A GIS-based gray-box approach for the estimation of heat demand at the urban scale

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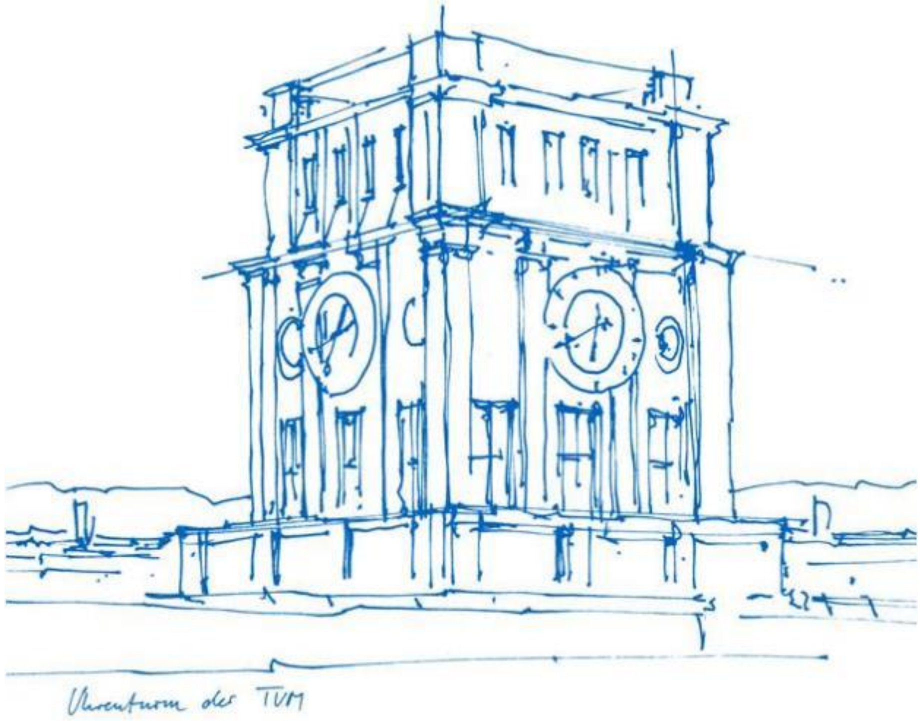

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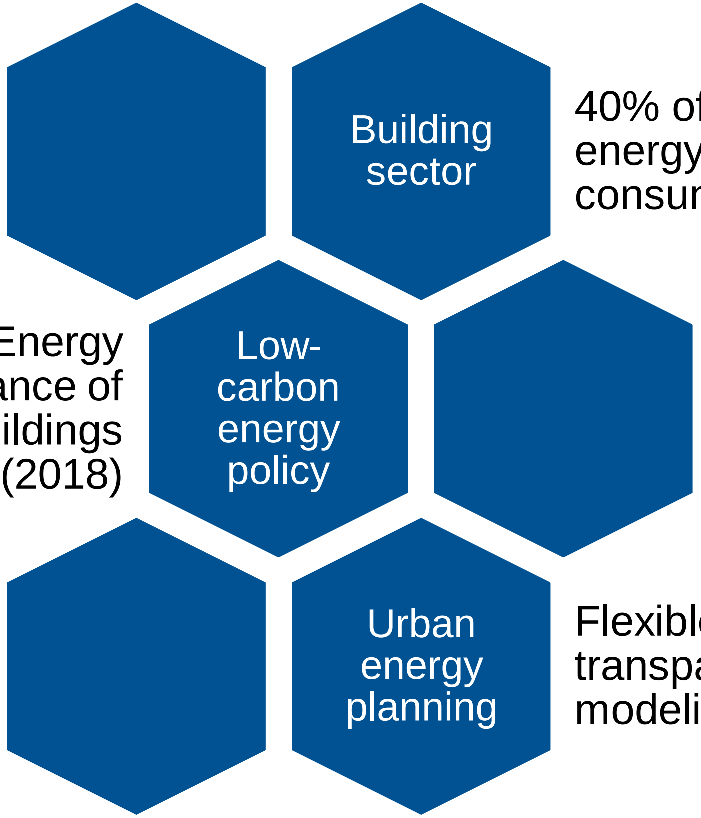
Motivation



40% of total energy consumption

36% of total CO_2 emissions

European/national policy not effectively transferred to local planning structures ← EU Energy Performance of Buildings Directive (2018)

Flexible and transparent modeling tools → Data intensive models → Poor data availability; Low-quality; Privacy concerns

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   UrbanHeatPro in the urban energy modeling world
2. Building model
   Modeling space heating and domestic hot water demand
3. Synthetic city
   Overcoming data challenges
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5. Conclusion

Modeling approaches

UrbanHeatPro

Heat demand profiles for urban areas

https://github.com/tum-ens/urban-heat-pro

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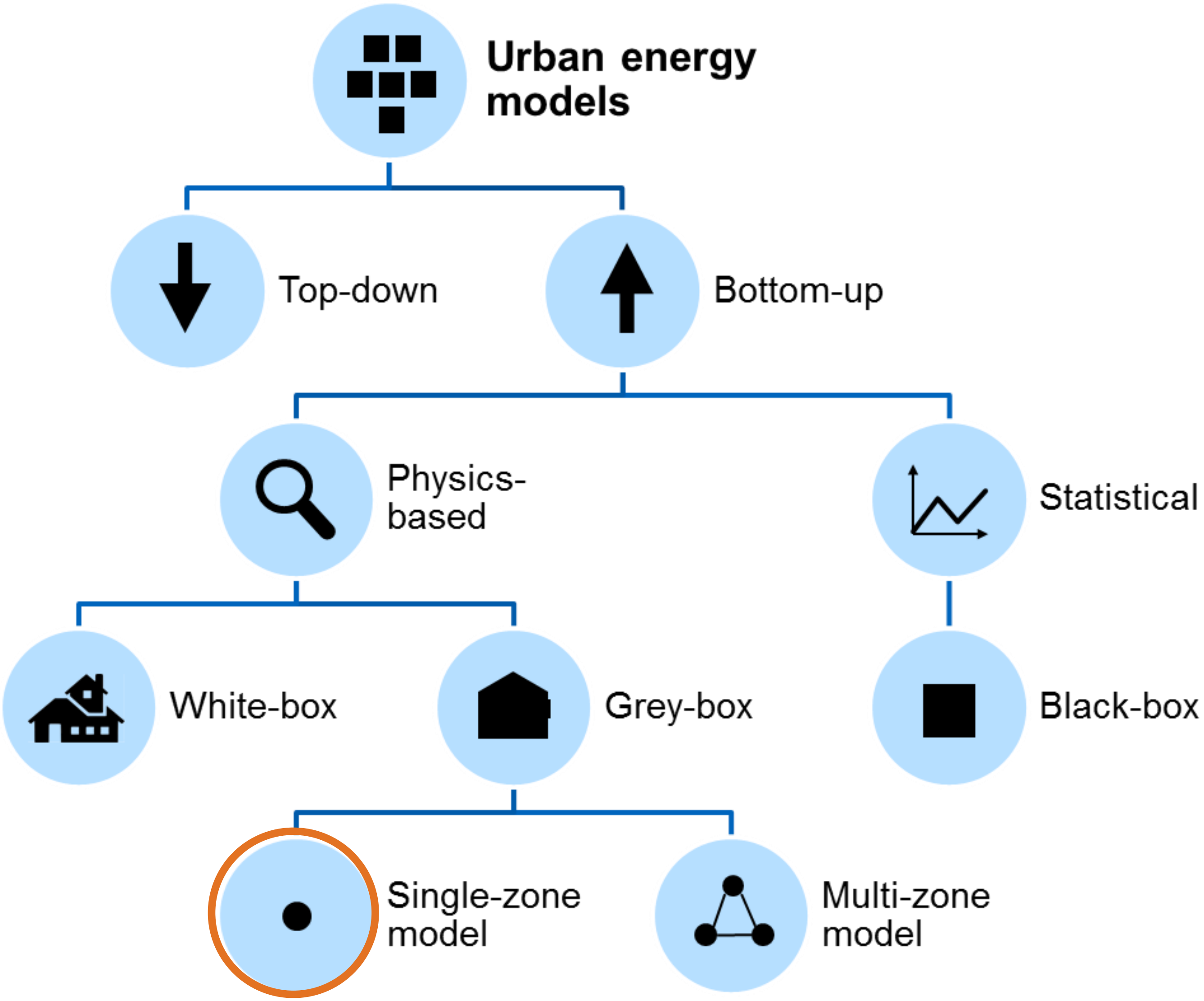
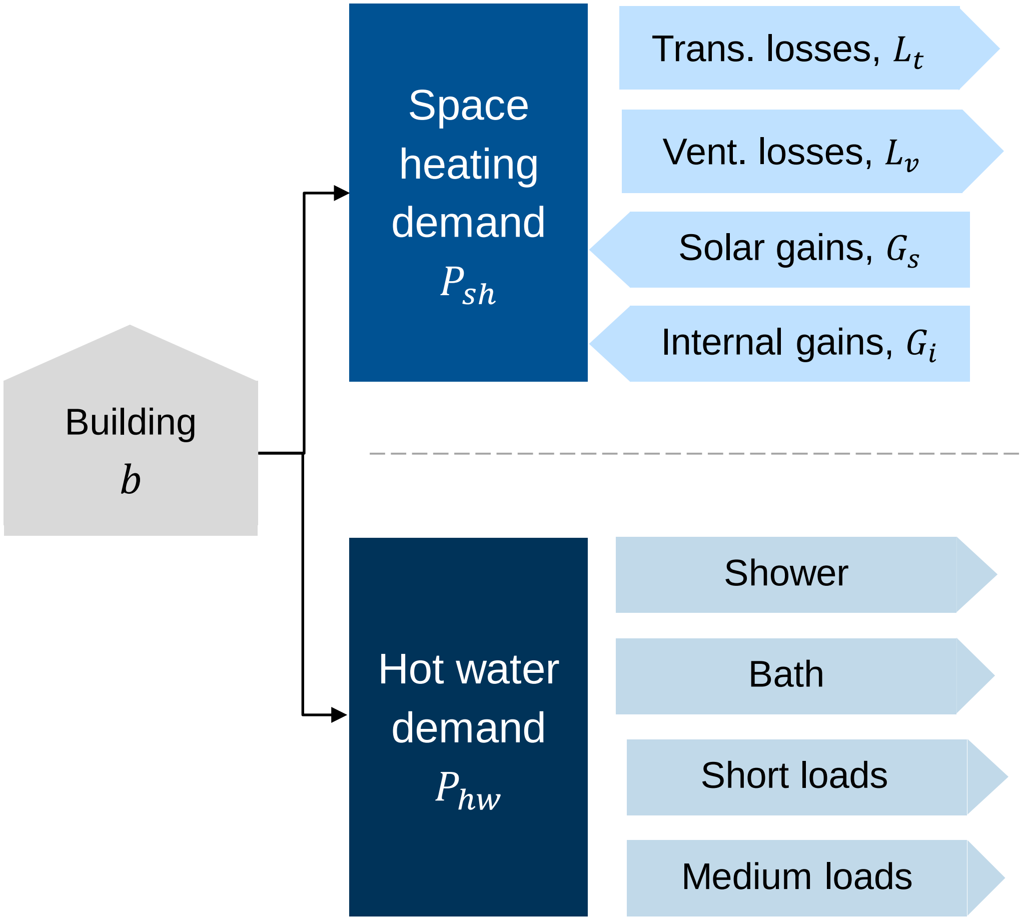
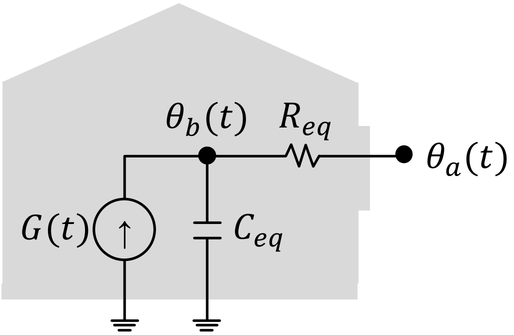
- Dynamic simulation of space heating and domestic hot water demand
- Simple building physics model allows the simulation of urban areas
- Building thermal properties and user behavior are explicitly modeled
- Variable spatial and temporal resolution



Building model



Grey-box building model: 1R1C

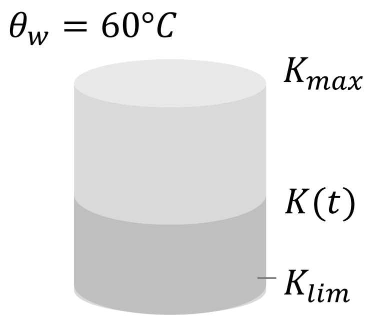


$$\frac{dQ}{dt} = L_t(\theta, t) + L_v(t) + G_i(t) + G_s(t) + P_{sh}(t)$$

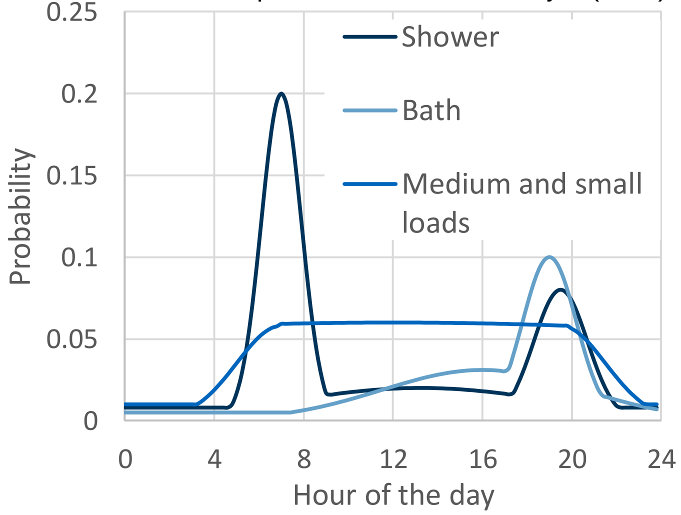
$$\frac{dT}{dt} = \frac{1}{C}\left(L(\theta, t) + G(t)\right)$$

$$\frac{dT}{dt} = \frac{1}{R_{eq} \cdot C_{eq}} \cdot \left(\theta_a(t) - \theta_b(t)\right) + \frac{1}{C_{eq}} \cdot G(t)$$

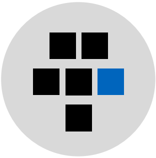
Probabilistic activity model



Adapted from Jordan and Vajen (2005)



Building input data



Geodata

Building footprint

Geographic location

Orientation

Ambient temperature

Solar radiation

Use

Envelope

Thermal transmittance (U-value) per element: roof, wall, window, floor

Surface area per element

Thermal mass

Infiltration and ventilation rate

Size and efficiency of system

Occupants

Number of dwellings

Number of occupants

Share of heated area

Activity profile

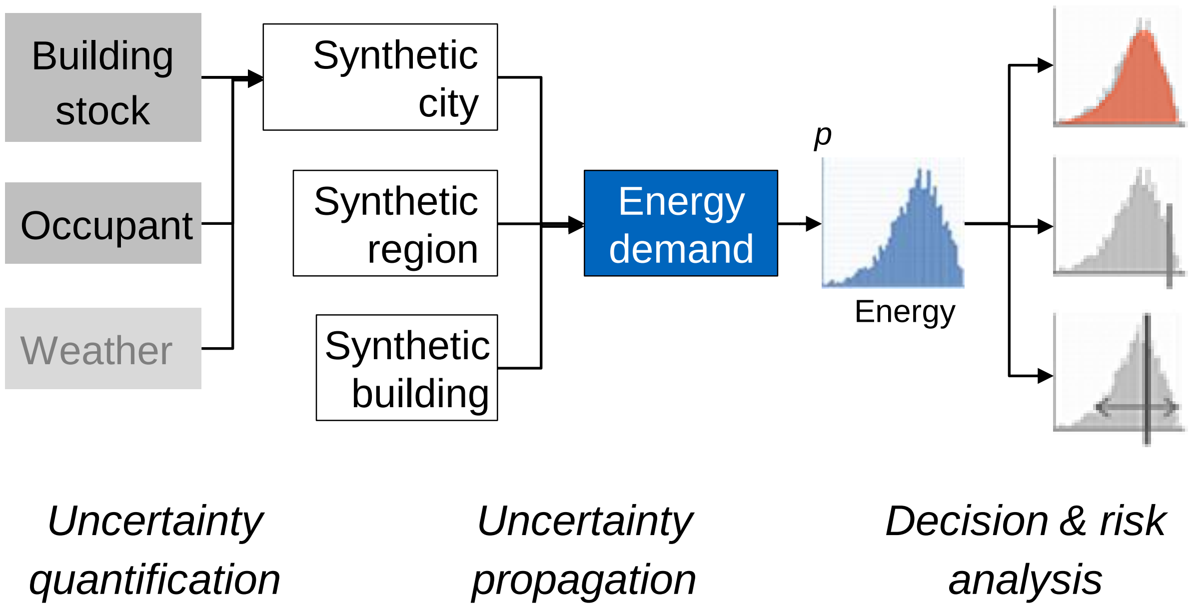
Comfort temperature

Night setback schedule

Overcoming poor data availability: synthetic city

- Simplified representation of the actual city by means of synthetically generated **populations of buildings and occupants**.
- Spatial **microsimulation** based on **aggregated statistics**.
- Better representation of the **heterogeneity** of the building stock and user-behavior while protecting the **user's privacy.**
- **Probabilistic** approach: Every synthetic city is different

- Allows the **risk and uncertainty analysis** for a more effective energy planning:

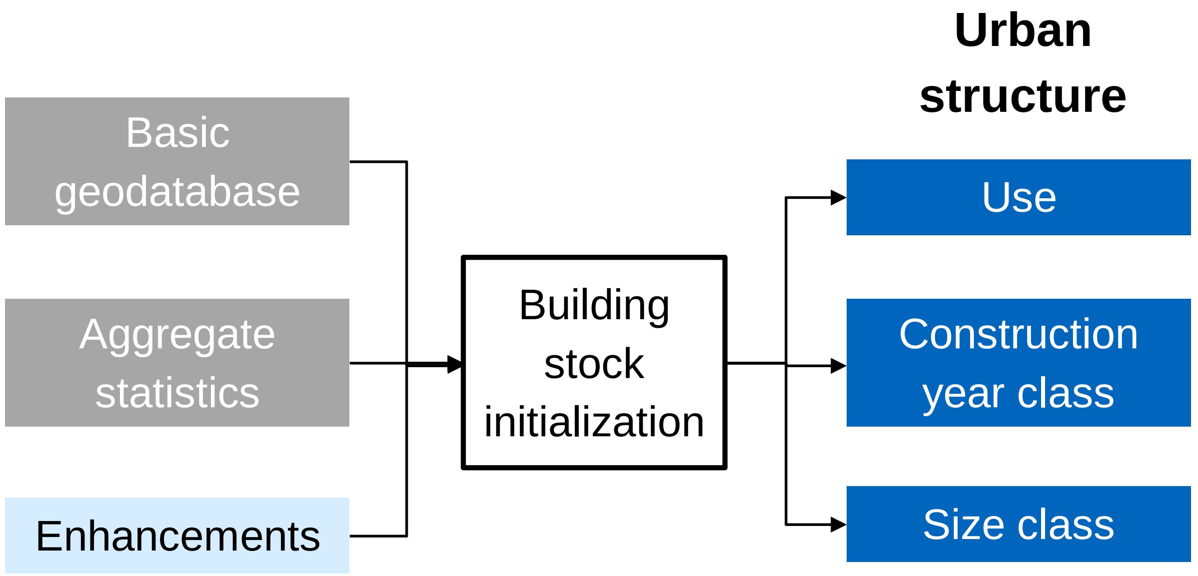


Overcoming poor data availability: synthetic city

1. Initialization of the building stock
2. Characterization of buildings
3. Characterization of heat supply tech.
4. Characterization of the occupants

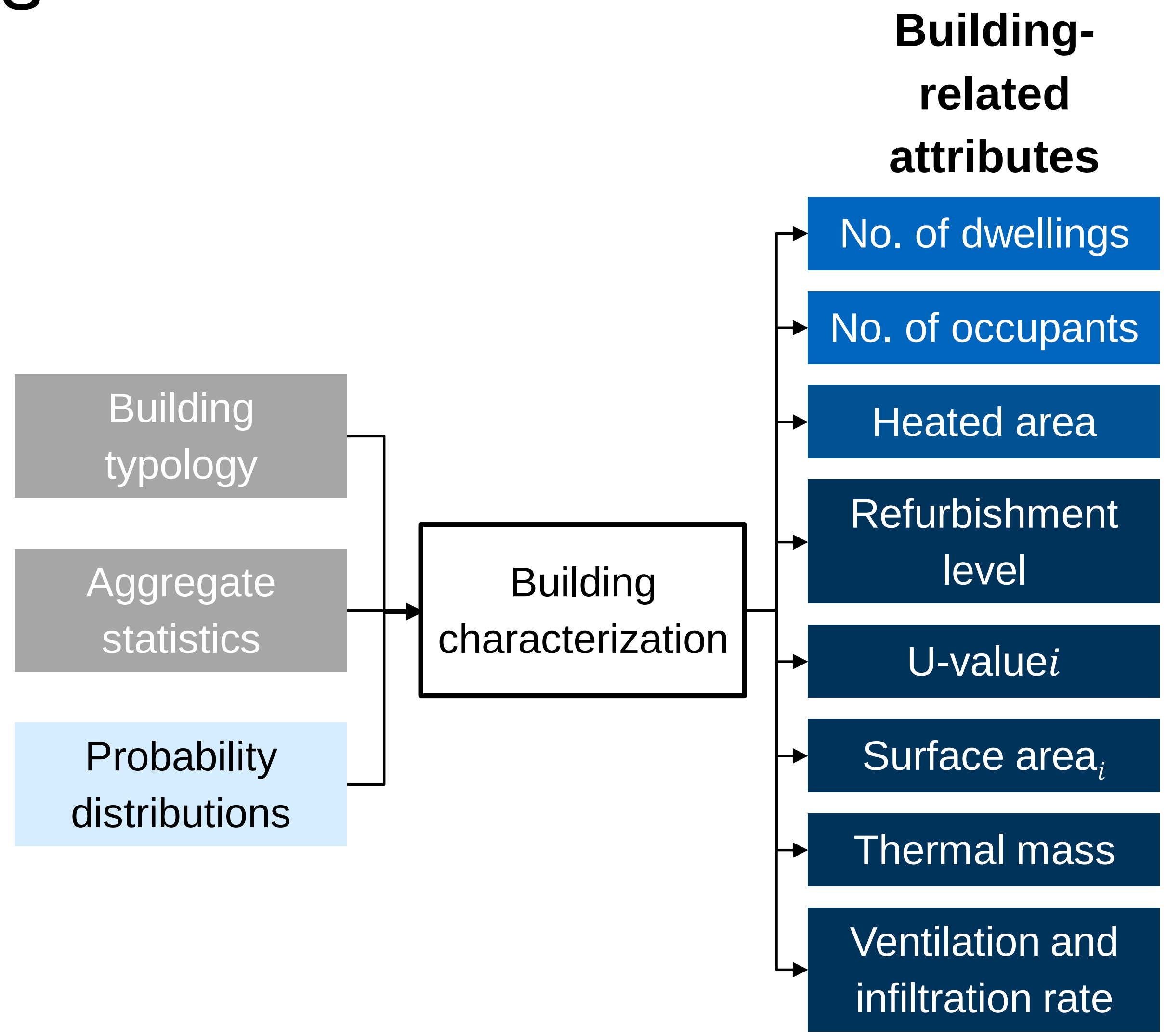
1. Initialization of the building stock

- Geodatabase with basic **structural information** of the building stock
- Generalized regression estimator algorithm to match **aggregate building stock statistics**
- Enhanced with:
    - Inverse distance weighting using the **typical ground floor area**
    - Construction year **probability map** based on historical urban growth



2. Characterization of buildings

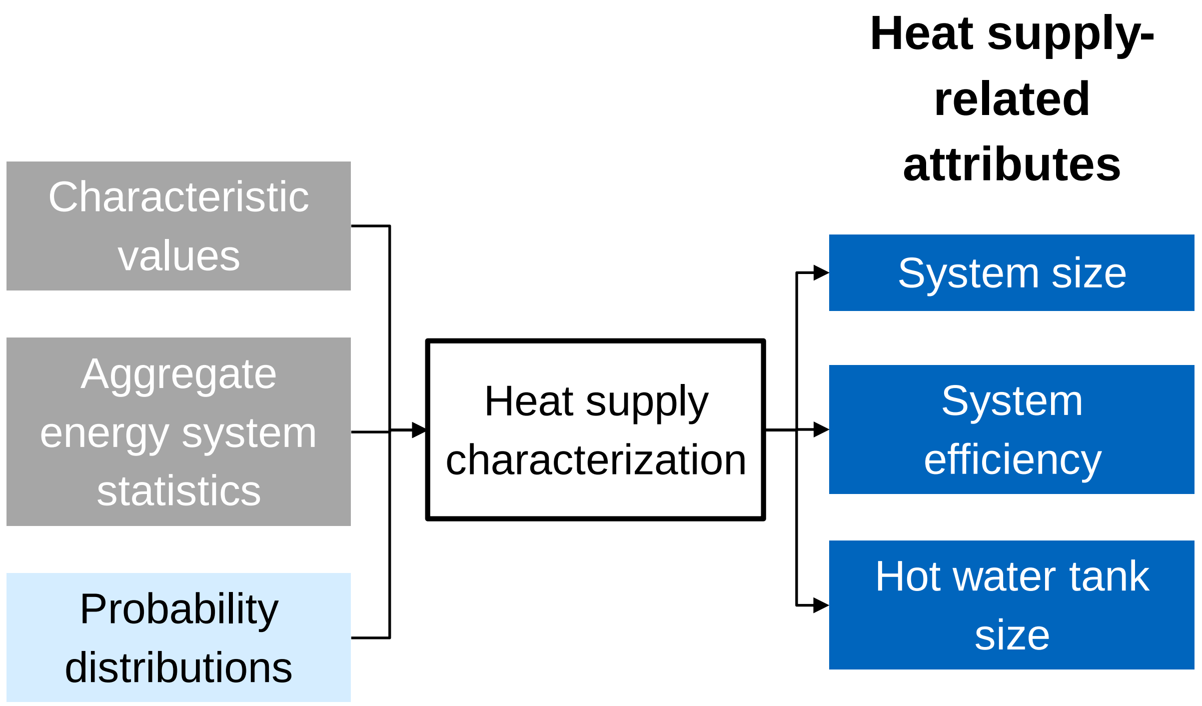
- Geodatabase with **building-related attributes** required for the heat demand model
- Algorithm to select single characteristics from a **building typology** and to match **aggregate dwelling statistics.**
- Enhanced with **probability distributions** for continuous (e.g. U-values) and discrete attributes (e.g. number of dwellings)



3. Characterization of heat supply technologies

- Geodatabase with **heat supply-related attributes** required for the heat demand model

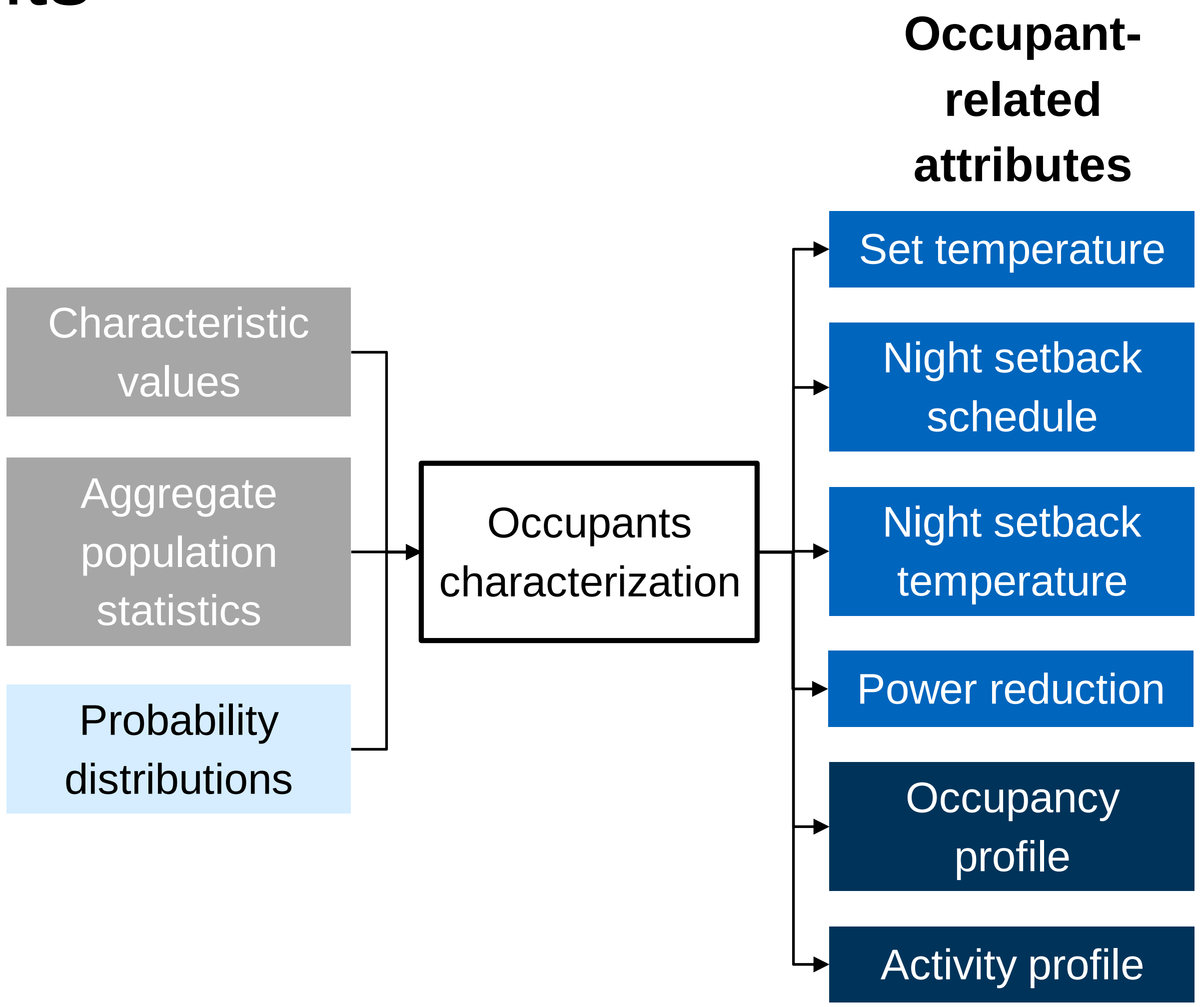
- Algorithm to sample user-behavior attributes from defined **probability distributions** or **characteristic values.** Matching to **aggregate heat supply statistics** is also ensured.



4. Characterization of occupants

- Geodatabase with **occupant-related attributes** required for the heat demand model

- Algorithm to sample user-behavior attributes from defined **probability distributions** or **characteristic values.** Matching to **aggregate population statistics** is also ensured.

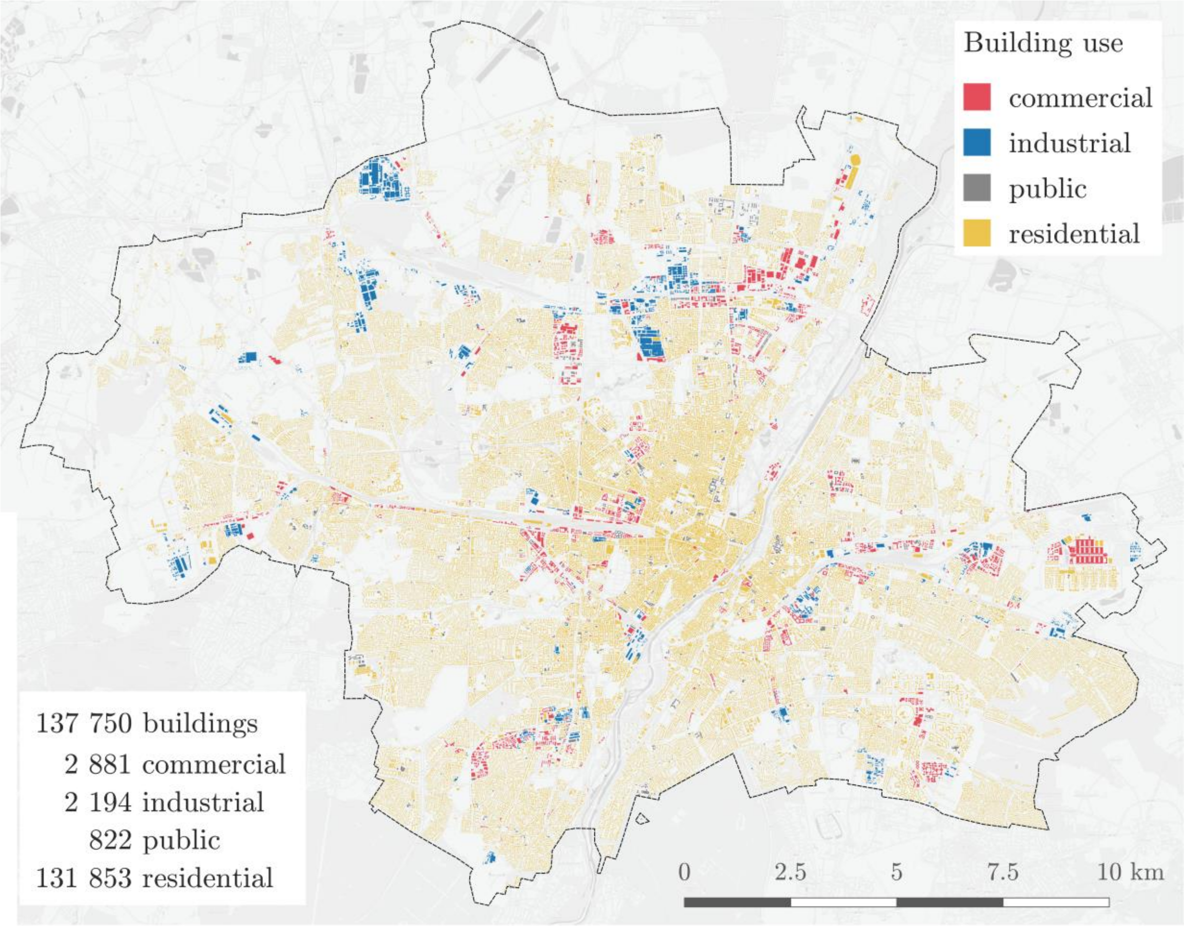


Study case: Munich

Building database

OpenStreetMap

Land use



Study case: Munich

Synthetic city

1. Initialization of the building stock

Residential building stock

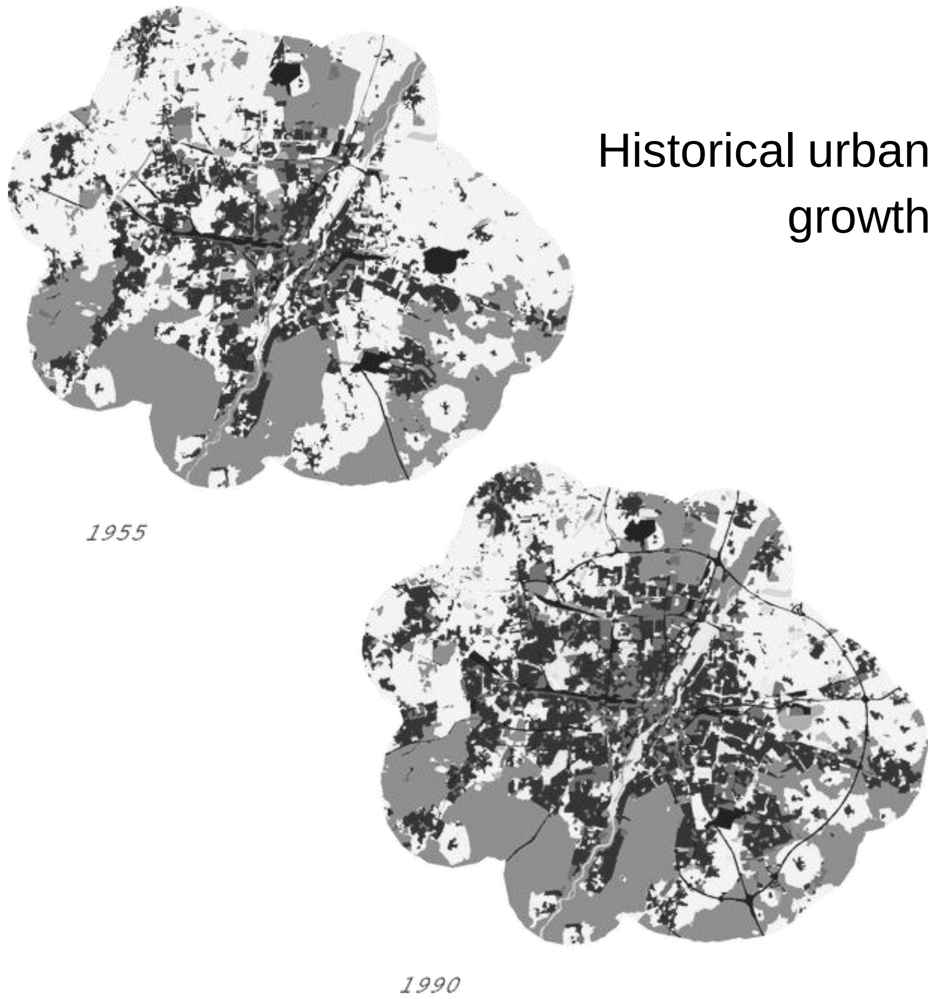
	Size class			
Const. year	SFH	TH	MFH	AB
<1859	0%	0%	0%	0%
1860-1918	1%	3%	3%	1%
1919-1948	2%	6%	6%	1%
1949-1957	2%	7%	5%	2%
1958-1968	2%	7%	5%	2%
1969-1978	2%	5%	3%	1%
1979-1983	2%	4%	2%	1%
1984-1994	1%	3%	1%	1%
1995-2001	1%	2%	2%	1%
2002-2009	2%	4%	3%	1%
>2009	1%	1%	1%	0%

Typical ground floor area in m²

	Size class			
Const. year	SFH	TH	MFH	AB
<1859	86	0	174	0
1860-1918	78	60	103	164
1919-1948	145	50	159	396
1949-1957	80	81	355	354
1958-1968	116	46	471	459
1969-1978	152	61	423	540
1979-1983	83	73	248	0
1984-1994	75	56	249	0
1995-2001	84	52	284	0
2002-2009	80	71	320	0
>2011	108	68	321	0

* SFH: Single-Family House, TH: Terraced House, MFH: Multi-Family House, AB: Apartment Block

Historical urban growth



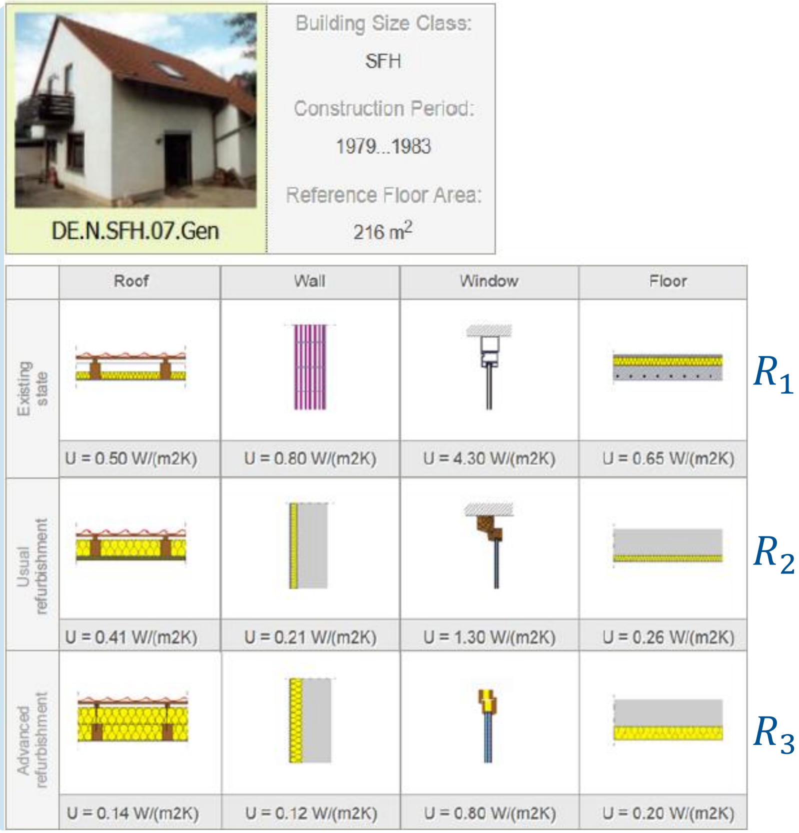
From European Environment Agency (2009)

Study case: Munich

Synthetic city

2. Characterization of buildings using TABULA (Typology Approach for Building Stock Energy Assessment)

Const. Year	SFH	TH	MFH	AB
… 1859				
1860 … 1918				
1919 … 1948				
1949 … 1957				
1958 … 1968				
1969 … 1978				
1979 … 1983				
1984 … 1994				
1995 … 2001				
2002 … 2009				



TABULA Web Tool (2017)

Study case: Munich

Synthetic city

3. and 4. Characterization of heat supply technologies and occupants

- Space heating supply: **+1°C/h, 90%**
- Hot water tank size: **Daily hot water demand** (m³/occupant * no. occupants)

- Set temperature [°C]

Building type	Tset	dT
Commercial	19	2
Industrial	17	2
Public	19	2
Residential	21	2

- Share of buildings with night setback: **50%**
- Night setback temperature: $\boldsymbol{T_{set} - 3°C}$
- Night setback schedule: According to **activity profile**
- Occupancy and activity profile from German Time Use Survey

Study case: Munich

Results

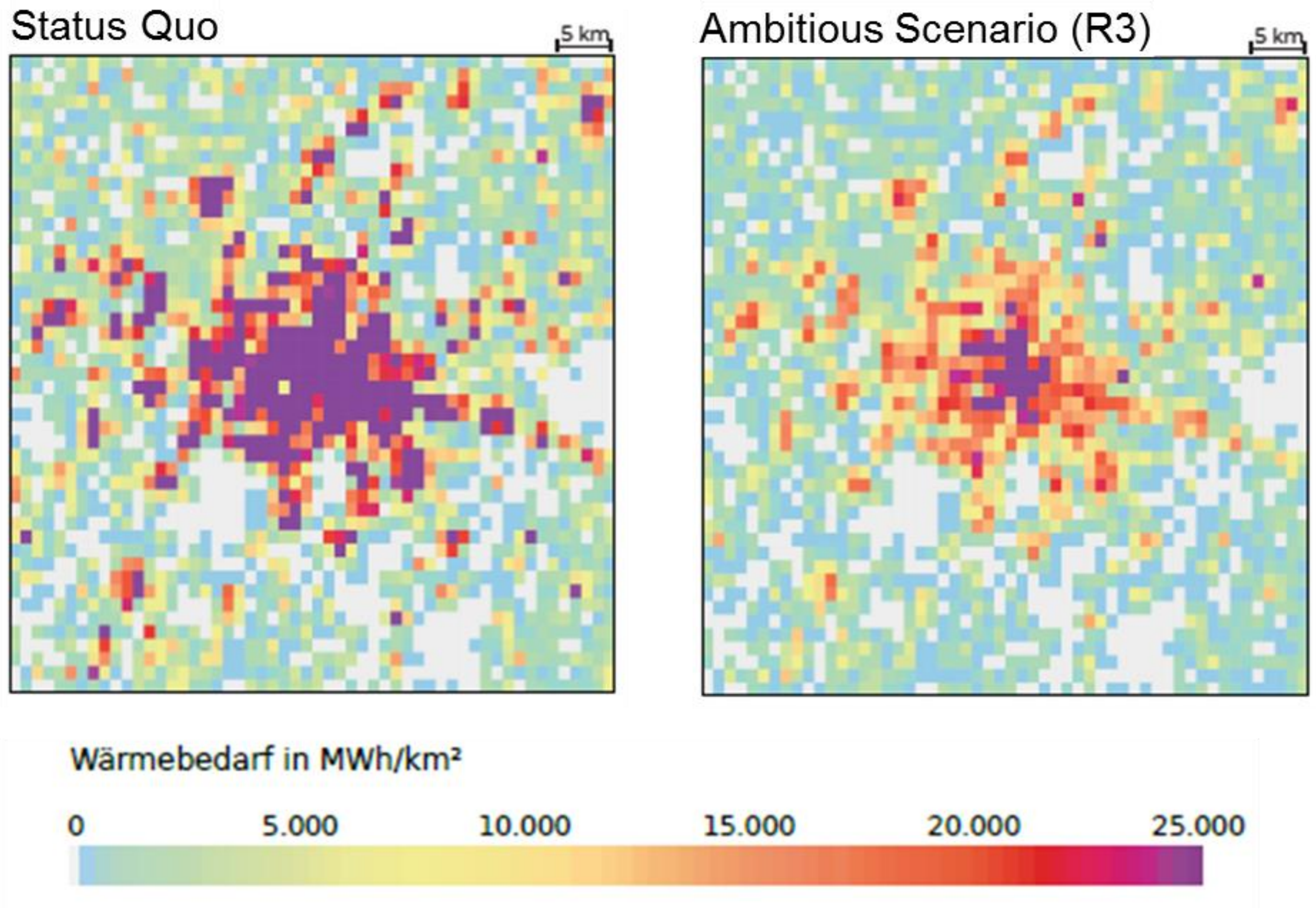
Status Quo

Current refurbishment statistics

Ambitious Scenario

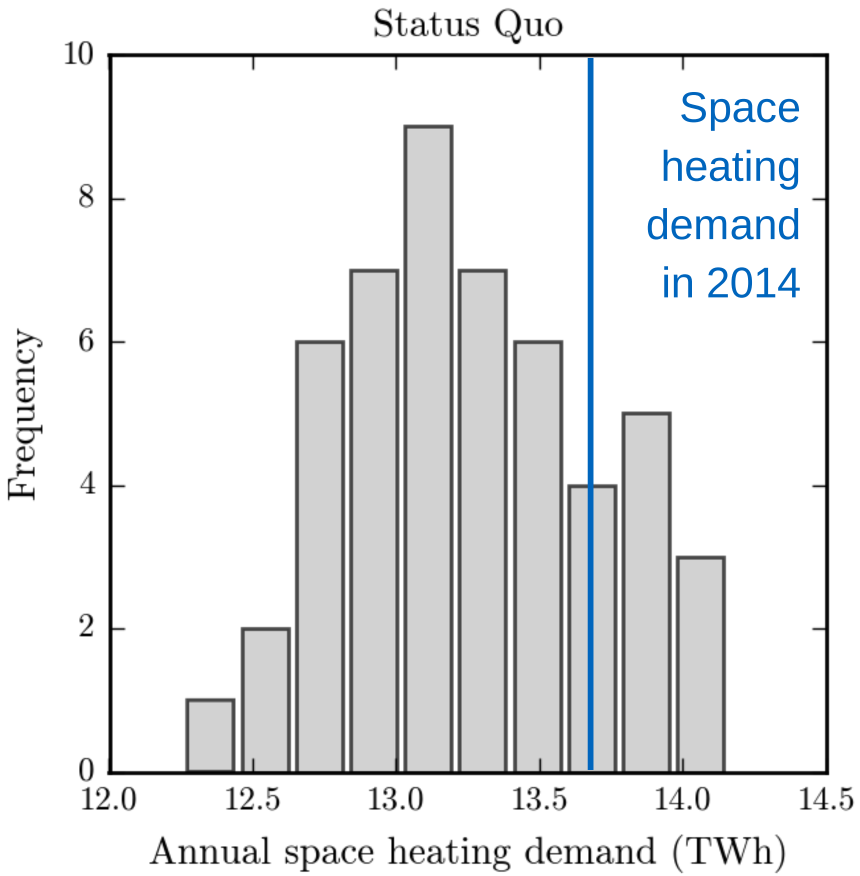
Buildings with advanced refurbishment

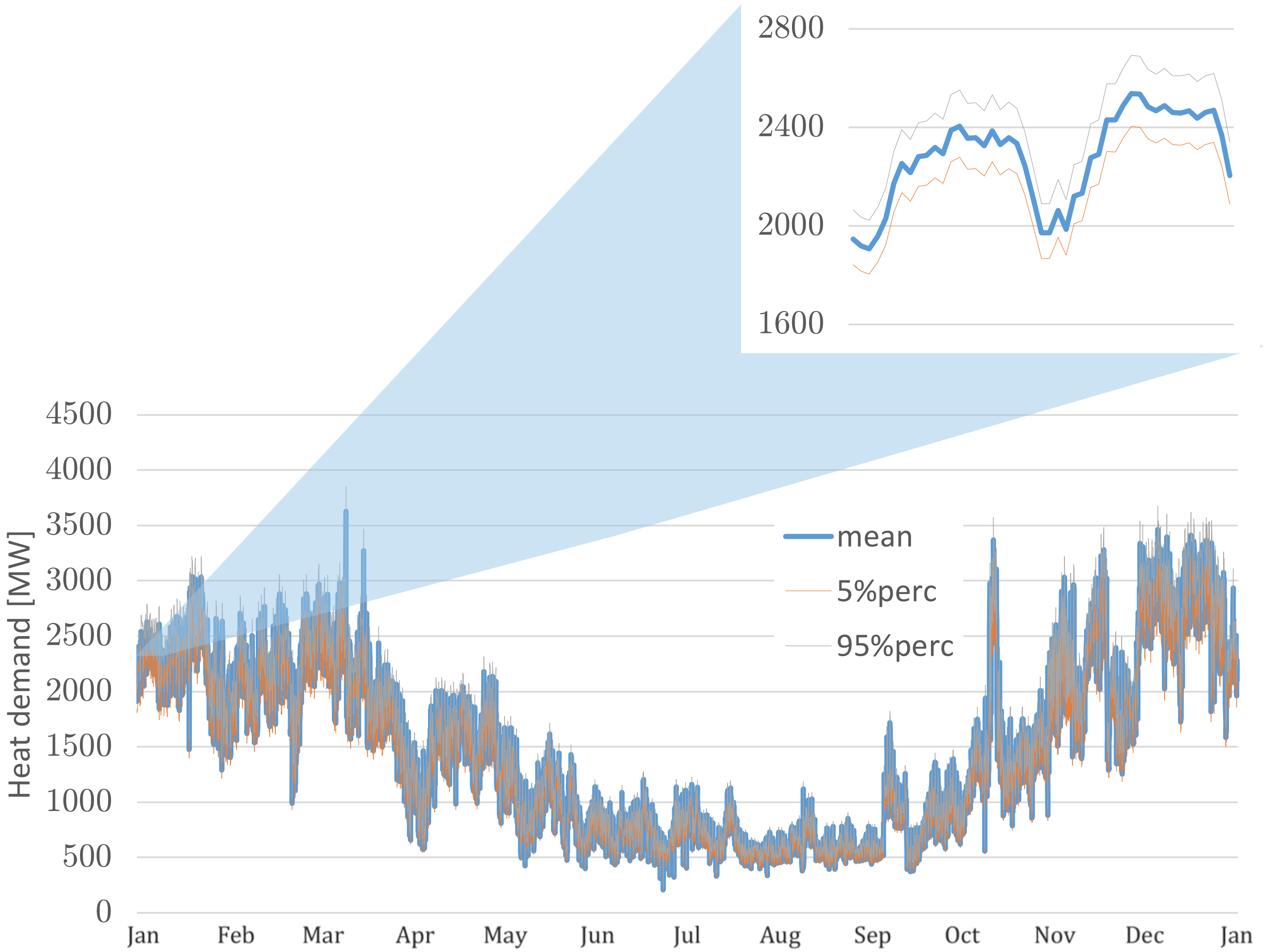
-51% heat demand



Study case: Munich

Results





Key messages

1. **Transparent and flexible tools** for the simulation of energy systems at variable spatial scales are needed for an effective urban energy planning.
2. **Gray-box modeling** is a suitable approach for modeling heating demand as it considers the **building physics** as well as the **user behavior**.
3. Analyses with **synthetic cities**…
   i. overcome challenges of poor **data availability** and low-quality datasets as well as data **privacy concerns**.
   ii. represent the **heterogeneity** of the building stock and use behavior.
   iii. allow the inclusion of **risk and uncertainty analysis** in the simulation of energy systems.
4. **GIS data** enhances the characterization of cities

tum-ens / **urban-heat-pro**

Code | Issues 0 | Pull requests 0 | Projects 0 | Wiki | Security

A bottom-up model for the simulation of heat demand profiles of urban areas

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