International Journal of
Sustainable Energy Planning and Management

The ODHeatMap Tool: Open Data District Heating Tool for Sustainable Energy Planning

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ABSTRACT

Building footprints are a geographical indication of the spatial distribution of built-up infrastructure, thereby reflecting energy demand patterns, including heating requirements. Heating demands spatial distribution shown in heat atlases are primordial for evaluating district heating systems feasibility, which are a key decarbonizing technology that offers more sustainable heat supply in dense urban areas. Sustainable energy planning frameworks utilize district heating potentials as metrics for the formulation of alternate system configurations aimed at decarbonizing societies and creating an understanding of heating transition pathways. However, the availability and accessibility of the data needed for assessing these potentials is highly contextual and often challenges modelling processes. Simultaneously, there is a growing potential for open data and software mechanisms that could aid in addressing these challenges and create otherwise unavailable heat mapping resources. This paper describes the development of the ODHeatMap tool, a workflow built with open data in python functions that transform building footprints into a heat atlas. Ulaanbaatar city is used as a demonstration area for the tools functionalities, with the outputs being applied in a broader study aimed at developing strategies for Mongolia's heating sector. The tool is accessible through a fully cloud-based environment and can be used in any given geographical context.

Keywords

Python;
GIS;
Sustainable energy planning;
District heating;
Heat atlas

http://doi.org/10.54337/ijsepm.8812

1. Introduction

Climate agendas emphasize the urgency of an energy transition decarbonising societies [1–3] within a critical timeframe to avoid irreversible global consequences [4]. Heat represents the largest energy end-use worldwide, comprising nearly half of the total global final energy consumption as of 2021 [5]. District heating (DH) systems play a significant role in decarbonising the heating sector. In DH systems, heat is centrally produced and distributed through a network via an energy carrier such as vapour or water [6–8].

Compared to individual household heating, DH systems offer multiple benefits at the system level by enabling higher integration of renewable energy [9], e.g., geothermal, and solar thermal, as well as excess heat resources from industries [10], power-to-X plants and other low-temperature sources such as datacentres [11]. The utilisation of seasonal thermal storage and large-scale heat pumps in DH systems can also provide system flexibility [12] to ease the balance of the overall energy system. Also, the need to expand electricity grids will be reduced when implementing DH in the system instead of individual heat pumps.

The planning of DH networks is a long-term investment that requires system thinking under more connected energy systems. Various technologies must be in place to increase renewable penetration and system

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Abbreviations

DH	District Heating
AOI	Area of Interest
Colab	Google Collaboratory
OSM	OpenStreetMap
HDD	Heating Degree Days
CDD	Cooling Degree Days
EO	Earth Observation
GIS	Geographic Information Systems
ML	Machine Learning
GHSL	Global Human Settlement Layer
CDS	Climate Data Store

flexibility by enabling sector coupling and promoting energy efficiency from supply to end-users [3]. Geographic information and data on local heating systems, especially the heating demand and corresponding spatial distribution, are needed for DH network developers and municipality energy planners to facilitate system design. This is for sustainable energy planning in general, whether the aim is to expand existing DH networks or develop new DH projects.

To estimate heat demands, a characterization of the building envelope and the thermal requirements for the geographical climate zone are needed [13] at a defined level of detail. Literature has assessed building energy performance at the individual building [14–17] and district level [18], while Geographic Information Systems (GIS)-based approaches are more prevalent at the DH system level [19–23] analysing a broader geographical scope. Specific applications of GIS are seen in heat supply and demand management studies performed for European countries [24] and cities [25–29], including higher resolution assessments of the costs of DH expansion at production, distribution, and transmission levels [26,30–32]. More recently, feasibility assessments of DH include studies in America [21], Turkey [33], Chile [34], Africa [35], and China [36], ranging from city to regional, and up to national geographical scales.

GIS-based heat demand mapping, also defined as heat atlases in some studies [32,37–39], forms the ground base of comprehensive studies of DH systems with a focus on low-carbon waste heat sources [40–43], effective infrastructure dimensioning for DH systems [44,45], as well as more complex energy system analyses of holistic energy systems based on advanced models [46–49] where DH systems are part of a whole energy sector matrix in transition. While the studies mentioned above show a potential for replicability, challenges remain for DH and energy planners when data or resource availability and accessibility are low, which is often the case in the context of economically emerging countries [9]. Data and resources are essential to scientific quality, productivity, and recognition, as emphasized by Pfenninger et al. in [50], and a community of practice in energy modelling by Niet et al. in [51]. Consequently, recent tool and data availability developments can be seen.

Tools for DH: Efforts have been made to facilitate the generation of heating demand mapping for DH, utilising open-source code. In the SimStadt urban simulation environment [52] used in Ref. [53,54], geometries are needed as input to generate hourly energy demands and heat demand mapping. The CityEnergyAnalyst simulation tool [55], described in [56], uses default or user-uploaded databases on 3D geometries and works with a limited set of buildings to generate energy-related data at the building level. The DiGriPy tool [57], described in [58], performs DH simulations given a heat grid input containing heat consumers, heat sources, and pipe outlining.

The THERMOS tool [59] is an energy simulator for DH networks in which different thermal parameters are assessed for a network layout to be generated from building footprints. Both Hotmaps [60] and Planheat tools [61] utilise light detection and ranging (LIDAR) data for building canopy detection and weather data for generating potentials for heating and cooling supply, using QGIS software.

The Pan-European Thermal Atlas (PETA) [62] shows a visualisation of already generated heat density mapping amongst other identified heat sources for DH in Europe. Tool accessibility for tailoring and editing the models is acknowledged with open-source code in these tools. However, SimStadt and CityEnergyAnalyst require 3D data of buildings and have a computationally intensive building-level energy simulation focus which limits the area of assessment. The network design focus of DiGriPy and the THERMOS tool introduces a degree of technical complexity to the evaluation.

While comprehensive, this is particularly suitable for post-feasibility studies, conducted after heat demand mapping is validated and potential DH areas are identified and refined. The inputs required for the Hotmaps and Planheat tools are resource-intensive, and GIS knowledge is a requisite, which restrict accessibility. Lastly, visualization tools such as PETA offer an effective method for conveying findings of a specific area once an assessment has been performed externally.

Open data for DH tools: Open data is used as input to some of the tools, such as OpenStreetMap (OSM) databases where building footprint and road networks are retrieved [63,64]. Weather data for heat demand assessments is utilised for hourly temperature profiles such as Renewables.ninja [65] that use reanalysis databases such as ERA5 [66]. Moreover, topologies like the ones included in catalogues such as Tabula [67] are used to characterize buildings.

With recent open data practices and coding infrastructure development, the availability of open databases has increased significantly, and updates occur at a more frequent pace, representing vast potentials to be exploited [68]. An example of this data availability is Earth observation (EO) that enables global and updated mapping of infrastructures, population, or pollution [69,70]. EO satellite applications relevant for energy planning are seen for building detection [71,72], water energy nexus [73], and robust spatial data infrastructure frameworks [74].

An example of this application is the Renewable Energy Space Analytics Tool (RE-SAT) which provides cloud-based energy analytics for pre-feasibility and strategic planning of new renewable energy infrastructure with various case studies in developing countries where ground data is a scarce resource [75].

1.1. Scope

The cited literature shows the opportunities that heat mapping provides for DH studies, enabling the modelling of alternate energy transition pathways across different geographical contexts. It also highlights the existence of several tools specifically engineered to accommodate limited or restrictive data inputs or designed to conduct analyses that diverge from those in preliminary studies. In heat demand mapping, heat demands are mapped, and potential DH areas are spatially identified and refined at a localized, user-defined level.

The tools are open-source code, offering accessibility; yet they require a local environment setup and are frequently configured as a whole block, which can pose challenges for users lacking coding skills. Another perspective brought in the literature is the current growing availability and accessibility of open data, which is already being utilised in various studies related to energy and urban planning. This includes accessing spatial and climate data infrastructure across different geographical areas which are key instruments to be exploited in energy modelling.

Therefore, this study presents the development of the ODHeatMap tool: Open data district heating tool for sustainable energy planning, addressing both the introduced necessity and the opportunity that lack of resources and open data pose for sustainable heat planning in resource-scarce contexts. The tool provides a spatial building envelope and heat demand estimation that result in a grid-level DH feasibility assessment of a determined geographical area of interest (AOI), using freely and globally available open data. The calculations run at a building level and are designed to run at a city level or on a small regional scale.

By acknowledging the need for flexibility, ODHeatMap is structured in steps that allow for customization and expansion using low code. The Python code is designed to run within a Jupyter notebook web application, which has become increasingly popular within the software development community due to its language versatility and configuration options. The tool is available in GitHub repository [76] and hosted in Google colaboratory (Colab) that requires no local setup by running entirely on a cloud-based environment that provides free GPU/TPU to balance performance.

The tool is considered pertinent for energy practitioners seeking informed support and conducting spatially based assessments for heating development within the framework of sustainable energy planning. Table A 1 in Appendix A presents a summary of the tools metadata.

To showcase the advantages of the ODHeatMap tool in a current energy planning environment, the tool has been implemented in a project aiming at developing a strategic heat plan for Mongolia where the heat mapping has been used to create alternative scenarios of renewable heat sources [77]. Mongolian studies include building level heat demand assessments [78,79], however, challenges remain when projecting building findings to a wider spatial scope due to data accessibility.

Therefore, the tool functionalities walkthrough uses Ulaanbaatar city as the AOI, including the workflow of the tools to show the overall step structures and outputs. User interface code snippets are also shown in Appendix C. The capital has been chosen as one of the case studies in the project because it hosts nearly 50% of the total Mongolian population, it is characterized by severe winter seasons, it stands as the most developed city in the country, and has an existing fossil fuelled and high temperature DH system in place.

Given the lack of locally available spatial datasets and heat demand mapping in the existing DH area, the city has an added challenge in documenting or registering the denominated ger areas, characterized by informal and nomadic housing infrastructure. In the Mongolian context, a ger is defined as a traditional rounded tent covered and insulated with animal skin used as a dwelling.

2. The ODHeatMap Tool

This section elaborates on the methods and data, and architecture used for the workflow of the ODHeatMap tool.

2.1. Tool methods and data

Three assessments are the main components of the tool: 1) Building envelope, 2) Building heat demand, and 3) DH feasibility. The formulae nomenclature for the equations used can be found in Table B 1. The components of the tool are detailed in the following:

Building envelope estimation: To estimate the surface area or envelope of a building, the starting point is to retrieve building footprints which in the model are obtained from open-source data sources. Two source choices are implemented in the code, the collaborative mapping project OpenStreetMap (OSM) [80] widely used in urban planning tools, and the Microsoft Global Machine Learning (ML) pattern recognition dataset with derived building footprints [81].

Both sources are deemed relevant due to their complementary benefit in terms of data coverage, OSM being more effective in urban areas than the Microsoft database. The user can check for data quality by using tools that compare different types of datasets such as Geofabrik [82] or visit the source data metrics for confidence and coverage scores for the specific AOI. The building footprints provide the planar geographical dimension of the spatial features for the analysis, and the result is a vertical dimension estimation of buildings where the Global Human Settlement Layer (GHSL) Data Package from the Joint Research Centre (JRC) [83] is used.

These data packages are available at the European Commission's science and knowledge service, where the Copernicus programme is the Earth Observation programme of the EU. The geographic layer utilised is the GHSL built-up Average of the Net Building Height (ANBH) from the GHS built-up series [84]. The height estimation, generalised on a 100m resolution, is a result from multi-scale linear regression models on various data structures such as global Digital Elevation and Surface Models (DEM, DSM), satellite imagery from NASA's topographic Mission and Sentinel-2 global data, amongst others.

The resolution means that the raster dataset shows the distribution of mean building heights within the resolution, for which it uses a reference to the year 2018, using Sentinel-2 composite imagery [85]. Calculations are performed to characterize the building envelope by shape area $A\left[m^2\right]$, height $H\left[m\right]$, and perimeter $P\left[m\right]$ using their geometric attributes. Subsequently, buildings are streamlined by assuming a cubical geometry, leading to the building surface area $b_{sa}\left[m^2\right]$ calculation in Eq. (1). This metric accounts for all external walls and floors which correspond to the building envelope.

$$b_{sa} = 2 * A + H * P \tag{1}$$

Building heating demand estimation: For this estimation, the heating and cooling degree days (HDD, CDD) method is incorporated in the coding. The method is common for current and future energy planning studies across different geographies and across time [86–89]. It is a simple representation of the outside air temperature influencing the thermal dissipation in buildings. The building dissipation or heat loss is associated to the cumulative degree days relative to a reference temperature below which heating becomes necessary in buildings.

This methodology serves as a proxy calculation for estimating the annual building heating requirements. For the HDD calculation, hourly temperature data from the Copernicus Climate Data Store (CDS) is retrieved [90], namely the ERA5 dataset. ERA5 is the fifth generation of a global climate and weather reanalysis where data is available from 1940 onwards and data is updated with a five-day latency, and it is also used widely for time-series assessments of renewable power potentials [91]. Reanalysis is a model that combines data with observations from the globe to forecast weather parameters.

The reanalysis model development is documented in [92] and the documentation of the datasets are provided in [66]. Provided a given year, the hourly data is averaged daily, and cumulative degree days are calculated as seen in Eq. (2). In the equation, daily temperature averages T_{ave} are subtracted from a temperature of reference T_{ref}, and these differences are cumulatively summarized over the course of a year in ˚C. Estimating building heating demand responds to a variety of characteristics such as building type, usage, age, and material [93,94], which means that all buildings vary in terms of thermal insulation.

As a default in the model, no building characteristics for such distinction are available, therefore a generalisation of this loss is reached through an additional coefficient for heat loss, namely $U_{value}\left[\frac{W}{m^2K}\right]$ which is standardized to all buildings in the tool and adapted to the space heating demand $hd_{sh}\left[MWh\right]$ estimation. The domestic hot water heating demand $hd_{dhw}\left[MWh\right]$ is allocated as a share of the space heating demand $hd_{sh}\left[MWh\right]$ for the calculation of the total heating demand $hd\left[MWh\right]$, as shown in Eq. (3) and Eq. (4), respectively .

$$HDD = \sum_{i=1}^{n=365}\left(T_{ref} - T_{ave}\right);\ \ for\ \ T_{ave} \leq T_{ref} \tag{2}$$

$$hd_{sh} = b_{sa} * U_{value} * HDD \tag{3}$$

$$hd = hd_{sh} + hd_{dhw} \tag{4}$$

Grid level District Heating feasibility estimation: Once the heating demands are calculated at the building level, the tool estimates DH potentials. The potential for DH is quantified by considering a parameter that reflects the amount of heat that needs to be delivered per area, namely the heat density in Eq. (5). Therefore, all building heating demands are aggregated at the grid level in $\sum hd$, and divided by the grid cell area $\left[ha\right]$. Spatially, the level of feasibility of the DH potential can be identified through characterized levels of heat density as indicated in [42], adapted in Table 1.

The extension of the DH development can also be assessed through its network investment costs, which can be calculated via a regression analysis considering network investment costs for DH technologies in function of the heat density $q_L\left[\frac{GJ}{ha}\right]$, as explained in [37], generalised and adapted in Eq. (6). Note that the formula is shown as an example; the specific coefficients for annual investment cost per heat sold $C\left[\frac{€}{GJ}\right]$; x and y, need to be assessed within the context of the geographical area of interest. Users are advised to visit the source to perform specific coefficient calculations.

$$q_L = \frac{\sum hd}{grid\,cell\,area} \tag{5}$$

$$C = \left[x * q_L^{-y}\right] \tag{6}$$

2.2. Tool architecture

To facilitate the tool navigation, the methods are designed in four steps. These are:

- Step 1: Retrieving building footprints as data input to the rest of the workflow.
- Step 2: Estimating the building envelope as surface area input.
- Step 3: Estimating the heating demand at the building level.
- Step 4: Estimating District Heating (DH) potential at the aggregated grid level.

It is worth noting that despite the sequential design of the workflow, each step can be utilised independently if the users possess their own datasets, or if data handling is performed with the aid of GIS tools with the aim to upload data to the tool to continue the heat modelling for the DH assessment. A framework overview of the tool inputs, main processes, and outputs can be seen in Figure 1.

Table 1: Suitability for District Heating by heat density classification, from [42].

Heat density class	Heat density threshold [MJ/m²]	Concentration of heat demands	DH potential
0	0	No modelled heat demand	
1	$0 < q_L < 20$	Very sparse	Not feasible
2	$20 \leq q_L < 50$	Sparse	
3	$50 \leq q_L < 120$	Moderate	
4	$120 \leq q_L < 300$	Dense	Feasible
5	$q_L \geq 300$	Very dense	

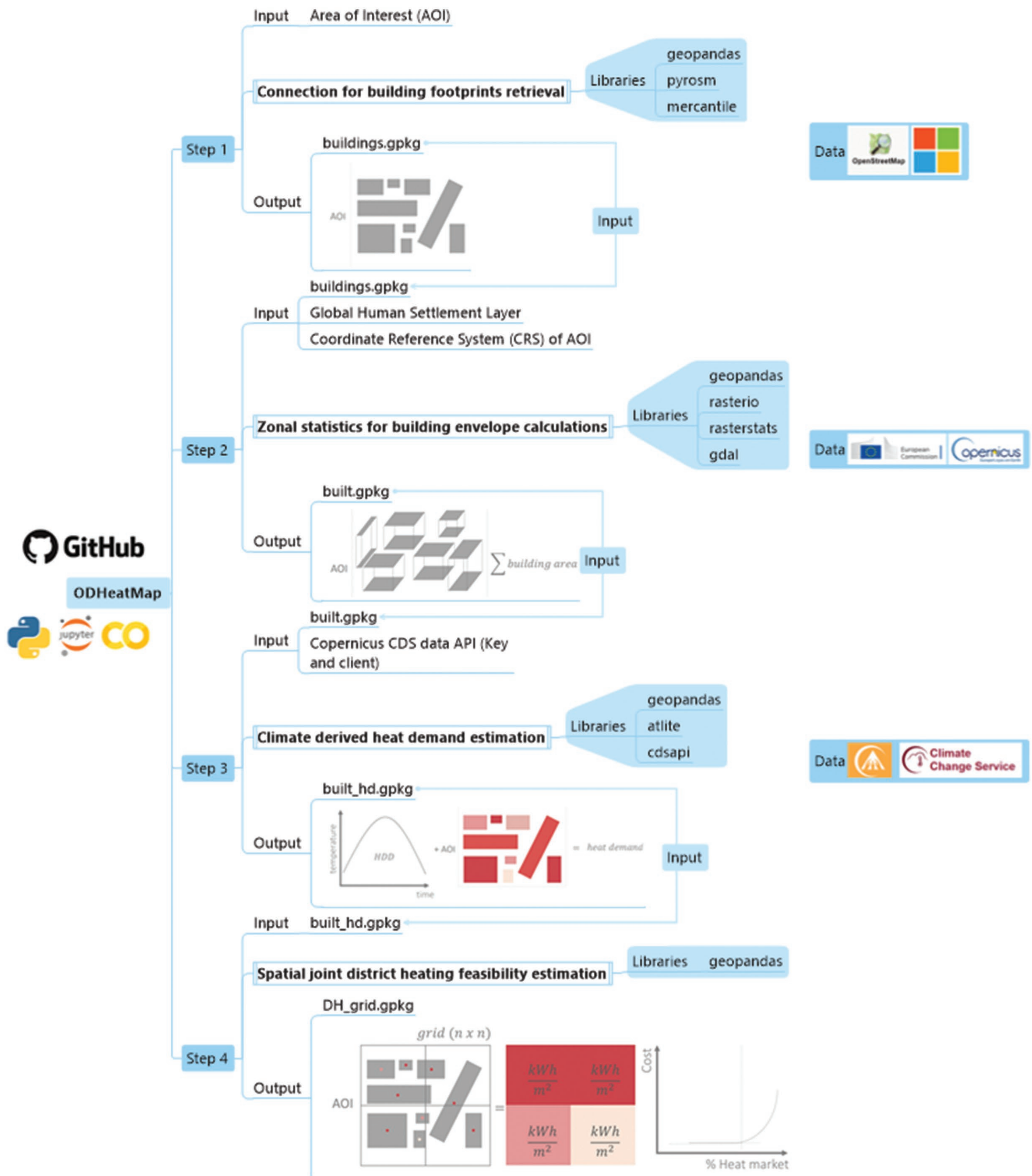


Figure 1: The workflow developed in the ODHeatMap tool provides an overview of data inputs, main processes and Python libraries. Sequential outputs are seen across the steps. Visualisation made in MindManager [95].

3. Tool Application

To showcase the tools functionalities, the tool runs for the AOI set for the Mongolian capital, Ulaanbaatar city. The study area is shown in Figure 2, denoting the geographical extension of existing DH system and ger areas. In the model, all geographic data handling in the tool is managed using the *geopandas* library [96] and other specialized libraries which are listed on each method and described in Table A 1.

3.1. Step 1: Retrieve building footprints

To start, the building footprint retrieval is performed for which the user is given three alternatives, see Figure 3.

The code enables the user to select a city and connect it to the OSM database server to retrieve building footprint data from querying the city with the *pyrosm* library [97]. The city level in the OSM retrieval is defined due to RAM limitations in Colab. However, a larger geographical extent can be used for the parsing using "subregions" or "regions" in the query, which can be edited via code.

The second alternative is the retrieval of the Microsoft Global ML building footprint dataset [81] for which the code allows the parsing of an AOI in geojson geometry format using the *mercantile* library [98] and the third through user-uploaded building footprint datasets. There is no required input other than the AOI set, depending on the method for data retrieval chosen.

For Ulaanbaatar, a combination of OSM and Microsoft has been used due to the lack of geographical definition of buildings in rural areas of OSM where the Microsoft dataset has enhanced coverage [81,99]. Both databases are supplementary in the example; however, OSM footprints are prioritised when overlapping geometries are found due to a finer resolution assumption. The resulting geodatabase containing the buildings is saved as buildings.gpkg. The output of this step is shown in Figure 4, while the user interface code snippets are provided in Figure C 1.

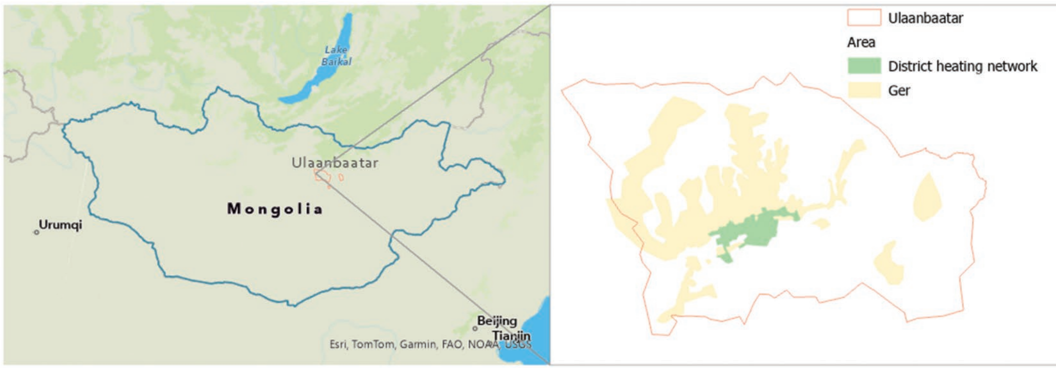


Figure 2: Area of Interest (AOI) used for showcasing the model.

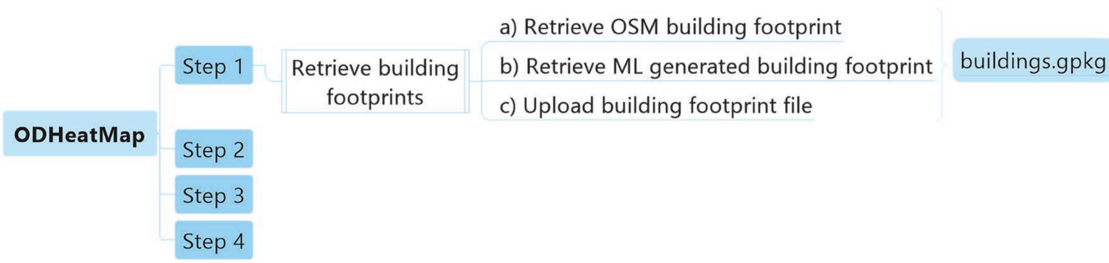


Figure 3: Step 1 workflow showing the user options for building footprint retrieval.

Figure 4: Step 1 output (buildings.gpkg) using ArcGIS Pro [100] for Ulaanbaatar city, published in Ref. [77].

3.2. Step 2: Estimate the building envelope

Once the building footprints are retrieved, Step 2 is designed to provide an estimation of each building's surface area, see Figure 5. First, it performs medium zonal statistics overlaying the GHLS built-up ANBH dataset [83]. The corresponding tile to the AOI is downloaded by the user from the Copernicus datastore and uploaded to the Colab notebook content. With a user-defined Coordinate Reference System (CRS) and the building dataset output from Step 1, the ANBH raster is clipped and reprojected to the AOI with *gdal* library [101].

The *rasterio* library [102] and the *rasterstats* library [102] are used in this step. The zonal statistics function using the median value of the ANBH raster is used to identify building height, not including buildings where the height is not identified. In addition to the height, the building area and perimeter are calculated to reach the total building surface area calculation, which relates to the enclosure of the building's total volume.

The tool adds an optional step for filtering out irrelevant geographical features for the analysis, which are extracted falsely as buildings derived from data sources. In the case example of Mongolia, these are the geometrical identification of ger tents, amongst other features deemed irrelevant upon manual inspection, such as planes, statues, and small polygons. The latter is especially relevant when ML pattern recognition methods are used for building identification. The resulting geodatabase containing the building envelope calculations is saved as built.gpkg. The output of this step is shown in Figure 6, while the user interface code snippets are provided in Figure C 2.

3.3. Step 3: Estimate the building heat demand

Step 3 is where the heat demand is estimated at the building level using the calculated building envelope and gathering climate data, see Figure 7. The total heat demand is a compound estimate of the space heating (SH) and domestic hot water (DHW) demand. The SH demand is the total surface heat loss calculation for each building, which uses an average sum of the thermal resistances of the layers of a building element. In

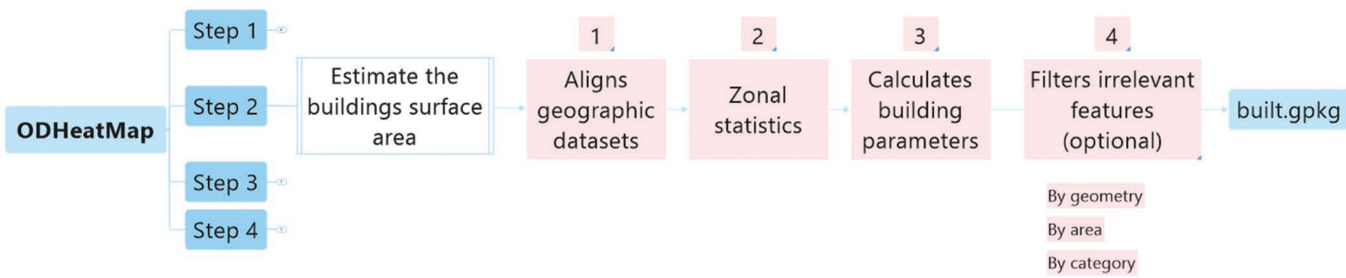


Figure 5: Step 2 workflow showing the steps for estimating the buildings surface area.

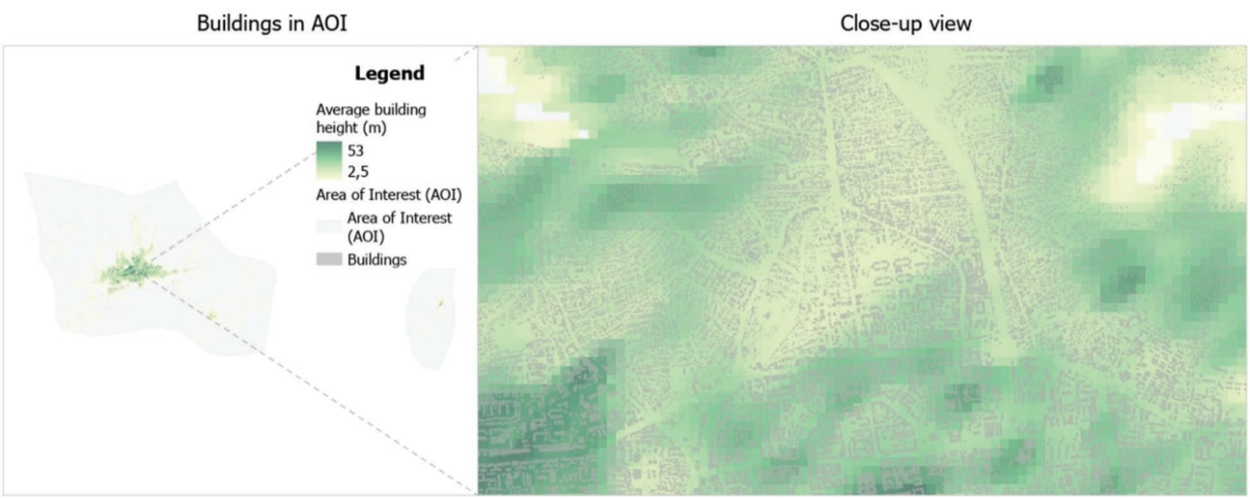


Figure 6: Step 2 output (built.gpkg) using ArcGIS Pro [100] for Ulaanbaatar city, published in Ref. [77].

the model, individual building characteristics are unknown and therefore an average coefficient for heat loss is used for all buildings, namely the U value. This provides an indication of the thermal insulation of the buildings.

The share of domestic hot water (DHW) heating demand is also calculated as a share of the SH demand, given as an input. The *atlite* library [91] is used for climate data retrieval, where the user needs to create an account at the Copernicus Climate Data Store and input the Uniform Resource Locator (URL) and key for the data store Application Program Interface (API) connection using the *cdsapi* library [103]. Since the ERA5 data is a re-gridded subset of 0.25 degrees, the built.gpkg from Step 2 is used for accessing the total geographical bounds and therefore perform an adjustment to ensure a minimum of 0.25 degrees width in the *atlite* cutout parameter, if needed.

The user is then prompted to provide a year of analysis and the temperature of reference for the HDD and CDD calculations. Here, a heating season can be set up for limiting the calculations of HDD. The space heating demand estimation follows, which is set up as the function resulting from the building surface area, by a user input U value and the calculated HDD. The resulting geodatabase containing the buildings' heat demand estimations is saved as built_hd.gpkg, and the HDD and CDD calculations are saved as a text file to HDD_CDD.csv. The output of this step is shown in Figure 8, while the user interface code snippets are provided in Figure C 3.

3.4. Step 4: Estimate district heating feasibility

Heating demands at the building level are aggregated on a user-defined grid for the DH feasibility, see Figure 9. This is done by laying a fishnet over the localized building centroids with their respective total heating demands. A heat density grid is then calculated in $\frac{kWh}{m2}$ which can be filtered or used as a whole. For the Ulaanbaatar case, ger areas were filtered out since they are deemed unfeasible for DH developments.

For grid filtering, users can generate heat density clusters and select these for DH assessment, select the

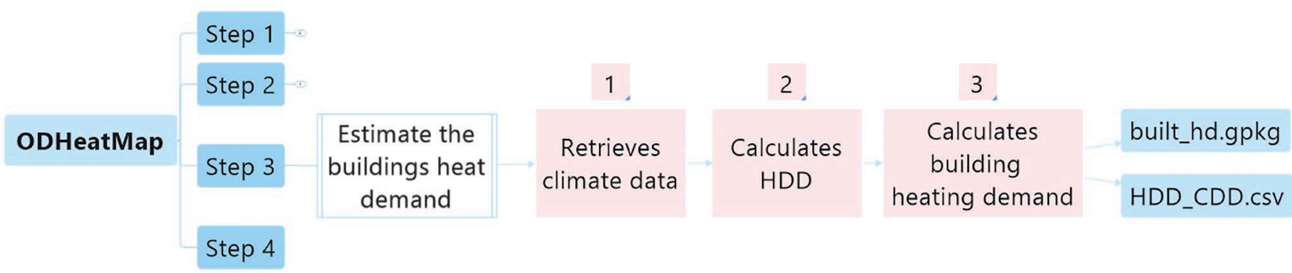


Figure 7: Step 3 workflow showing the steps for estimating the buildings heat demand.

Figure 8: Step 3 output (built_hd.gpkg) using ArcGIS Pro [100] for Ulaanbaatar city, published in Ref. [77].

area setting at a distance from the grid centroid with the option of selecting the highest density, or analyse a user-defined area by uploading a characterising geodatabase to perform a spatial connection with the areas. DH feasibility can be evaluated through heat density classes or network investment cost estimates. The first option offers spatial insight into feasible DH areas, while the second adds an extra dimension by illustrating the relationship between the share of total heat market and costs.

The resulting geodatabase containing the gridded DH assessment is saved as DH_grid.gpkg, where heating demands both within and outside DH potential areas are included in the output. The output of this step is shown in Figure 10, while the user interface code snippets are provided in Figure C 4.

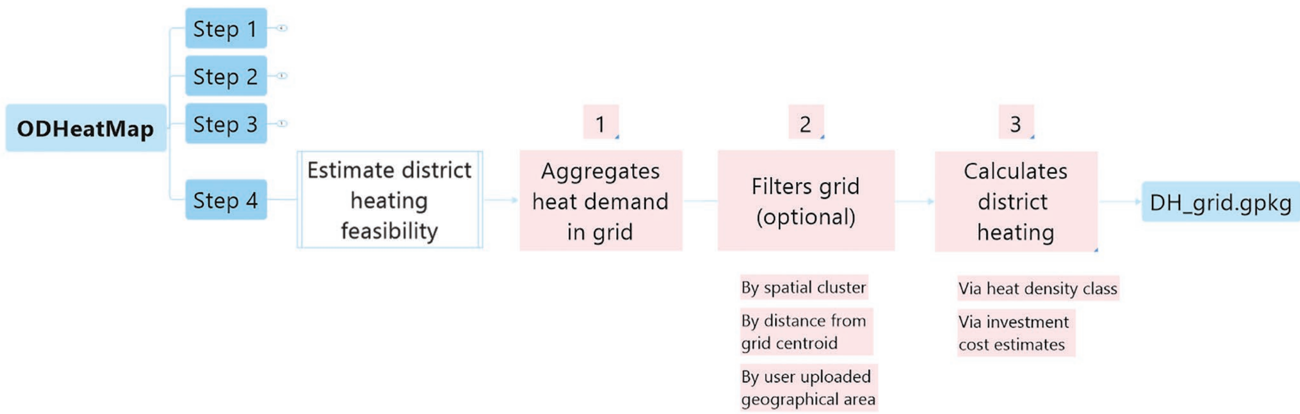


Figure 9 Step 4 workflow showing the steps for estimating district heating feasibility.

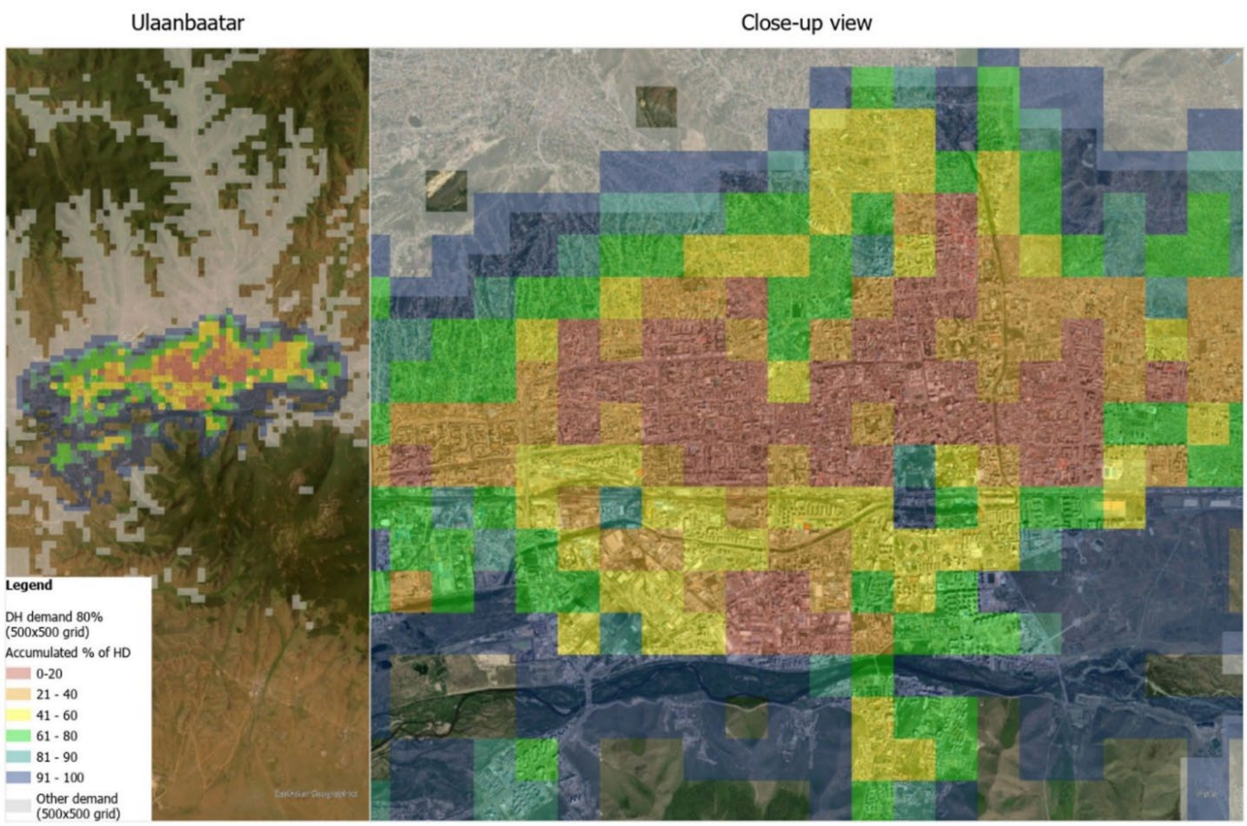


Figure 10: Step 4 output (DH_grid.gpkg) using ArcGIS Pro [100] for Ulaanbaatar city, published in Ref. [77].

4. Tool Validation

Several validation means can be performed after the heat demand mapping at building and grid level is obtained from the ODHeatMap tool. The validation will depend strictly on the data available for contrasting results and how it is used for assessing the tools estimations. For the Ulaanbaatar case, a way to validate the heating demands obtained from the tool is at a systemic level with datasets available from the existing DH network area.

The dataset includes buildings attributes such as floor area, number of floors, and peak heat capacity which is translated into heat demand assuming the peak capacity factor of the DH system based on 8760 full load hours of operation. Out of the 13,010 buildings in the dataset, 9158 buildings are matched, which corresponds to roughly to a 20% set of the total buildings mapped with the ODHeatMap. Within the existing DH area, the tool underestimates total heat demands by within a 1% margin for both SH and DHW heating demand, as seen in Table 2.

Table 2: Annual Heat demand [MWh] systemic validation of ODHeatMap in Ulaanbaatar DH system.

	Tool	**Observed**	**Validation error [%]**
Space heating $[hd_{sh}]$	2154	2172	0.8%
Domestic hot water $[hd_{dhw}]$	926	923	–0.3%
Total heat demand $[hd]$	3080	3095	0.5%

Other means of validation can include the use of literature including estimates or measured heat demand at a building level. Ulaanbaatar building heat demands have been studied in Ref. [79,104,105]. Compiling the references, individual heating demand ranges for buildings [217–562 kWh/m^2], and houses [405–500 kWh/m^2]. These estimations taken into consideration heated areas in buildings which are a proportion of the total floor area calculated with the ODHeatMap tool. This means that the values for validation are expected to be slightly higher than the ones estimated by the tool, which show a mean heating demand of 250 kWh/m^2 for buildings with > 50 m^2 floor area. However, smaller buildings show a mean closer to 750 kWh/m^2 which could reflect the model performing better in multi-story buildings rather than single houses.

The dataset available for validation enabled a grid level validation, this to identify the best performing grid cell size for the DH assessment, without compromising the scale of analysis. Grid cell sizes from 100, 250, 500, and 1000 meters were tested for the heat demand aggregation, and the performance was assessed with categorized grid heat densities. As the grid resolution decreases, regardless of the heat density category, the tool exhibits poorer performance, see Figure 11. Additionally, worse performances are seen in the lowest heat density categories where the least share of the total heating demand lies. An expanded version of this validation is available in full report, where the ODHeatMap is employed to map heat demands, aiding the energy system analysis for developing a strategic heat plan for Mongolia [77].

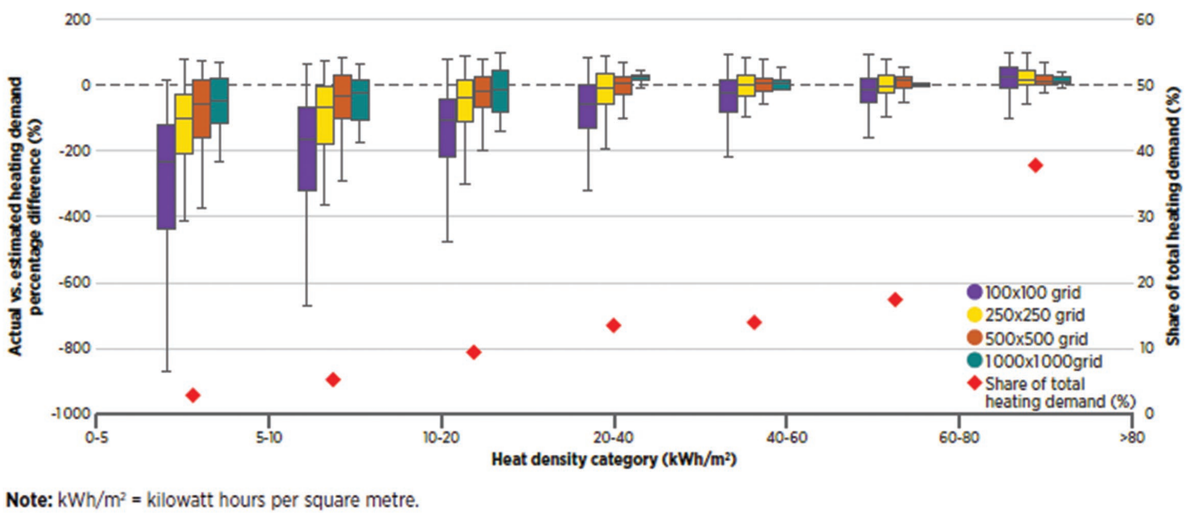


Figure 11: ODHeatMap tool validation using heat density categories and aggregation grid sizes, from Ref. [77].

5. Tool Implementation in Energy System Analysis

This section seeks to explain how the heat demand mapping output from the tool can be implemented in energy system analysis. In the energy system, the heat demand for DH potential will be derived to the technologies powering DH systems, while the heat demand outside the identified DH areas will be derived to technologies supplying individual heating solutions. There is an array of tools for energy system analysis to choose from, depending on the capabilities and scope and the purpose intended [106], some of which already have coupled GIS systems [107].

The integration of the outputs from the ODHeatMap tool into energy system analysis is pivotal for informing the formulation of energy scenarios and enhancing the precision of analysis. The tool is adept at providing geographical inputs for energy models, facilitating the creation of nuanced scenarios that reflect not only current heat demands but also their projection into the future. From there, cost effective heat savings potentials and DH grid expansions with local constraints affecting choice of technology can be reached. Such scenarios are instrumental in assessing the feasibility and impact of potential heating strategies and respond to a deep and complex description. This section, however, exemplifies and provides a brief description of what can be evaluated with the outputs from the tool.

For the case of Ulaanbaatar, the outputs of the tool are utilized in the development of a strategic heat plan for Mongolia [77]. The tool provided detailed input on heat demand projections distributed over DH areas, including new cost-effective grid expansions, heat savings and estimation of grid losses, as well as individual heating areas divided into building types such as single-storey, multi-storey and ger tents. The division by building types was pivotal in selecting feasible technologies tailored to local needs. Consequently, this facilitated the energy system analysis of two heating strategies: a baseline scenario and a highly renewable scenario across district heating and individual heating areas for both 2030, and 2050. Results of the energy system analysis of the DH system are displayed in Figure 12, which represents the optimal heat supply capacities for supplying the heat demand input from the ODHeatMap tool for both scenarios. This enables a greater impact assessment and thereby playing a critical role in formulating a strategic heating plan.

6. Discussion

The evaluation of alternate scenarios for infrastructure deployment is fundamental for sustainable energy planning across geographical scales. The ODHeatMap tool enables evaluations for heat planning, facilitating the creation of geographical representations of heating demand and screening assessments for DH feasibility in any area of interest. Its impact stems from making use of open data sources, enabling assessments when data is unavailable or inaccessible. The tool is open-source code that allows free usage with minimal code requirements that make it editable and scalable to meet specific

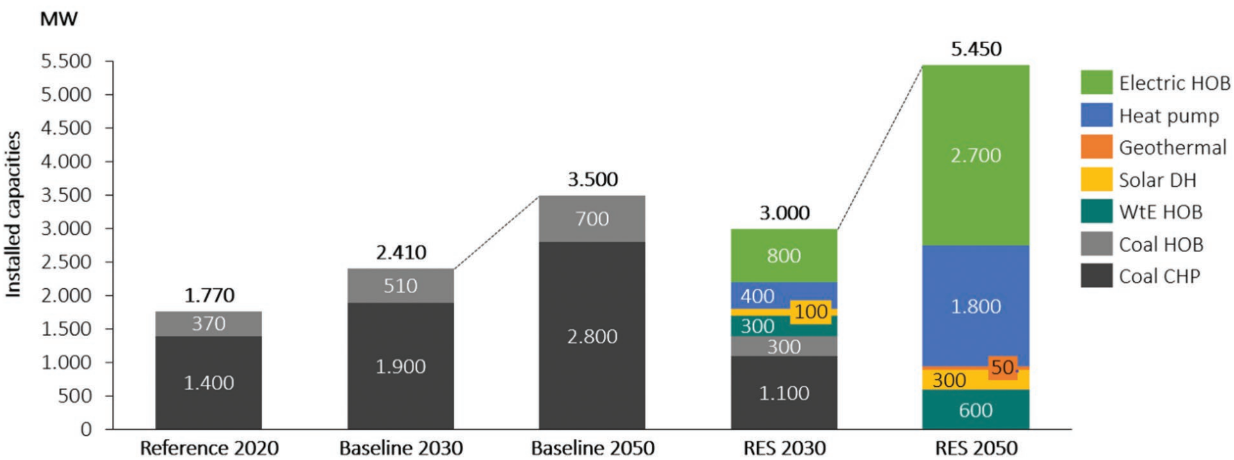


Figure 12: Ulaanbaatar energy system scenarios, distributed on the deployed technologies, from Ref. [77].

purposes and runs in a fully cloud-based environment without local installations for enhanced usability. The tool design has, however, both strengths and limitations worth highlighting.

The tool creates a geographical representation of built-up areas and heating demands that can be used to assess heating supply and demand strategies that otherwise are unattainable. This mean an accessibility to a global 3D building stock estimation, beneficial to mapping infrastructure in contexts where such information may be limited or even absent in national statistics or local registries, or even when energy supply companies fail to provide comprehensive data. The tool gives access to extended data beyond urban areas that are now mappable and identifiable though pattern recognition in satellite imagery. This capacity alone fills critical gaps of spatial information not only for energy planning but also urban planning and resource management.

The building generalisation assumption simplifies heating demand assessments by reducing unnecessary complexities often encountered in estimations conducted at the building level. By avoiding these complexities, often hindering spatial assessments of DH areas, an initial screening can be made. Subsequently, this initial screening can be enhanced by focusing on highlighted areas with greater resources and heating densities, enabling a finer mapping of where these demands could be targeted. This approach represents a more effective and efficient resource management strategy, particularly in contexts where resources are limited. Moreover, the geographic emphasis of the tool addresses a gap in Geographic Information System (GIS) usage resulting from the software complexity, licensing and technical handling of geographic data, and bridges this gap via a user-friendly configuration and setup. The absence of ground data represents both an opportunity and a challenge for the creation and validation of the tool. However, alternative means exist for conducting validation at the system, building, or grid level. The same applies to the heat demand estimation that might inherit errors related to the building envelope. Therefore, it is advisable to perform data denoising and validation as early as during the building footprint retrieval stage to minimise errors at the later processing stage in the model. The ongoing usage of the tool will enable the evaluation of its performance across various geographical contexts to reach a better understanding for improving the tool's capabilities.

Ground and local-level building stock data is acknowledged for its accuracy compared to the open-source data used, which can potentially introduce errors to the model. Continuous improvements in OSM are driven by community mapping efforts that enhance the accuracy and coverage of data. At the same time, the effectiveness of pattern recognition ML algorithms implemented in geographical imagery is advancing and already demonstrates improved coverage in rural areas when compared to OSM datasets. As seen throughout the showcasing of the tool, manual inspections and validations of raw building footprint data like the one performed in Ref. [108] are key for feature filtering and data denoising, especially in mixed urban/rural areas where height estimation accuracy suffers due to database resolution limitations [109,110].

The most significant errors are anticipated when building envelope estimations are underperforming, particularly in sparsely populated areas or regions with uneven infrastructure within the same grid cell area. Such inaccuracies may lead to an underestimation of heat demand in densely built-up areas and an overestimation in areas with lower built-up density. This is because the building envelope directly influences the heat demand, and discrepancies in its calculation can result in corresponding inaccuracies in heat demand estimation.

The tool simplification of energy performance estimation overlooks the complexity of heat demand variations. In the model, all buildings are assumed to be equal and to require heat, which may differ from reality. Each building's thermal insulation coefficient varies depending on factors such as building material, type, age, and usage. Various buildings, especially those in public administration and industrial sectors, may not need heating.

Additionally, as to simplify the building heat demand density, the floor area equals the heated floor area in the model. In practice, the heated floor area constitutes a portion of the total floor area in a building, which decreases the building heat density estimated. Suggestions for DH assessment refinement include incorporating building typology-specific energy consumption and efficiency data, as well as expanding on HDD estimations with multi-year climate data or specialised datasets like the HDD and CDD dataset from the CDS, which includes projections into 2100 [90].

Validation against alternative sources, such as building-level studies [79], metered data [31], or building topology catalogues like TABULA [67] is deemed essential for result accuracy and reliability. Expansions on the investment cost analysis might include costs reflecting linear heat density using network length for optimal sizing as in Ref. [44]. Additionally, while the ODHeatMap lacks functionality for DH network design, furthering the assessment with tools like the THERMOS tool [59] could address this gap, offering hyper-local DH design capabilities, as in [111].

Overall, the authors acknowledge the ODHeatMap tool as a foundational structure for future development. It could benefit from improvements in heating demand estimation such as additional calculations to account for future scenarios, considering energy efficiency measures in buildings and network grid losses that are related to pipeline type and operating temperature level in DH systems.

Similarly, enhancing the cost assessment for DH feasibility could involve integrating additional investment parameters that can be tailored by users. Additionally, the geographical assessment could incorporate potential heat sources for DH system distribution by means of publicly available sources such as excess heat sources [112]. The authors acknowledge that the presented tool is relevant to the scientific community by providing a feasible and practical approach with current accessible data and tool capabilities. The outputs of the ODHeatMap tool serve as both a starting point for discussion and a transformative and dynamic tool across all stages of energy planning and decarbonisation strategies.

7. Conclusions

The ODHeatMap has been introduced to reach pre-feasibility of DH potentials independently of data availability. We exploit the dynamicity and interactivity of current programming systems like Colab, for developing the tool. The tool is considered pertinent for energy practitioners seeking informed support and conducting spatially based assessments of heating development within the framework of energy planning.

ODHeatMap can be directly used for local heat planning at the district or city level and can also provide input to advanced energy system analysis at different geographical levels, including city [28], country [34,113], and even continental level as in Europe [114,115]. The Ulaanbaatar heat mapping output from ODHeatMap tool is employed to create alternative scenarios of renewable heat sources in Mongolia, a data resource-scarce context. While this paper focuses on the tool itself, the usage of the tool's outputs can be found in the full report titled Renewable Energy Solutions for Heating Systems in Mongolia: Developing a Strategic Heating Plan in Ref. [77].

Overall, the tool's design allows users to modify partially or entirely the set of processes to better align with their objectives. This flexibility ensures that ODHeatMap can be adapted to various contexts, enhancing its utility in diverse geographical areas. Ultimately, ODHeatMap represents an enabling mechanism for district heating planning, promoting sustainable energy solutions and supporting the global transition to greener energy systems.

Acknowledgements

The authors acknowledge with gratitude the developers of the open python libraries utilised in the ODHeatMap tool, including geopandas, pyrosm, mercantile, rasterio, rasterstats, gdal, atlite, and cdsapi. They also acknowledge the open-data contributions from OSM, Microsoft GlobalMLBuildingFootprints, and the Copernicus programme. The authors would like to thank Mette Reiche Sørensen for scientific proofreading, and constructive criticism in editing this paper.

Appendix A: Metadata

Table A 1: ODHeatMap tool metadata.

Metadata	Description
Current code version	v1
Permanent link to code/repository used for this code version	https://github.com/dismaps/ODHeatMap
Permanent link to reproducible capsule	https://colab.research.google.com/github/dismaps/ODHeatMap/blob/main/ODHeatMap.ipynb
Legal code license	MIT License (MIT)
Code versioning system used	git
Software code languages, tools and services used	Python, Google Collaboratory, Jupyter Notebooks
Compilation requirements, libraries, operating environments and dependencies. (see "Import of libraries and environment" section at the start of each step of the tool)	*geopandas*: Python library designed for working with geospatial data in a structure format called GeoDataFrames. *pyrosm*: Python library for reading and converting OpenStreetMap files into geopandas GeoDataFrames. *mercantile*: Python library for spherical mercator coordinate and tile utilities. *rasterio*: Python library designed to facilitate the processing of geospatial raster data. *rasterstats*: Python module for summarizing geospatial raster datasets based on vector geometries. *gdal*: Python translator for raster and vector geospatial data formats. *atlite*: Python library for handling big weather datasets while maintaining low computational requirements. *cdsapi*: Python Copernicus Climate Data Store API.
Support email for questions	Diana Moreno diana@plan.aau.dk

Appendix B: Nomenclature

Table B 1: Nomenclature of formulae

Equation	Symbol	Unit	Description
1	b_{sa}	m^2	Building surface area
	A	m^2	Building shape area
	H	m	Building height
	P	m	Building perimeter
2	HDD	˚C	Heating degree days
	T_{ref}	˚C	Temperature of reference
	T_{ave}	˚C	Daily temperatura average
3	hd_{sh}	MWh	Space heating demand
	U_{value}	$\frac{W}{m^2K}$	Coefficient for heat loss
4	hd	MWh	Total heating demand
	hd_{dhw}	MWh	Domestic hot water heating demand
5	q_L	$\frac{GJ}{ha}$	Heat density
6	C	$\frac{€}{GJ}$	Annual investment cost per heat sold
	x,y	–	Investment cost equation coefficients

Appendix C: Code snippets

Step 1: Retrieve building footprints

- We choose one of the three methods for accessing building footprint open data.
- Note: The coordinate reference system we manage in this step is "EPSG:4326", i.e. in global lat/lon format.

Input	Output
Area of Interest (AOI)	buildings.gpkg

Import of libraries and environment

[1] Show code

a) Retrieve OSM building footprint

[ ] 5 cells hidden

b) Retrieve ML generated building footprint

[ ] 6 cells hidden

c) Upload building footprint file

[ ] 2 cells hidden

Import of libraries

Show code

```
Ok - All libraries installed
```

Area of Interest

Choose the city to query from OSM

city: UlanBator

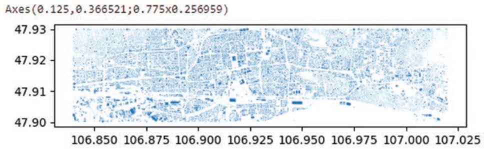
Show code

```
You selected UlanBator
```

```
#Alternate geographical extents to replace string in the variable city.
#Note that regional/subregional query #demands stronger RAM capacity and
#data retrieval and parsing time.
#regions = list(pyrosm.data.available.get('regions'))
#subregions = list(pyrosm.data.available.get('subregions'))
#print(regions, subregions)
```

```
#Parses OSM to readable object in GeoDataframe
fp = get_data(city)
# Initialize the OSM parser object
osm = OSM(fp)
#landuse = osm.get_landuse()
buildings = osm.get_buildings()
print(buildings.plot())
```

```
Axes(0.125,0.366521;0.775x0.256959)
```




```
#Prints Geodataframe properties
buildings.shape
buildings.crs
buildings.columns
```

```
<Geographic 2D CRS: EPSG:4326>
Name: WGS 84
Axis Info [ellipsoidal]:
- Lat[north]: Geodetic latitude (degree)
- Lon[east]: Geodetic longitude (degree)
Area of Use:
- name: World.
- bounds: (-180.0, -90.0, 180.0, 90.0)
Datum: World Geodetic System 1984 ensemble
- Ellipsoid: WGS 84
- Prime Meridian: Greenwich
```

```
#Saves the resulting footprints to file
buildings = buildings.to_crs('EPSG:4326')
buildings.to_file(filename = "buildings.gpkg", driver="GPKG")
```

Figure C 1: Upper: Overview of Step 1 in ODHeatMap; Bottom: Code snippet showing option a) Retrieve OSM building footprint.

Figure C 2: Upper: Overview of Step 2 in ODHeatMap; Bottom: Code snippet showing raster cut and ANBH histogram for AOI.

Step 3: Estimate the buildings heat demand

- We connect to the Copernicus Climate Data Store (CDS) using the API and set the user {url} and {key} in the *Import of libraries and environment* cell.
- We calculate the daily Heating and Cooling Degree Days (HDD and CDD) setting a reference temperature.
- We calculate the heating demand seting a heat loss U-value, and a domestic hot water (DHW) demand share.

Input	Output
`built.gpkg`	`HDD_CDD.csv`
`Copernicus CDS API key and client`	`built_hd.gpkg`

Import of libraries and environment

Show code

Functions definition

Show code

Step 3.1. Retrieves climate data using the Climate Data Store (CDS) Application Program Interface API

[ ] ↳ *5 cells hidden*

Step 3.2. Calculates daily heating and cooling degree days (HDD and CDD)

The formulas used in this section are the following:

$$DD = \sum_{i=1}^{n=365} \Delta T^i$$

$$\Delta T_{HDD}{}^i = T_{ref} - T_{ave} \text{ for } T_{ave} \le T_{ref}$$

$$\Delta T_{CDD}{}^i = T_{ave} - T_{ref} \text{ for } T_{ave} > T_{ref}$$

[ ] ↳ *5 cells hidden*

Step 3.3. Calculates heating demand at building level

The formulas used in this section are the following:

$$hd = \text{Building surface} * U - value * HDD$$

[ ] ↳ *6 cells hidden*

Step 3.4. Export interactive plot as an html file (optional)

[ ] ↳ *1 cell hidden*

Step 3.5. Saves output

[ ] ↳ *1 cell hidden*

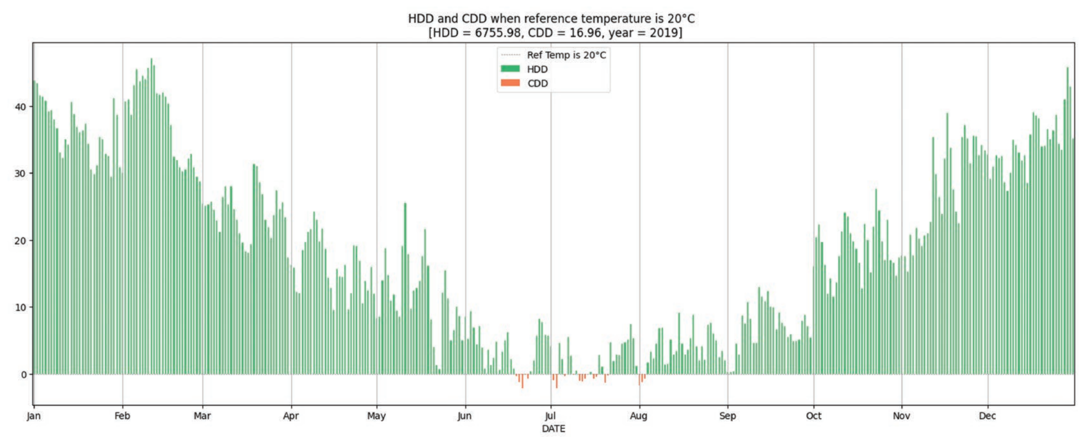


Figure C 3: Upper: Overview of Step 3 in ODHeatMap; Bottom: HDD and CDD calculation plot for a given set of parameters where x-axis is the date and the y-axis represents the HDD in green and CDD in orange, respectively.

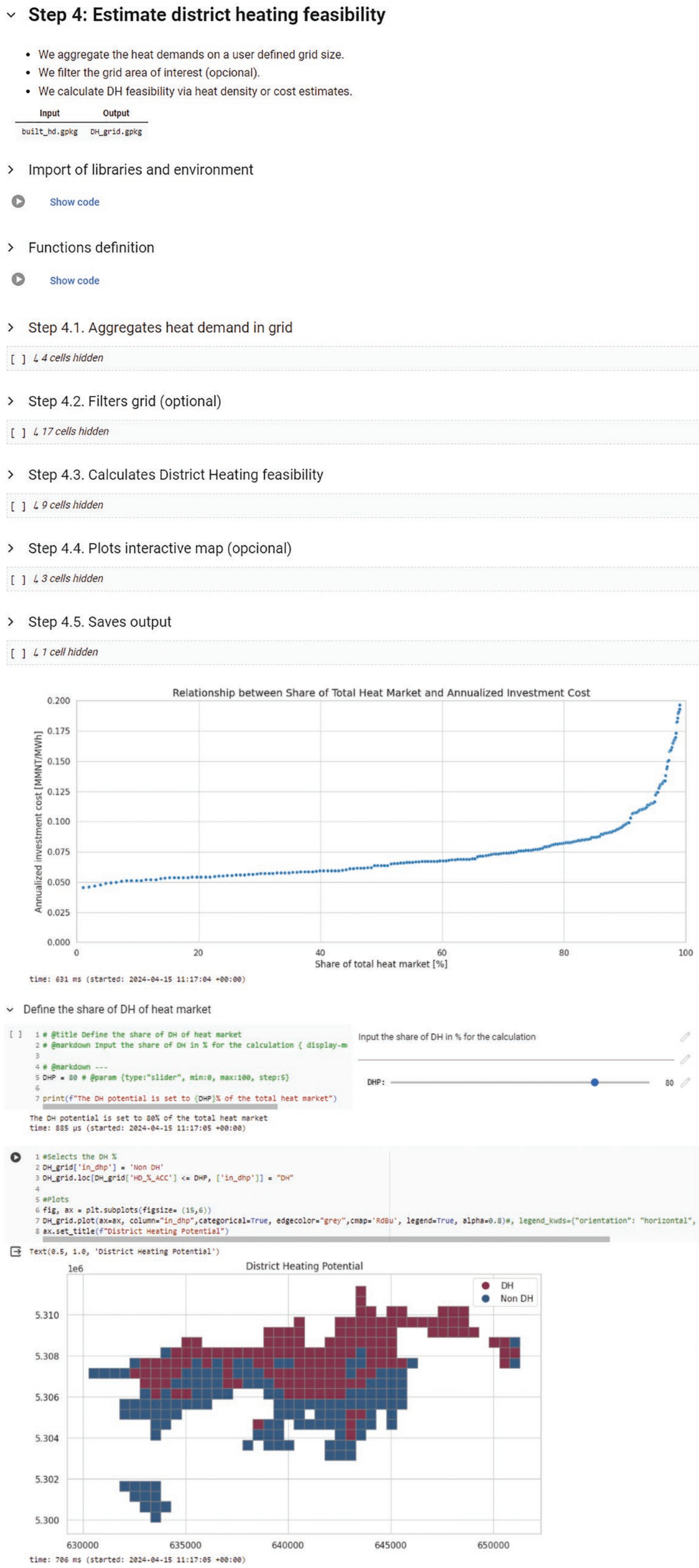


Figure C 4: Left: Overview of Step 4 in ODHeatMap; Right: Code snippet showing DH feasibility via cost assessment for filtered grid.

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