts per distance, highlighting a clear concentration between 0.6 km and 8.5 km, encompassing about 79 % of all allocated buildings. Dashed lines represent the cumulative building count, showing that 96 % of all buildings are allocated within 11 km for all scenarios, implying that the waste heat potential is largely exhausted within this distance.

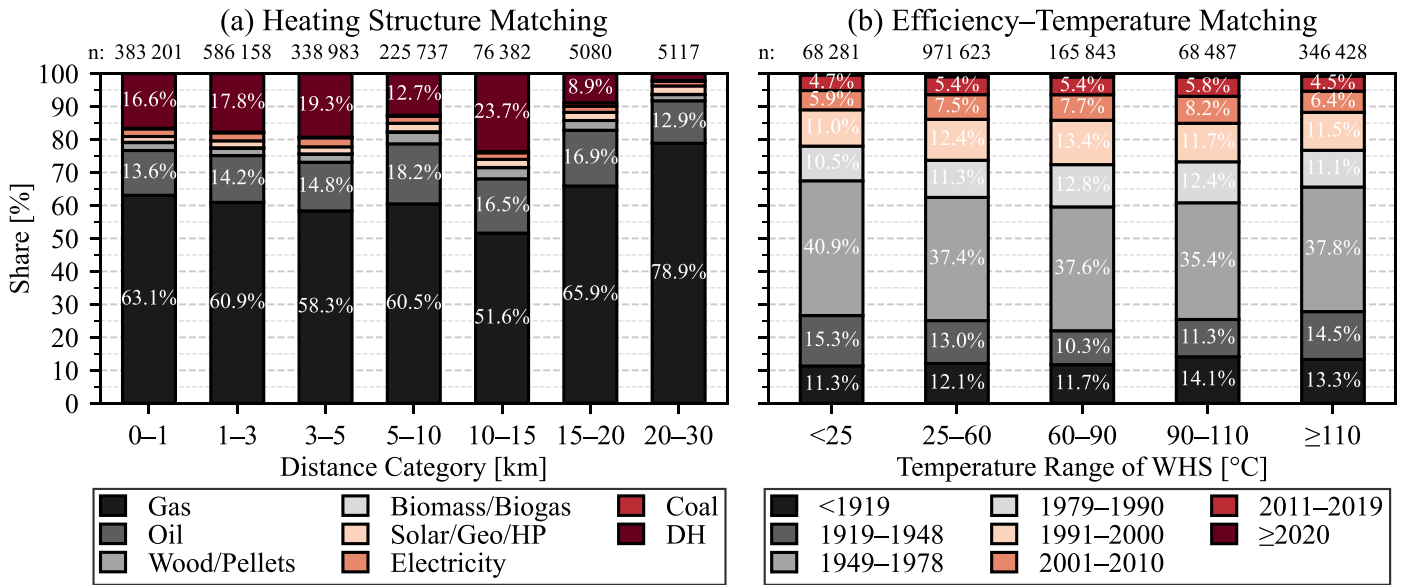
### 3.2. Distributional and typological building characteristics

**Spatial distribution.** Fig. 6 presents the first result of the spatial matching between WHSs and buildings. It illustrates the distance distribution of allocated (matched) buildings from the WHSs. The distribution is analyzed for the three calculated building efficiency scenarios: REF, STD, and ADV. As shown in Fig. 6, the number of buildings that can be supplied increases with higher energy efficiency, ranging from approximately 1.8 million for REF, to 2.8 million for STD, and 5.7 million for ADV. The *Kernel Density Estimation* analysis (represented by the shaded areas) reveals that the majority of buildings are concentrated within a core range of approximately 0.6 km to 8.5 km, which encompasses about 79 % of all allocated buildings. The maxima of the building-count density curves occur at around 794 m for REF and STD, and 855 m for ADV, indicating that the highest concentration of potential consumers is located close to the WHSs. The density curves further indicate that beyond approximately 13 km, only a very small number of buildings is allocated, suggesting that most WHSs already reach their potential consumers within this distance and that the available waste heat potential is largely exhausted. The cumulative distribution of building counts (represented by the lines) shows that approximately 96 % of all buildings are allocated within 11 km for all scenarios, suggesting that the waste heat potential is largely exhausted within this distance. The distributions across scenarios show a similar shape with different magnitudes, implying that efficiency upgrades (STD and ADV) do not significantly alter the spatial concentration of buildings but primarily affect the absolute number of buildings within the core distance ranges.

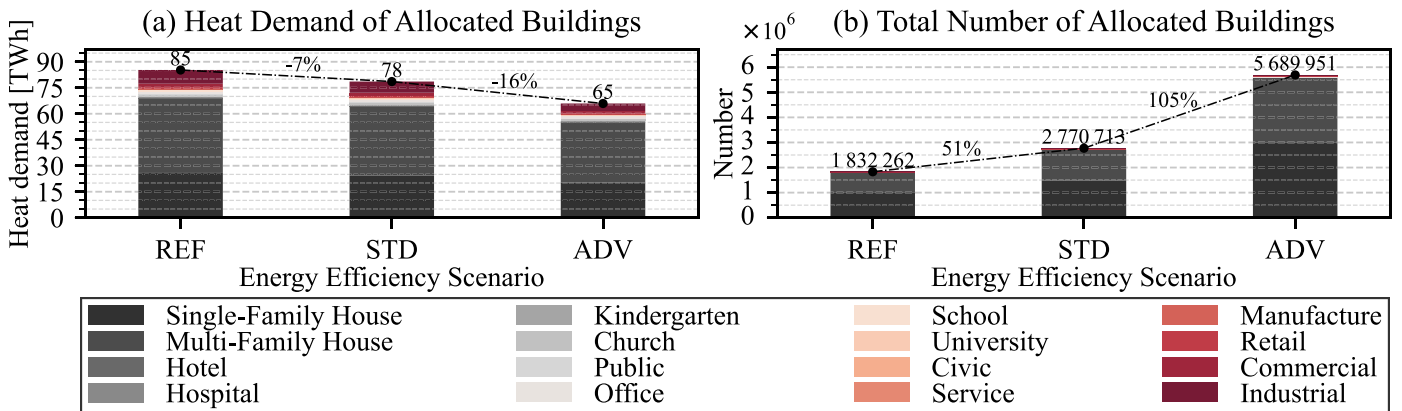
**Typological characteristics.** Beyond spatial allocation, the typological characteristics of the allocated buildings are analyzed. The type of currently installed heating systems is examined in Fig. 7a for different distance categories. The absolute number of buildings ( $n$ ) is indicated above each bar, showing that relatively few buildings are allocated in the outer distance categories of 15–20 km and 20–30 km, reflecting the limited remaining waste heat potential at larger distances. The stacked bars represent the percentage distribution within each distance category and highlight the potential for replacing fossil heating systems or integrating district heating. Across all distance categories, gas heating systems dominate, accounting for approximately 51–63 % of buildings, followed by oil-based systems with around 13–18 %. District heating represents roughly 18 %, while other energy carriers such as coal or electricity account for only minor shares. The distribution remains

largely consistent across all distance categories, indicating no distinct clustering around specific waste heat sources. Instead, the observed shares closely resemble the typical composition of heating systems in the German building stock, suggesting that proximity to WHSs is largely independent of the currently installed heating technology. In Fig. 7b, the construction year of buildings is used as a proxy for energy efficiency to assess the temperature-based feasibility for direct utilization of WHSs. A substantial share (63 %) of the buildings was constructed before 1978, i.e. prior to the first German thermal insulation regulation (“Wärmeschutzverordnung”). These older buildings typically require higher supply temperatures for space heating, often exceeding 70–80 °C, due to lower envelope efficiency and radiator-based heating systems. In contrast, buildings constructed after the introduction of stricter efficiency regulations (e.g. EnEV or GEG, particularly post-2000) are generally able to operate with lower supply temperatures. Setting a threshold for heat pump application at 60 °C implies that approximately 64.2 % of the allocated building stock would require temperature upgrading for space heating or domestic hot water, of which 4.2 % are allocated to WHSs with temperatures below 25 °C. Conversely, 35.8 % of buildings are allocated to WHSs with temperatures above 60 °C, potentially enabling in many cases direct use without heat pump integration. The relatively small share of 4.2 % in the 90–110 °C range results from the limited number of WHSs at these temperatures (cf. Fig. 4), whereas the largest high-temperature share (21.4 %) is attributed to sources at 110 °C or above, which are directly suitable for district heating applications without further upgrading. Overall, the distribution of both heating systems and construction periods among the potentially supplied buildings largely reflects the typical structure of the German building stock. No distinct clustering or structural patterns related to the proximity of waste heat sources can be observed.

Further insights are provided in Fig. 8, which illustrates the effect of energy efficiency upgrades on the supplied building heat demand (a) and the number of allocated buildings (b) across 12 building types and the three scenarios (REF, STD, ADV). The results show that only about 85 TWh of the reported theoretical waste heat potential of 243 TWh (approximately 35 %) can be utilized under spatial constraints. This limitation arises mainly because large WHSs are often spatially clustered, so that nearby heat consumers are already fully supplied and additional waste heat potential remains unused (as detailed in Section 3.3). Energy efficiency improvements further reduce the required heat demand. Renovation to STD decreases the supplied heat demand by about 7 % to 78 TWh, while ADV reduces it by an additional 16 % to approximately 65 TWh (Fig. 8a). In contrast, Fig. 8b shows that the number



**Fig. 7.** (a) Distribution of heating systems among buildings allocated to the WHSs, highlighting the potential for substituting fossil heating systems or integrating district heating. (b) Construction period is used as a proxy for energy efficiency to assess the compatibility between the allocated buildings and the waste heat temperature, indicating where direct integration is feasible or where temperature upgrading (e.g., via heat pumps) could be required. Percentages within each category are shown in the stacked bars, while absolute total numbers of buildings (n) are indicated above each bar.



**Fig. 8.** Effect of energy efficiency upgrades on building heat demand (a) and the number of buildings allocated (b) across 12 building types and three scenarios (REF, STD, ADV). Higher efficiency (lower demand) allows more buildings to be supplied with waste heat.

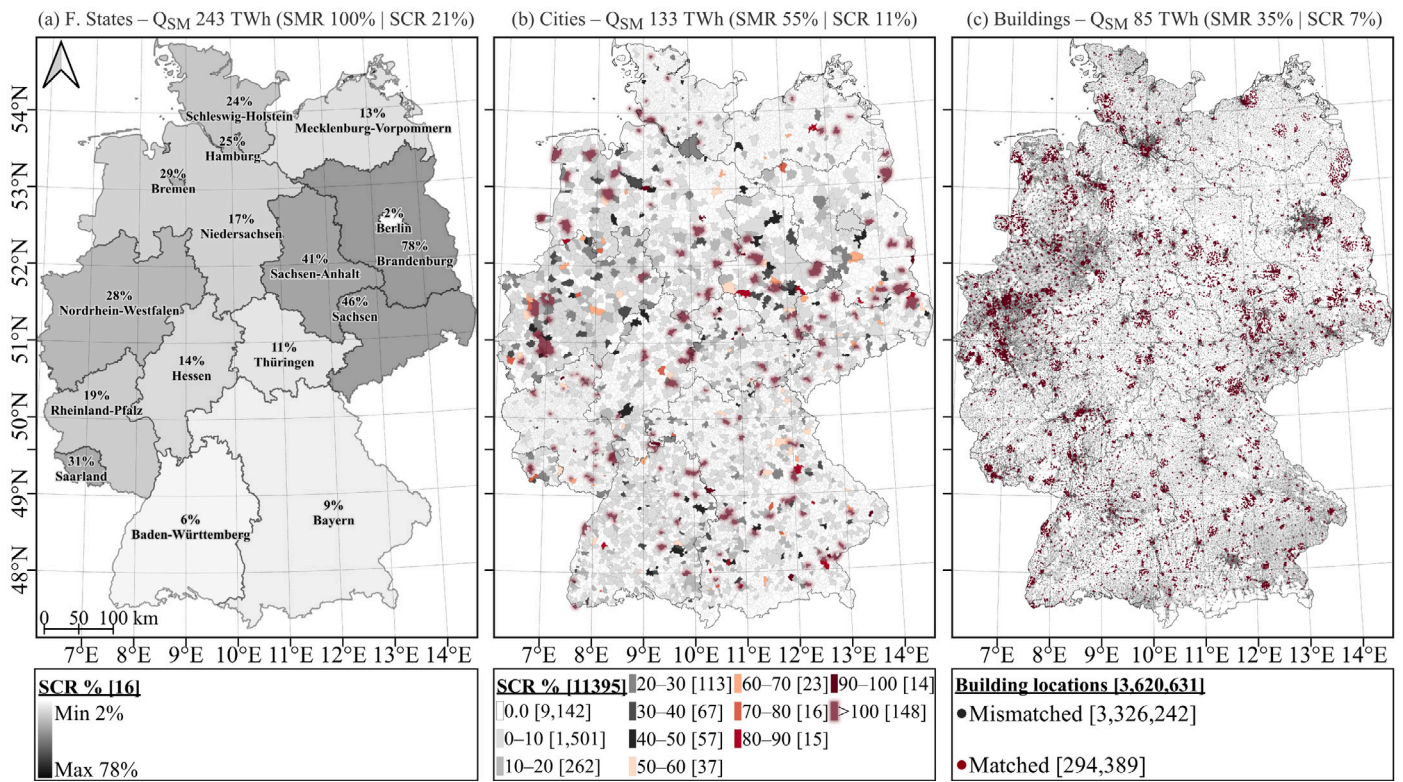
of buildings that can be supplied increases substantially with improved efficiency and may nearly double compared to the reference scenario. The figures also provide a detailed breakdown of the allocated building types. Although non-residential buildings account for only about 2% of the supplied building count, they represent between 16–19% of the covered heat demand, reflecting their considerably higher average heat demand compared to residential buildings.

### 3.3. Evaluation of spatio-temporal matching

**Regional variation in matching patterns.** A multi-scale spatial matching analysis reveals a strong dependence of achievable waste heat utilization on spatial constraints. As illustrated in Fig. 9a, at the federal state level the SMR reaches 100%, as waste heat supply and heat demand are aggregated over large spatial areas, allowing a complete theoretical matching and utilization of the available waste heat potential, thereby covering 21% of the total building heat demand in Germany (denoted as SCR). With increasing spatial resolution, spatial constraints become more restrictive. This effect is mainly explained by the spatial clustering of multiple sources, often including particularly

large WHSs at the urban periphery, and the relatively limited availability of nearby heat consumers. Consequently, the SMR decreases to 55% at the city level (Fig. 9b) and to 35% at the building level (Fig. 9c), reducing the SCR to 21% and 7%, respectively, and confirming the spatial matching challenges discussed in Section 2.3.1.

At the federal state level, the SCR ranges from 2% in Berlin to 78% in Brandenburg, highlighting substantial differences in the potential contribution of WHSs to regional heat demand. At the city level, the SCR varies strongly across the 11 395 German cities. A total of 9142 cities (80%) have no reported WHSs, resulting in a SCR of 0%. In contrast, 148 cities exhibit SCR values above 100%, indicating that the locally available WHS potential exceeds the local heat demand, mostly driven by one or several heavy-tail WHSs. At the building level, Fig. 9c shows the locations of the spatially allocated 1 832 262 buildings in the REF scenario, corresponding to 9.4% of the total 19 595 855 buildings. It should be noted that the administrative boundaries of federal states (Fig. 9a) and cities (Fig. 9b) do not represent technical limits for waste heat utilization. Therefore, these boundaries are overcome in the building-level analysis (Fig. 9c) by applying the spill-over



**Fig. 9.** Multi-scale spatial matching analysis evaluating the SMR and SCR at three spatial levels: (a) federal states, (b) cities, and (c) buildings. The SMR, indicated in the panel titles, decreases from 100% in (a) to 35% in (b), as spatial constraints become more restrictive. In (a) and (b), the SCR is represented by the color scale. At the federal state level, the share of heat demand that can be covered by WHS ranges from 2% to 78%. At the city level, the SCR varies strongly, from 0% for 9142 cities without reported WHSs to above 100% in 148 cities with WHS potentials exceeding local heat demand. Panel (c) shows the number of spatially matched and mismatched building locations, encompassing 19 595 855 buildings in total. Numbers in square brackets denote the number of locations.

logic described in Section 2.3.1, which allows spatial matching across administrative borders.

Fig. 10 illustrates the spatial distribution of WHSs according to their SMR, TMR, and combined STMR. Individual WHSs are shown as circles, sized by waste heat potential and colored by matching ratio (darker colors indicate higher feasibility). Aggregated matching ratios per federal state are displayed as vertical bars, where the bar height represents the state-level indicator. No pronounced geographic clustering of the WHSs is observed; however, aggregation at the federal-state level reveals notable regional differences. Specifically, the SMR shown in Fig. 10a tends to decrease in states with higher SCR (cf. Fig. 9a), reflecting increased competition among WHSs for nearby demand within the spatial allocation approach. At the same time, the aggregated SCR at the state level does not capture the considerable spatial dispersion between individual sources and potential consumers. In contrast, the TMR shown in Fig. 10b varies only slightly across federal states, ranging from approximately 54% to 69%. This indicates that temporal compatibility between waste heat supply and building demand profiles is relatively uniform across regions, whereas spatial constraints remain the primary factor limiting utilization potential.

**Heat load profiles.** While the previous results describe the energetically balanced spatio-temporal matching at the annual scale, Fig. 11 illustrates the simulated hourly heat demand of each building, classified by building type and represented by its SLP (Fig. 11a), and compares these demands with the individually allocated WHSs (Fig. 11b). As described earlier, the residual heat load  $\dot{Q}_{r,t}$  results from the difference between aggregated heat demand and waste heat supply; positive residual loads therefore indicate deficits, while negative values represent surplus heat. The hourly representation reveals a pronounced seasonal concentration of demand and substantial surplus-deficit cycles. As WHSs and buildings are already spatially matched, the aggregated

annual heat demand amounts to 85.3 TWh, resulting in a net annual residual close to zero and indicating that the system is energetically balanced at the annual scale. However, only 59.1 TWh (approximately 69%) of the annual demand can be directly covered on an hourly basis without storage. The remaining 26 TWh (absolute sum of deficits, approximately 31% of demand) represents uncovered demand requiring backup supply. Simultaneously, 26 TWh (absolute sum of surplus heat) remains unused due to temporal mismatch, confirming that the limitation is not energetic scarcity but temporal asynchrony.

Categories such as Retail combine high energetic potential with strong synchronization, whereas residential buildings (multi-family and single-family houses) exhibit pronounced winter-dominated demand peaks (Fig. 11a). These translate into large residual amplitudes (Fig. 11b), requiring storage capacity to fully utilize the available waste heat potential. The strong seasonal concentration of heating demand shown in Fig. 11a is quantified by a PAR of 9.2, indicating that a heating system sized to meet peak demand would operate at an average load corresponding to only 10.8% of its installed capacity. In practical terms, this is comparable to a heating system designed to withstand very cold winter days while operating at only a small fraction of its capacity during most of the year.

The descriptive statistics of the hourly residual load provide further insight into the structural balance and temporal volatility of the system. Across all building categories, the mean residual load is approximately  $-33$  kW, indicating that, on average, annual supply and demand are nearly balanced at the system level. The minimum and maximum residual values (approximately  $-5.8 \times 10^6$  kW and  $8.4 \times 10^6$  kW, respectively) reveal the presence of extreme deficit and surplus hours. These peak residuals are particularly relevant for infrastructure planning, as they determine potential storage sizing or backup capacity requirements. The hourly error metrics (Mean Absolute Error MAE =  $5.98 \times 10^6$  kW

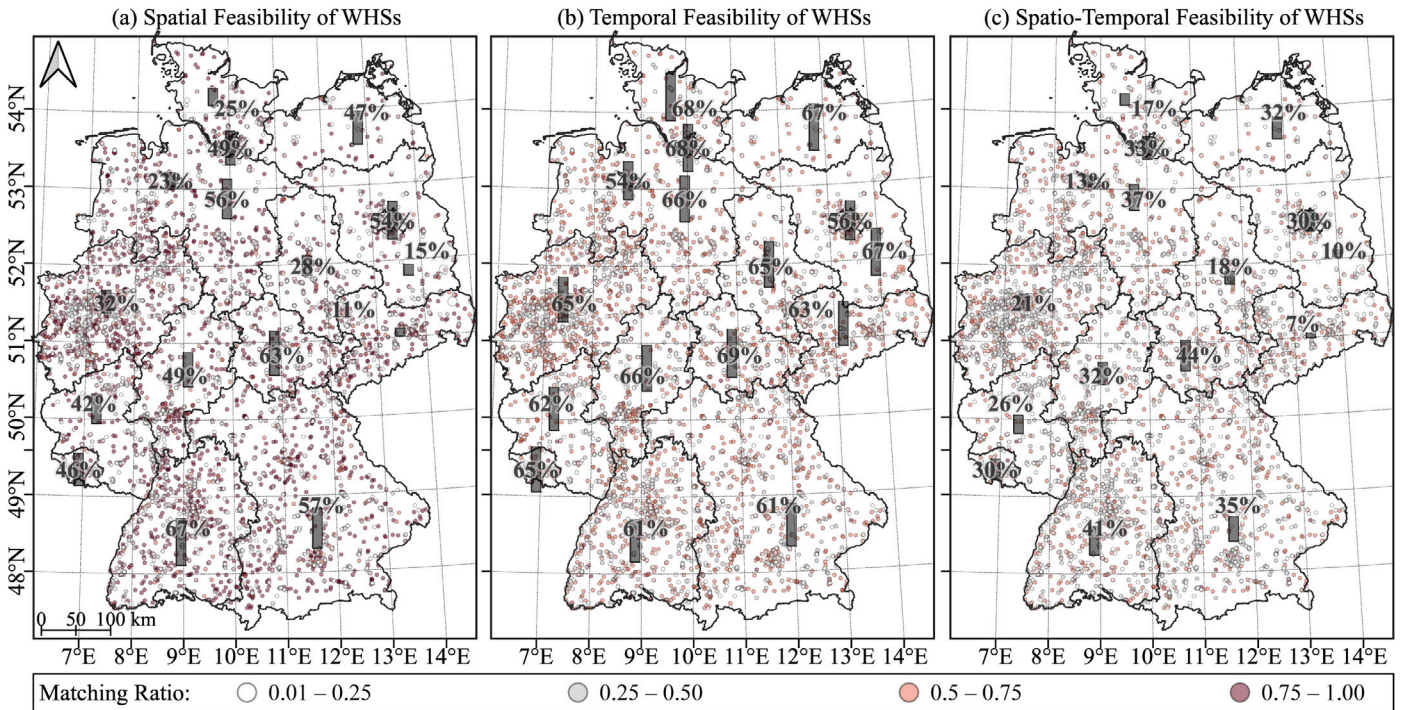


Fig. 10. Spatial distribution of waste heat sources classified by matching ratio for (a) spatial feasibility (SMR), (b) temporal feasibility (TMR), and (c) combined spatio-temporal feasibility (STMR). Individual sources are represented as circles, sized by waste heat potential and colored by matching ratio (darker colors indicating higher feasibility). Aggregated matching ratios per federal state are displayed as vertical bars, where the bar height represents the state-level indicator.

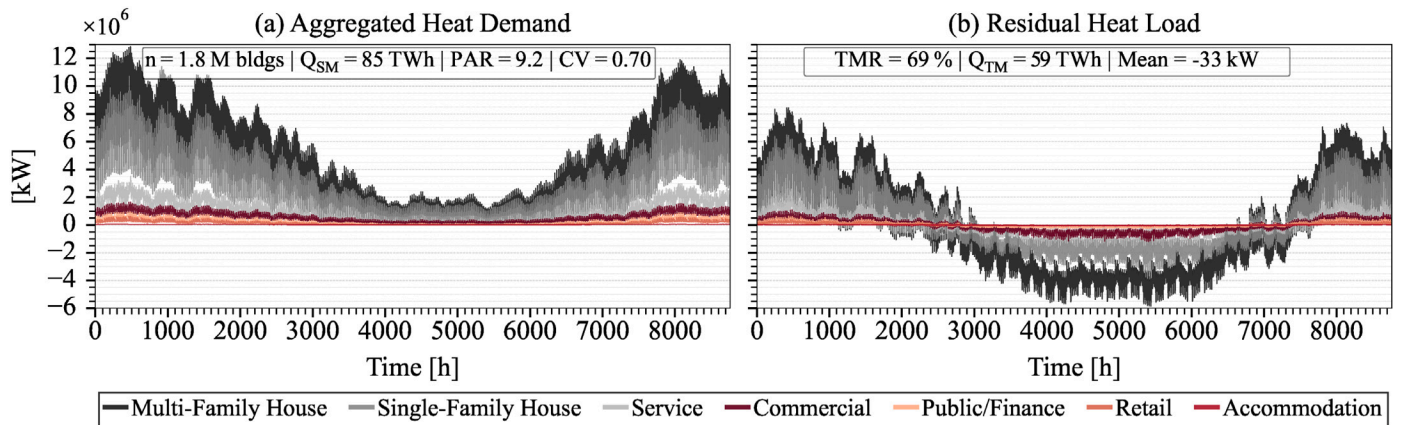


Fig. 11. Hourly heat demand and residual heat load of spatially allocated buildings and WHSs. (a) Aggregated heat demand for seven SLs. (b) Corresponding residual load, revealing seasonal surplus-deficit cycles despite annual balance; positive values indicate heat deficits and negative values surplus heat.

and Root Mean Squared Error  $RMSE = 6.91 \times 10^6$  kW) provide additional insight: since the RMSE penalizes large deviations more strongly than the MAE, the moderate difference between them ( $RMSE/MAE \approx 1.16$ ) suggests that deviations are broadly distributed throughout the year rather than dominated by extreme outliers. The mismatch is therefore structural and seasonal rather than driven by short-term peaks.

Overall, the system is energetically balanced on an annual scale but temporally highly volatile. The integration challenge therefore lies primarily in managing temporal mismatches rather than energetic scarcity. Consequently, flexibility mechanisms such as storage and load shifting are required to unlock the full energetic potential by enabling the utilization of strongly intermittent waste heat sources beyond periods of direct source-demand coincidence. Their practical implementation, however, would depend on further considerations such as economic feasibility, contractual arrangements, and security-of-supply requirements. In summary, the theoretical waste heat potential

of 243 TWh (20.5% of Germany's total heat demand of 1186 TWh) decreases to 85 TWh (7.2%) after accounting for techno-spatial constraints and further to 59 TWh (5.0%) when temporal source-demand mismatches are considered. Building refurbishment substantially extends the reach and effectiveness of waste heat utilization, increasing the number of potentially supplied buildings from approximately 1.8 million in the REF scenario to 2.8 million and 5.7 million in the STD and ADV scenarios, corresponding to increases of 56% and 217%, respectively.

#### 4. Discussion and limitations

The results presented in this paper support previous evidence suggesting that, while high-temperature waste heat provides greater flexibility and a wider range of utilization pathways due to its higher energy quality [10], mid-temperature sources dominate the practically

available potential. Previous studies have made rather coarse statements and applied varying definitions of “low-temperature”, typically indicating that the greatest share of waste heat potential lies in low-temperature ranges [14], more specifically below 200 °C [10,22]. Our results confirm and refine these findings, showing that approximately 95 % of the potential lies below 200 °C and 84 % below 100 °C. Furthermore, by differentiating across 25 temperature–schedule categories, we show that the largest share of potential originates from continuously operating WHSs (7d–24h) with temperatures of 25–60 °C, accounting for approximately 56 % of the total reported potential, followed by sources with  $\geq 100$  °C (11 %) and 60–90 °C (10 %). The available potential is found to scale proportionally with the number of WHSs, indicating that future heat planning should place particular emphasis on these spatially widespread WHS categories to maximize effective utilization. The practical utilization of these sources is further influenced by the age of the building stock, as approximately 63 % of buildings were constructed before 1978 and thus require higher supply temperatures or additional technologies such as heat pumps. Consequently, our allocation approach is sensitive to waste heat quantities, which may lead to cases where lower-temperature sources are prioritized over higher-temperature sources due to slightly larger available capacities. This reflects the strategic focus of our model on maximizing utilization, while alternative prioritization schemes could be implemented depending on system design objectives.

Techno-spatial constraints are widely identified in the literature as a primary limiting factor for waste heat utilization. Bühler et al. [9] found that only 5.1 % of district heating demand in Denmark can be supplied by excess heat under spatial and demand constraints. Similarly, Persson et al. [18] show that only 46 % of excess heat in the EU27 is located within strategically suitable regions, while Xu et al. [10] emphasize that industrial sources are often spatially separated from building demand. Our results support these findings, indicating that approximately 35 % of the reported potential can be utilized under techno-spatial constraints. Temporal mismatches further reduce the practically utilizable potential. Our results indicate a reduction of approximately 30 % when hourly synchronization between supply and demand is considered, which is in close agreement with the 27 % reduction reported by Bühler et al. [9]. While the storage of surplus heat, particularly in summer, represents an important option, it is beyond the scope of this study. As noted by Xu et al. [10], a detailed differentiation between storage technologies is required, where sensible and latent thermal storage are suitable for short-term balancing, while thermochemical storage may address seasonal mismatches.

The distribution of supplied heat across building types is also broadly consistent with previous findings. Our results show that approximately 80 % of supplied heat is allocated to residential buildings and 20 % to non-residential buildings, compared to 70 % and 30 %, respectively, reported by Bühler et al. [24]. In this context, particularly for critical infrastructure such as hospitals, it is important to consider that reliance on industrial waste heat introduces systemic risks, as highlighted by Yu et al. [6], since industrial activity may decline or relocate, directly affecting heat availability. Another important uncertainty relates to future developments in industrial processes. Previous studies indicate that the transition towards low-carbon and more efficient production, including increased internal heat recovery, may reduce available waste heat by 78–92 % compared to current levels, with a corresponding reduction in utilizable district heating supply of around 50 % [5]. This highlights a fundamental trade-off between climate neutrality and the long-term availability of WHSs. Beyond availability, technical integration into existing DH systems remains challenging. Mismatches in temperature levels and geographical location complicate integration [19], while decentralized heat injection may lead to operational issues such as reversed mass flows, increased thermal stress [54], pump energy [55], and pressure cones that affect reliable supply for some consumers [56]. These aspects are not explicitly represented in our work but may further constrain practical implementation.

Unlike many previous studies that apply fixed distance thresholds, often determined by economic break-even considerations [57] (e.g., 10 km in [14,16]), our methodology assesses all source–demand pairs and derives distance distributions directly from the data. The residual demand tracking enables a precise source–demand allocation until the waste heat potential is exhausted. The results show that the majority of buildings are located within a core distance range of approximately 0.6–8.5 km, covering about 79 % of all allocated buildings. Approximately 96 % of buildings are allocated within 11 km across all building energy efficiency scenarios, indicating that, after building retrofits, the algorithm tends to prioritize nearby buildings around each WHS rather than extending connections over longer distances. While this is a minor issue in large-scale potential assessments, it becomes highly relevant in the detailed planning of DH networks.

Finally, although our approach is applied to officially reported WHSs in Germany — providing novel insights based on this first-of-its-kind dataset — it remains transferable to any site-specific heat sources within the context of spatio-temporal source–demand matching (e.g., extending techno-spatial evaluations of waterbody heat utilization [58]). For countries lacking comparable datasets, open-data repositories and tools such as *sEnergies Open Data Hub* [59] and *citiwatts* (formerly *Hotmaps*) [60] provide relevant alternatives, which can be complemented by standardized profiles for temporal waste heat characterization [30,61]. While these platforms primarily provide static and aggregated datasets without further spatio-temporal source–demand matching, they additionally offer valuable datasets on economically feasible DH areas, particularly through the interactive *citiwatts* calculation modules. As the primary objective of the present study is a large-scale techno-spatial evaluation of the guided matching between WHSs and the overall building stock, the inclusion of economic indicators and specific references to feasible DH areas would represent a meaningful extension of this work. Furthermore, future work should further develop the proposed algorithm towards residual-aware guided allocation across larger and more diverse heat source portfolios (e.g., geothermal energy, wastewater, and water bodies) while considering different temperature levels and temporal availability.

## 5. Conclusion

High-resolution data on energy systems increasingly enable detailed analyses that capture the complexity of multi-source, sector-coupled networks. In this work, we develop a guided source–demand allocation approach to match WHSs with potential consumers at high spatial and temporal resolution. The results reveal that while small- and mid-scale sources are most frequent, a limited number of high-capacity, heavy-tail WHSs dominate the total potential. Continuously operating, low-to mid-temperature sources provide reliable base-load supply, whereas intermittent sources require storage or demand-side flexibility. The potential of waste heat utilization proves highly promising, with results indicating that even under worst-case conditions, the heat demand of more than 1.8 million buildings in Germany can be covered. Most buildings are allocated within 0.6–8.5 km, covering the majority of potential consumers. Energy efficiency improvements further increase this number to 5.7 million buildings, highlighting the significant role of waste heat in supporting the transition towards a climate-neutral energy system. Despite the theoretical potential of 243 TWh, only about 85 TWh can be allocated under techno-spatial constraints, of which 69 % can be directly covered on an hourly basis without storage, while the remaining 26 TWh require backup supply or balancing. Approximately 36 % of matched buildings can be supplied directly, while the remainder require temperature upgrading. Regional disparities are substantial, with some cities exceeding local demand due to heavy-tail sources. These findings highlight clear priorities for deployment: targeting high-capacity heavy-tail sources, integrating stable 7d–24h mid-temperature heat into district heating systems, and improving demand-side energy efficiency.

## CRediT authorship contribution statement

**Abdulraheem Salaymeh:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stefan Holler:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Irene Peters:** Writing – review & editing, Supervision, Conceptualization.

## Declaration of Generative AI and AI-Assisted Technologies

During the preparation of this work, the authors used a generative AI tool, specifically OpenAI GPT5 provided by HAWK University and ChatGPT (based on GPT-5.3), in order to improve the readability and language of certain parts in the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

As the German Platform for Waste Heat states that the original dataset may only be redistributed in an unaltered form, the processed geocoded and simulated research datasets generated in this study are not redistributed as supplementary material. Instead, to ensure transparency and reproducibility of the developed algorithm, the supplementary material includes the Python scripts `wasteheat_profiling.py` and `heat_demand_profiling.py`, which provide the processing and simulation workflow required to reproduce the presented spatio-temporal source–demand matching methodology. Users are asked to independently obtain the datasets while complying with the corresponding platform-specific data-use conditions. Furthermore, the generated hourly operational and demand profiles represent simulated approximations derived from reported annual and operational parameters and may therefore contain uncertainties. The provided workflows are intended for large-scale techno-spatial analyses and methodological research rather than site-specific operational assessments.

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.segy.2026.100258>.

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