

Urban building energy modeling using a 3D city model and minimizing uncertainty through Bayesian inference

A case study focuses on Amsterdam residential heating demand simulation

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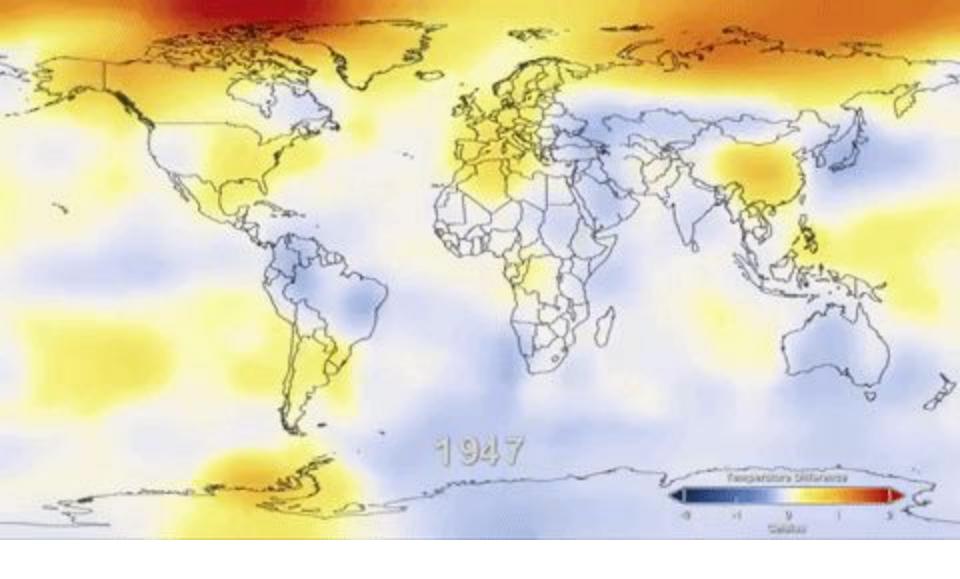






54% **>** 66%

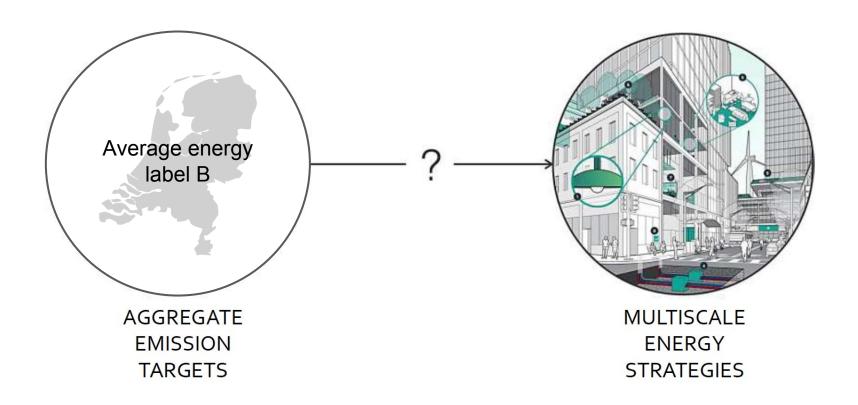
2014 2050 Source: [1][2] ²

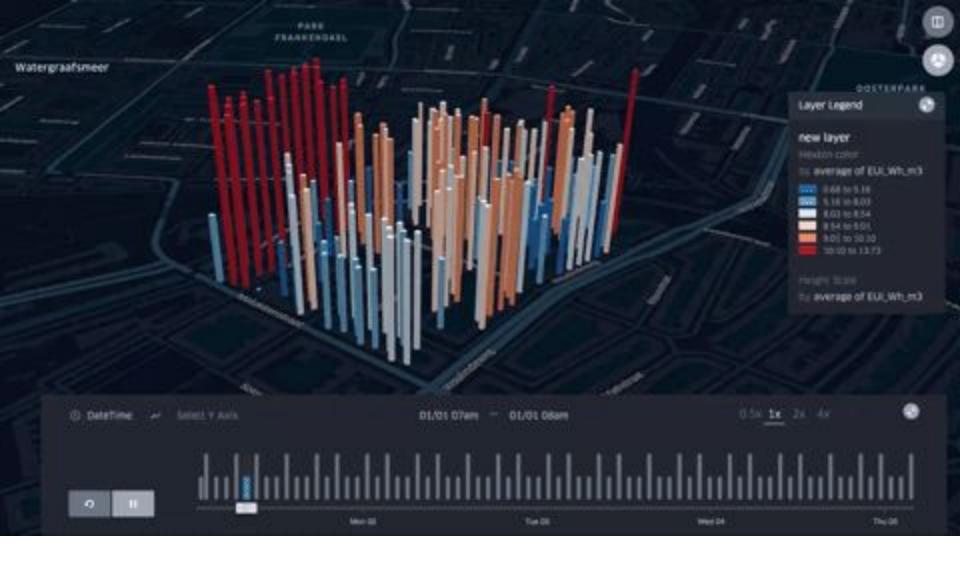


Increased energy demand per capita in the last 40 years

32%

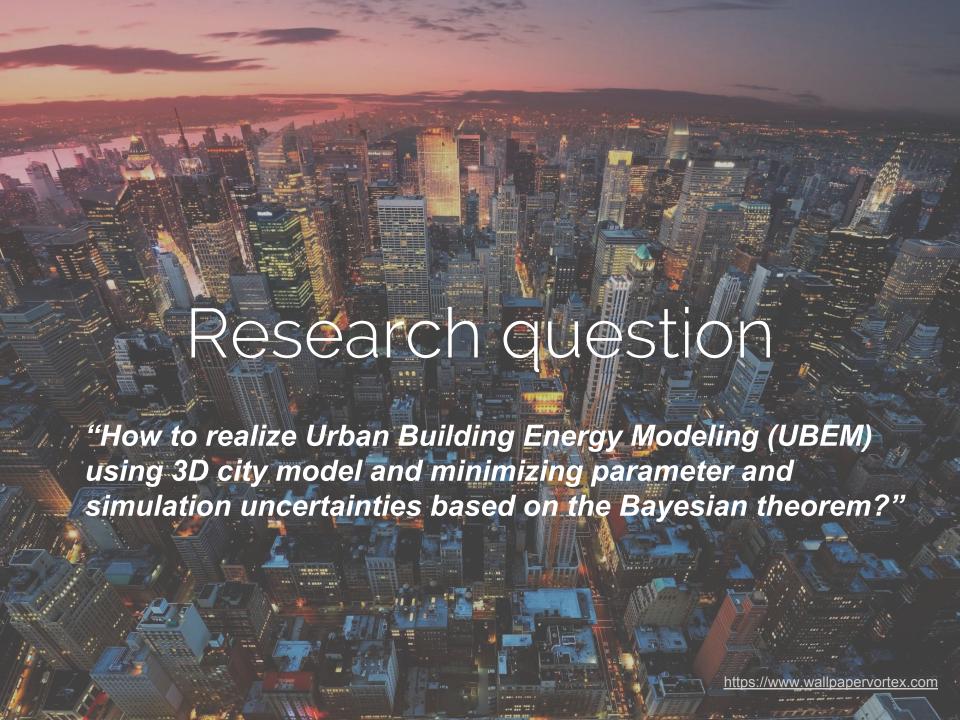
Challenges and opportunities





Simulation performance gap can deviate from the measurement

4% up to 66%



Intro. to energy simulation



Data preparation 3D city model



Uncertainty Sensitivity analysis



Bayesian inference and calibration



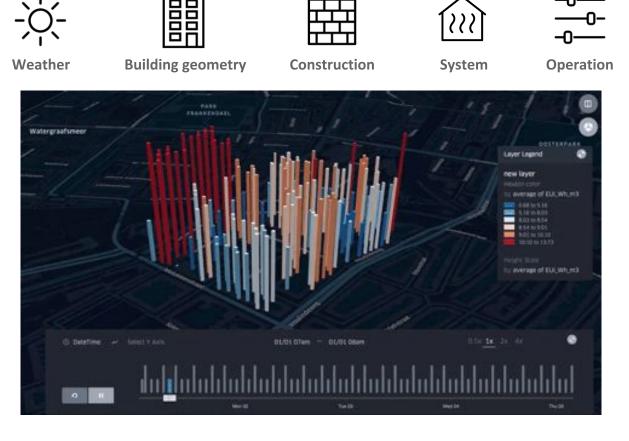
Discussion and conclusion



Modeling approaches

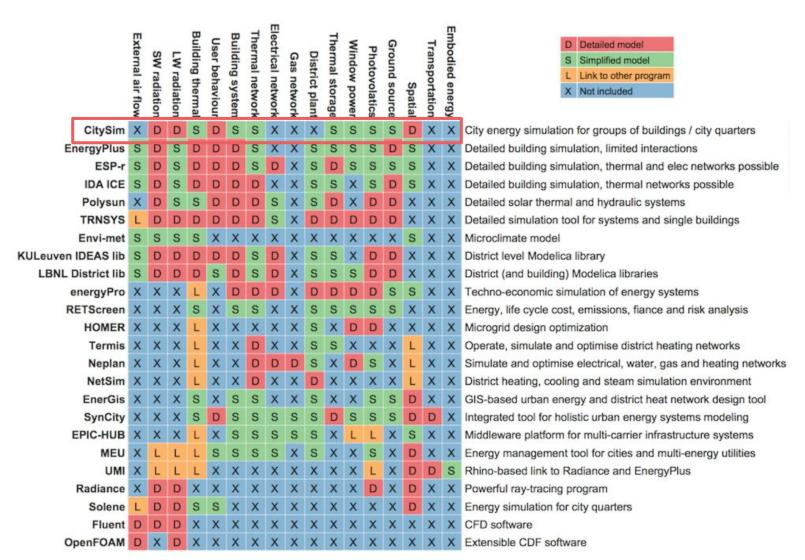
Approach	Advantage	Disadvantage
Top-down	 Long term forecasting in the absence of any discontinuity Inclusion of macroeconomic and socioeconomic effects Simple input information Encompasses trends 	 Reliance on historical consumption information No explicit representation of end-uses Coarse analysis
Bottom-up statistical	 Determination of typical end-use energy contribution Encompasses occupant behaviour Inclusion of macroeconomic and socioeconomic effects Uses billing data and simple survey information 	 Reliance on historical consumption information Multicollinearity Large survey sample to exploit variety
Bottom-up engineering	 Determination of each end-use energy consumption by type, rating, etc "Ground-up" energy estimation Model new technologies Determination of end-use qualities based on simulation 	 Assumption of occupant behaviour and unspecified end-uses Detailed input information Computationally intensive

Urban building energy modeling (UBEM)

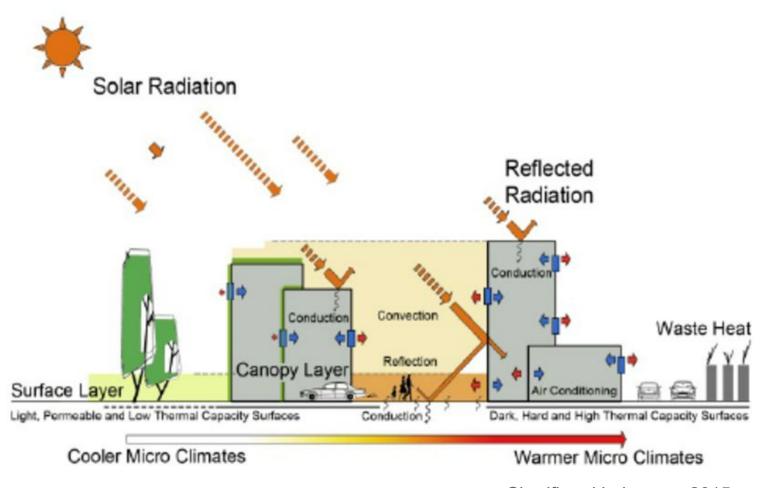




Simulation engines & CitySim



Simulation engines & CitySim



Sharifi and Lehmann, 2015

CitySim energy simulation features

SW radiation
LW radiation
Spatial
User behaviour

Building thermal
Building system
Thermal network
Thermal storage
Wind power
Photovoltaics
Ground source

External air flow
Electrical network
Gas network
District plant
Transporation
Embodied energy

Detailed Simplified Not included

Test area

- 2178 residential buildings in Amsterdam-Oost
- At least 84 postcodes have enough data to go through the complete simulation and calibration process



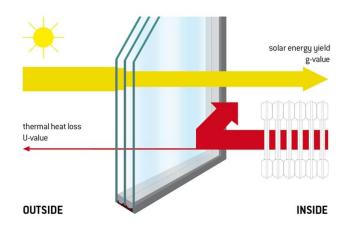


-\-\-\-\-\-\-\-\-\-\-\-\-\-\-\-\-\-\-\	Annual hourly observation data Irradiance data	-	-	
Building geometry	Building footprint Building height	- B_h	- m	
System	Heating system type and efficiency	Eta	-	
—0— —0— Operation	Building occupant numbers Occupancy schedule Minimum thermostat setting Window openable ratio	- - Tmin WOR	person - °C -	Energy simulation
Construction	Window to roof ratio Thermal transmittance coefficient of roof Thermal transmittance coefficient of wall Thermal transmittance coefficient of floor Thermal transmittance coefficient of window Solar energy transmittance of window glazing Surface shortwave reflectance Ground surface shortwave reflectance Infiltration rate (air change rate)	WWR WRR Uroof Uwall Ufloor Uwindow Gwindow SW GSW Ninf	- W/m ² K W/m ² K W/m ² K - - - - volume/h	Validate Calibrate
Metered data	Postcode 6 annual gas consumption	-	m³/yr	16



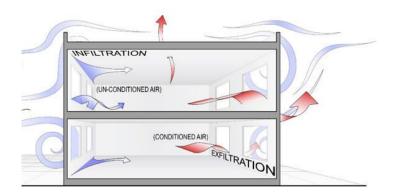


Minimum thermostat setting (**Tmin**)



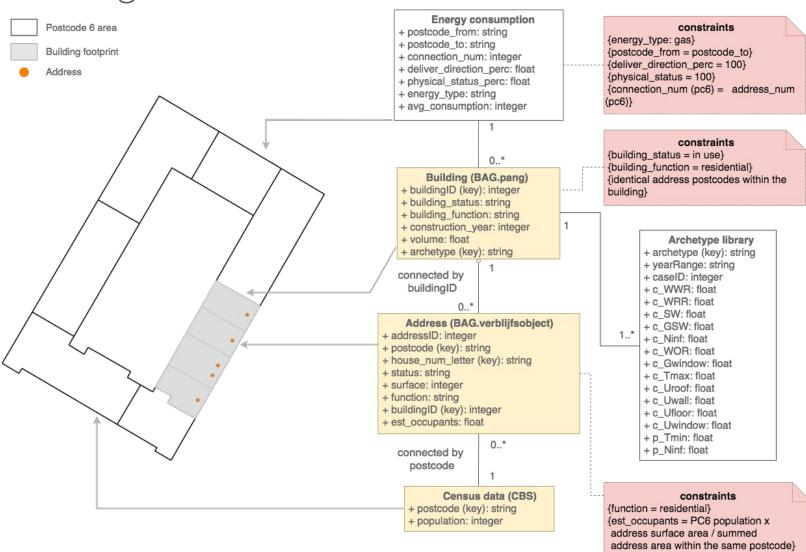


Thermal transmittance coefficient of roof (**Uroof**) Thermal transmittance coefficient of wall (Uwall) Thermal transmittance coefficient of floor (**Ufloor**) Thermal transmittance coefficient of window (**Uwindow**)





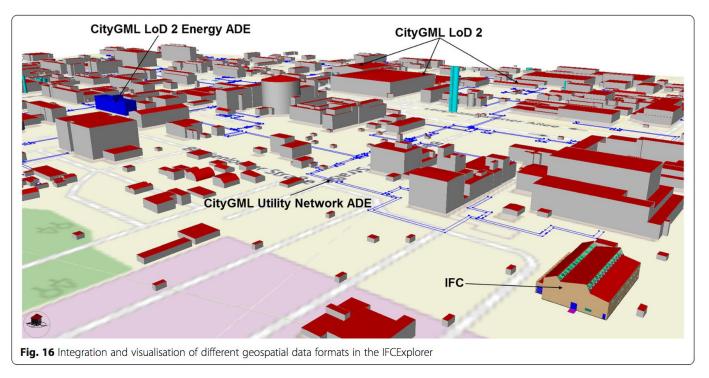
Infiltration rate (**Ninf**)



{est_occupants (integer): when aggregate

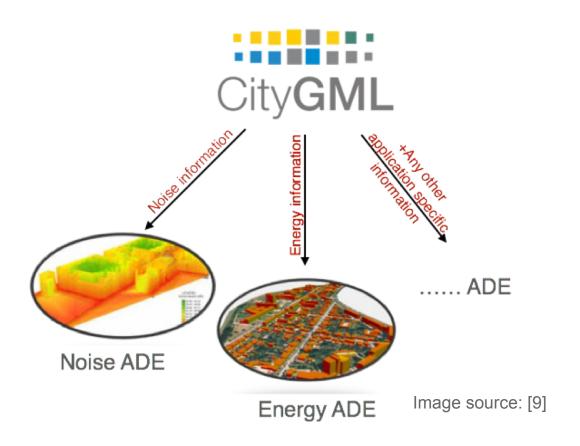
to building or pc6 level}

- Standardized 3D city model: CityGML
- XML based 3D data standard for the representation, storage, and exchange of 3D city models/data
- Open data model (Open Geospatial Consortium, OGC standard)

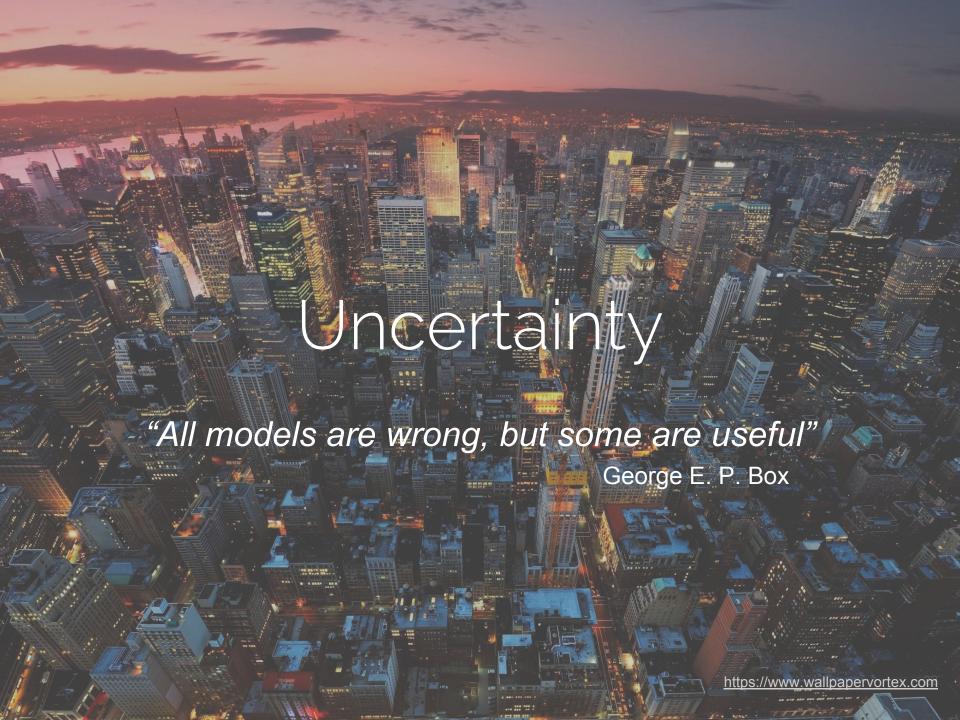


Agugiaro et al., 2018

- Energy ADE (Application Domain Extension) is developed for:
 - Ease data interoperability for Urban Energy Modeling
 - Allow for multi-scales, multi-domains energy modeling



```
Query
                                          Retrieving
                                                                                                   overwriting XML
                                                                deterministic/probabilistic
                                         Building IDs
                                                                    values in DB by ID
            CitySim.XML
                           BuildingID
<Building Name="" id="0" key="865" Vi="34976.9453" Ninf="0.1" BlindsLambda="0.2" BlindsIrradianceCutOff="100" Simulate="true">
   <HeatTank V="0.01" phi="20" rho="1000" Cp="4180" Tmin="20" Tmax="35"/>
   <CoolTank V="0.01" phi="20" rho="1000" Cp="4180" Tmin="5" Tmax="20"/>
   <HeatSource beginDay="1" endDay="365">
       <Boiler name="" Pmax="10000000" eta th="0.95"/>
   </HeatSource>
   <Zone id="0" volume="34976.9" psi="0" Tmin="20" Tmax="26" groundFloor="true" >
       <Occupants n="0" d="0" type="0"/>
       <Wall id="596" type="4" ShortWaveReflectance="0.2" GlazingRatio="0" GlazingGValue="0" GlazingUValue="0" OpenableRatio="0">
           <V0 x="681822.75" y="246715.59" z="9.00"/>
           <V1 x="681819.69" y="246709.88" z="18.00"/>
           <V2 x="681822.75" y="246715.59" z="18.00"/>
       </Wall>
```



Uncertainty











Weather

Building geometry

Construction

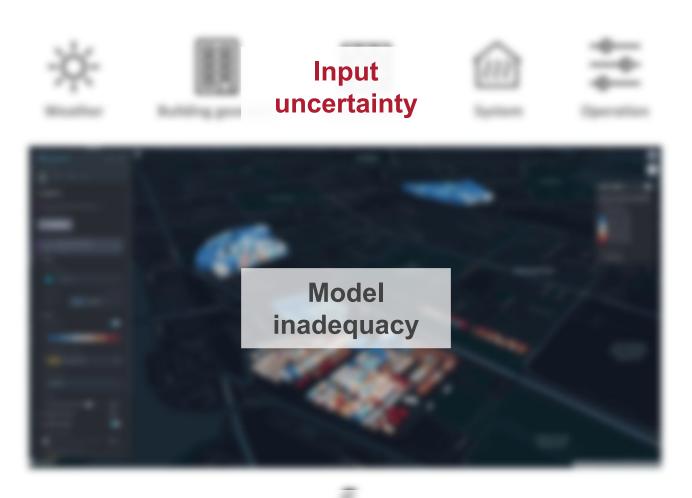
System

Operation





Uncertainty



Observation error

Data preparation - Uncertainty ranges

Table 3.8: Uncertainty ranges of simulation inputs

Parameters	Symbol	Unit	Uncertainty
Building construction parameters			
Window to wall ratio	WWR	-	U(0.15-0.45)
Window to roof ratio	WRR	-	U(0.00-0.15)
Thermal transmittance coefficient of roof	Uroof	W/m^2K	U(0.16-2.60)
Thermal transmittance coefficient of wall	Uwall	W/m^2K	U(0.21-2.55)
Thermal transmittance coefficient of floor	Ufloor	W/m^2K	U(0.27-2.09)
Thermal transmittance coefficient of window	Uwindow	W/m^2K	U(1.68-3.80)
Solar energy transmittance of window glazing	Gwindow	_	U(0.30-0.85)
Surface shortwave reflectance	SW	_	U(0.20-0.50)
Ground surface shortwave reflectance	GSW	-	U(0.20-0.50)
Infiltration rate (air change rate)	Ninf	Volume/h	U(0.19-0.81)
Operation parameters			
Minimum set-point temperature	Tmin	°C	U(15.0-20.0)
Window openable ratio	WOR	-	U(0.00-0.35)
System parameter			
Heating system efficiency	Eta	-	U(0.80-0.95)
Geometry parameter			
Building height uncertainty	B_h	: = :	U(0.90-1.10)



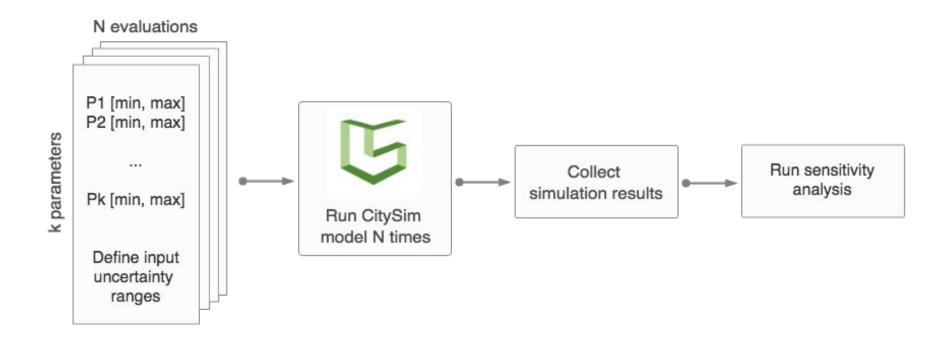
Sensitivity analysis

Table 2.4: Global sensitivity methods and characteristics. Adapted from Wei [2013]

Method	Characteristics	Subtype
Regression	 Fast and easy to interpret SRC and t-value are only suitable for linear models and can not be used in the presence of correlated factors SRRC and PCC can be used for non-linear but monotonic functions Applicable to observational study 	SRC SRRC PCC t-value step-wise adjust R square AIC
Screening	 Qualitative measures to rank factors, not suitable for uncertainty analysis Model free approach, suitable for large number of inputs and computationally intensive models No self-verification 	Morris
Variance	 Model free appraoch, suitable for complex non-linear and non-additive models Quantify all the variance of the output and consider interaction effects among variables Highest computational cost among all global methods FAST is not suitable for discrete distribution and only consider non-linear effects, but not interaction effects 	Sobol FAST
Meta-model	 Suitable for complex and computationally intensive models Quantify output variance of different inputs The accuracy dependent on the applied meta-model Applicable to observational study 	

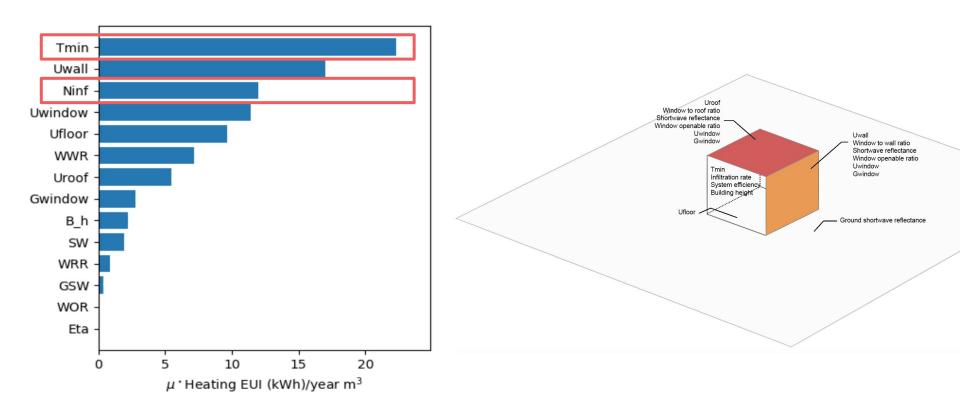
SRC: Standardized Regression Coefficients; SRRC: Standardized Rank Regression Coefficient; PCC: Partial Correlation Coefficients; AIC: Akaike Information Criterion; FAST: Fourier Amplitude Sensitivity Test; MARS: Multivariate Adaptive Regression Splines; ACOSSO: Adaptive Component Selection and Smoothing Operator; SVM: Support Vector Machine; GP: Gaussian Process; TGP: Treed Gaussian Process

Sensitivity analysis - Morris method



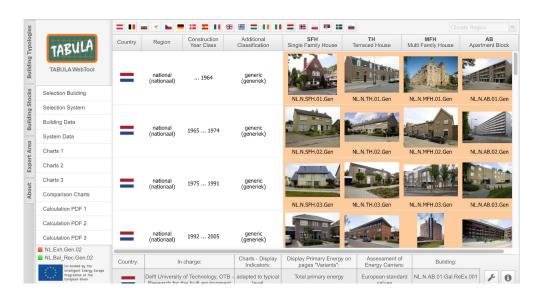
Sensitivity analysis - Morris method

- Building dimension: 13.5m x 13.5m x 13.5m
- Building height (volume) varies between 90% ~ 110% of the reference height to consider building height estimation uncertainty



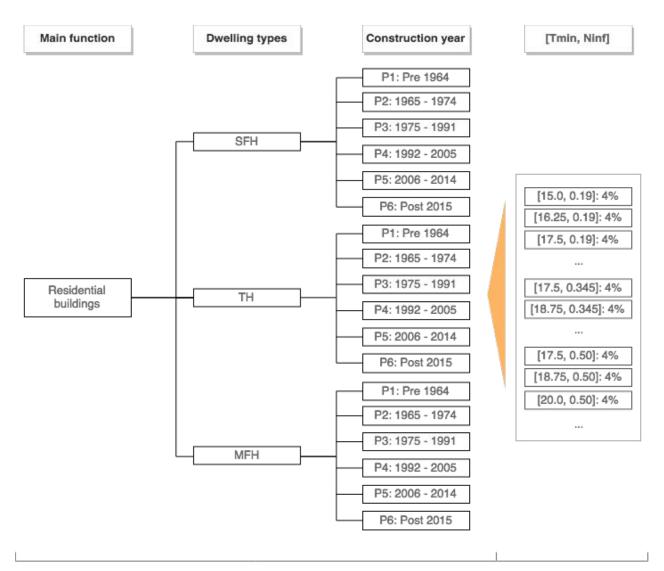
Archetype modeling - TABULA, National reference

- TABULA: 4 dwelling types, 6 construction periods: 24 archetypes
- National reference: 6 dwelling types, 6 construction periods: 36 archetypes





Archetype modeling

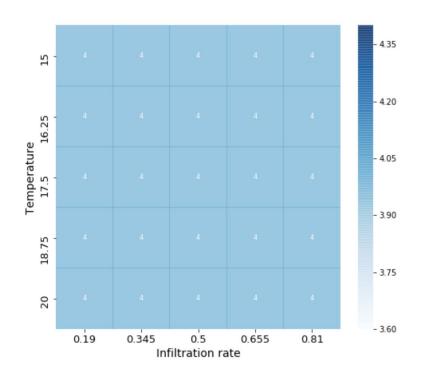


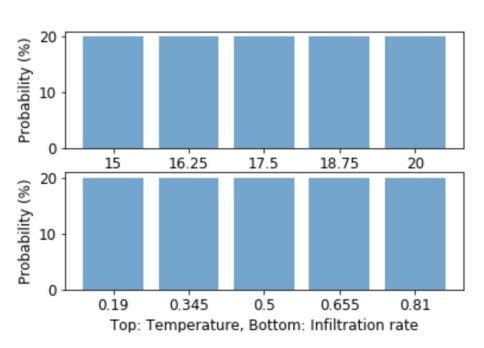
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Prior $P(\theta)$

- Assuming each variable (Tmin, Ninf) is independent to each other
- Each variable is divided into 5 sections
- Initialize the prior to have an equal probability distribution
- Given enough prior knowledge, non-uniform prior distribution is possible

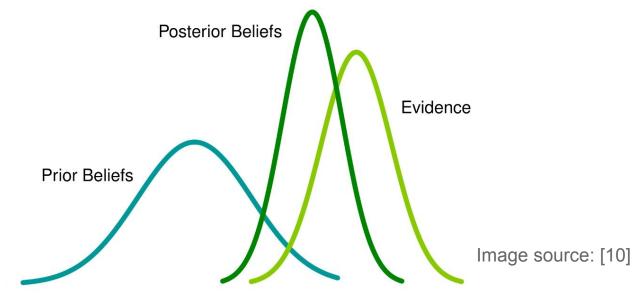




Bayesian inference and calibration

- Training data: 2010, 2011, 2012, 2013, 2014, 2015
- Validation data: 2016, 2017
- Calibration parameters: θ (Tmin, Ninf)
- Calibrating each PC6 parameters (θ_{pc6})

$$P(\boldsymbol{\theta}|g_{eui}) = \frac{P(g_{eui}|\boldsymbol{\theta})P(\boldsymbol{\theta})}{P(g_{eui})} \quad P(g_{eui}) = \int_{\boldsymbol{\theta}} P(g_{eui}|\boldsymbol{\theta}) \times P(\boldsymbol{\theta})d(\boldsymbol{\theta})$$



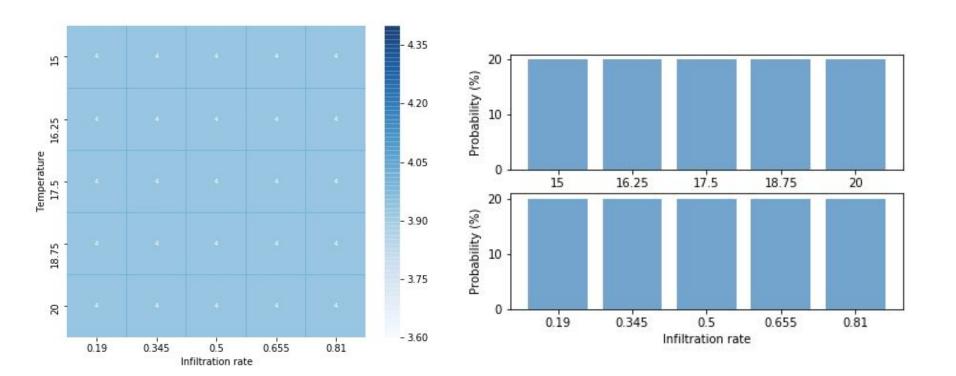
Likelihood $P(g_{eui}|\boldsymbol{\theta})$

- Apply Gaussian to evaluate model n likelihood P(d|θ_n)
- g_{eui} = postcode 6 annual gas EUI
- μ = simulation EUI with the θ_n input combination
- σ = standard deviation of the measured EUI distribution of the specific archetype group

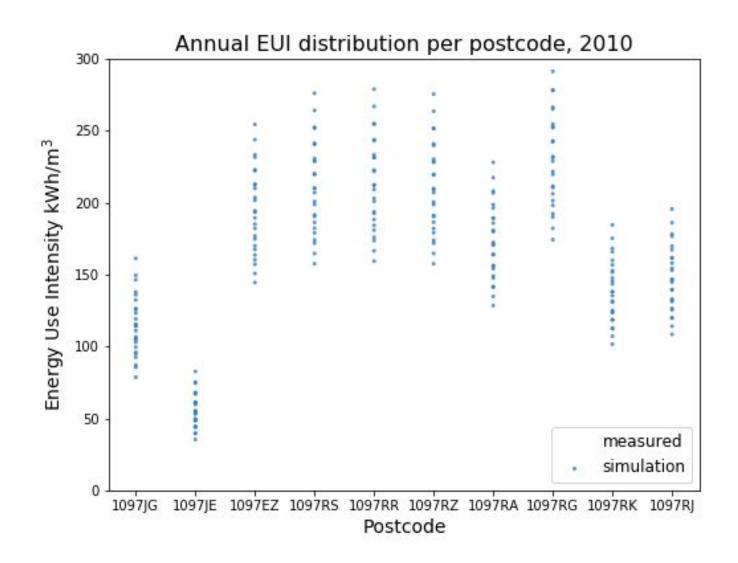
$$P(g_{eui}|\boldsymbol{\theta}) \approx P(g_{eui}; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp(-\frac{(g_{eui} - \mu)^2}{2\sigma^2})$$

Posterior $P(\boldsymbol{\theta}|g_{eui})$

- When measurements come in...
- Starts with the 1st year having an equal Prior distribution
- The Posterior of the N year becomes a Prior of the N+1 year

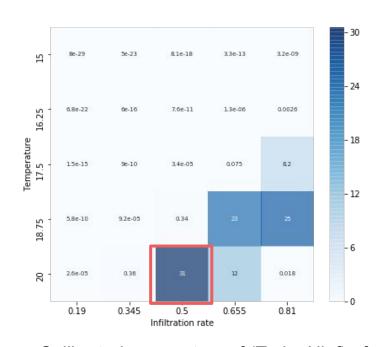


Bayesian calibration process



Validation

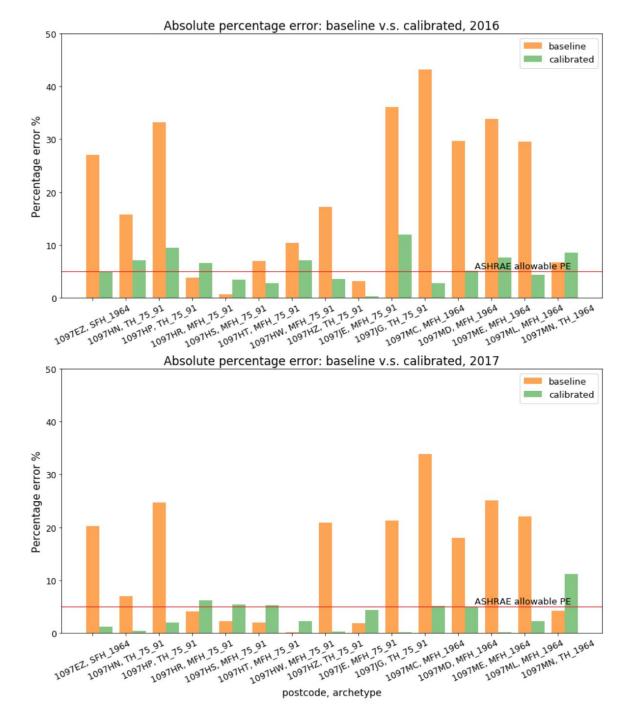
 Selecting optimal Posterior input combination of the final training year as calibrated inputs



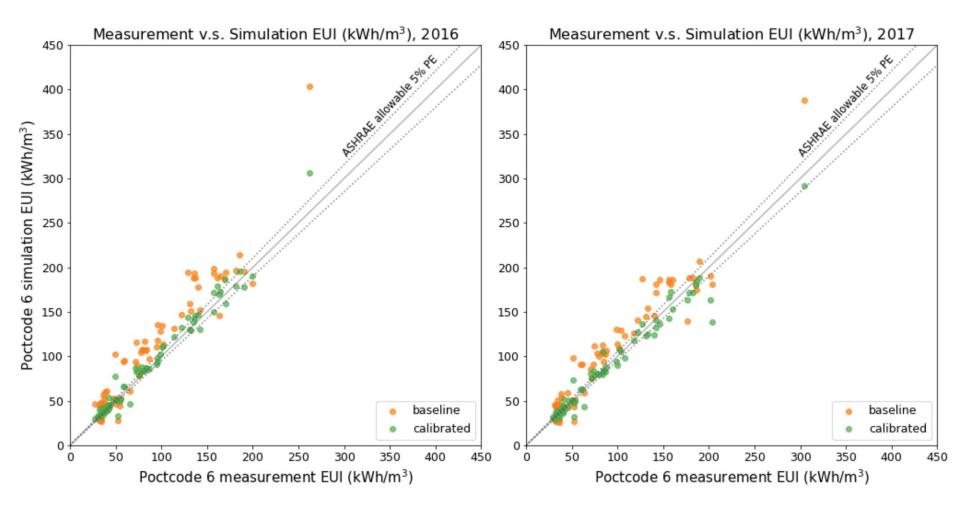
e.g. Calibrated parameters of (Tmin, Ninf) of postcode 6: 1094LW are (20, 0.5)

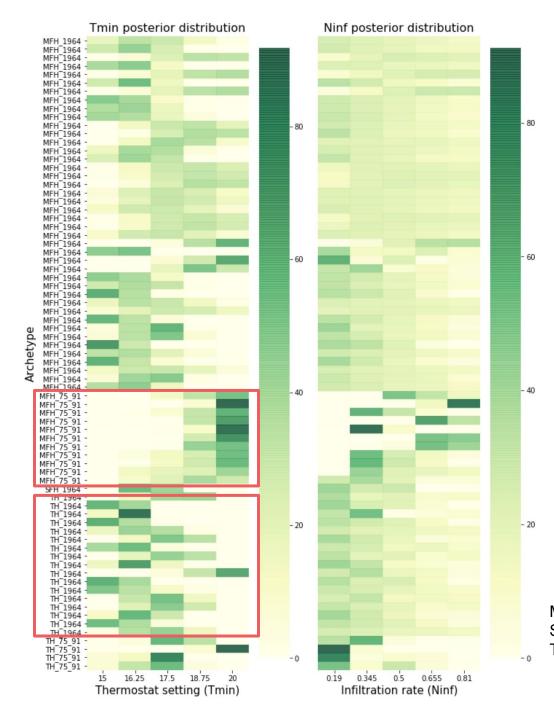
Absolute percentage error:

$$PE = \left| \frac{EUI_{metered} - EUI_{sim}}{EUI_{metered}} \right| \times 100\%$$



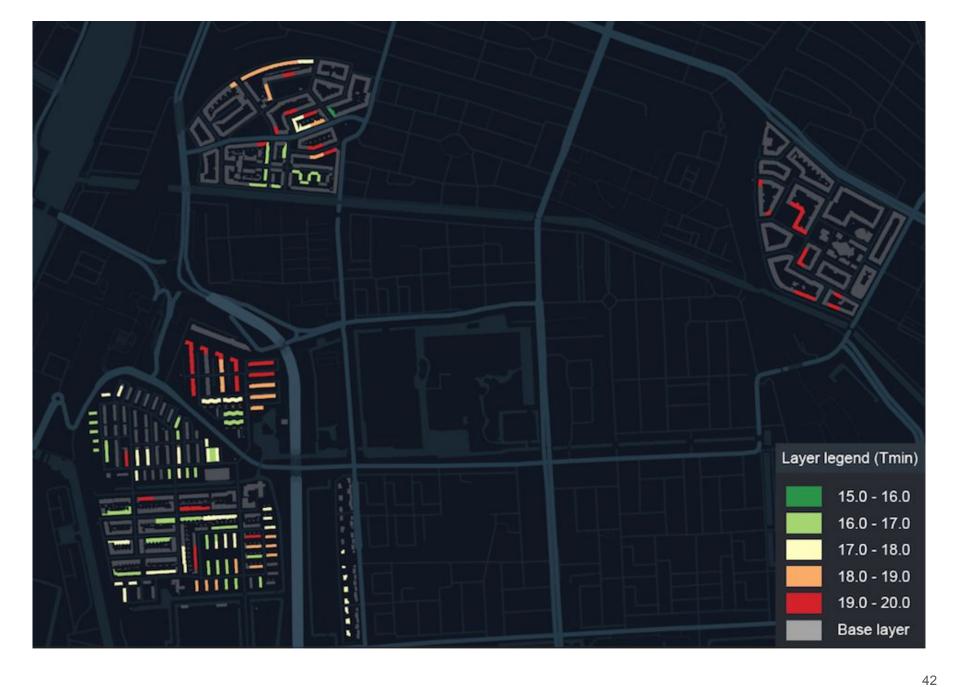
2016, 2017





MFH: Multi family house SFH: Single family house

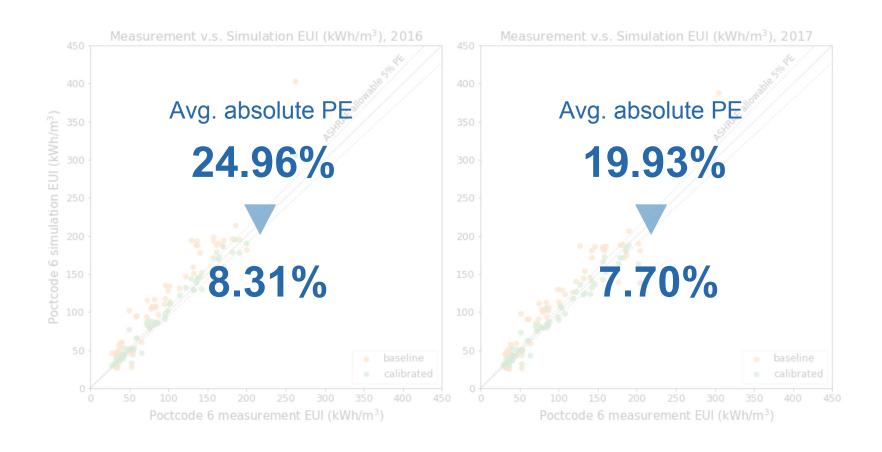
TH: Terrace house

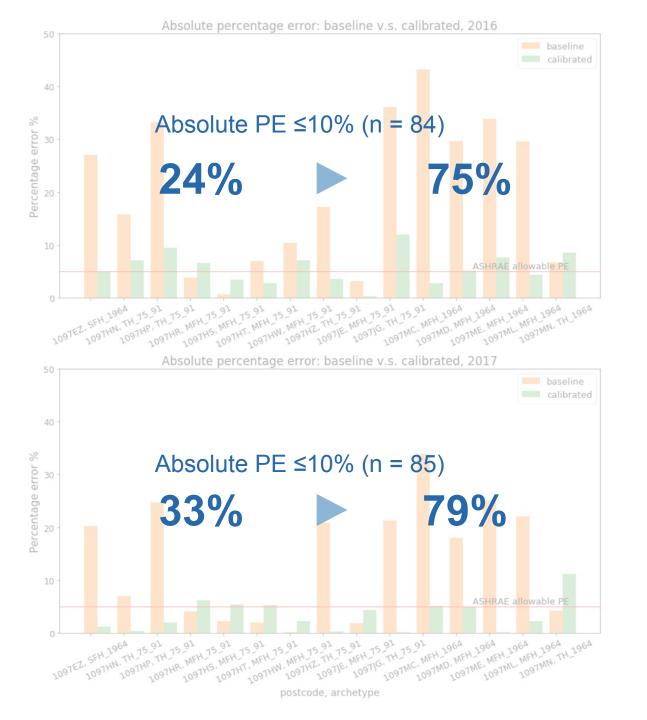






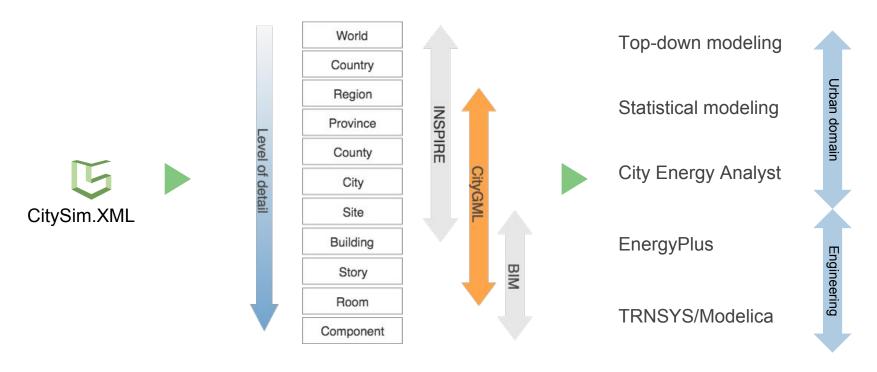
Discussion and conclusion





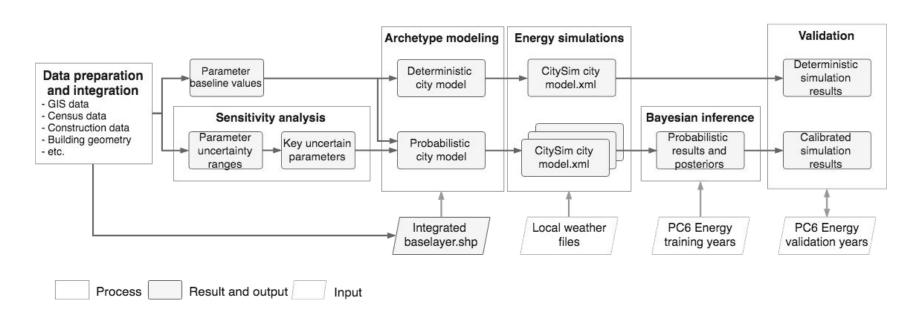
Discussion and conclusion

- Data preparation
 - Preparing and harmonizing data is time-consuming and challenging.
 An appropriate data model such as CityGML might alleviate this process and facilitate data interoperability



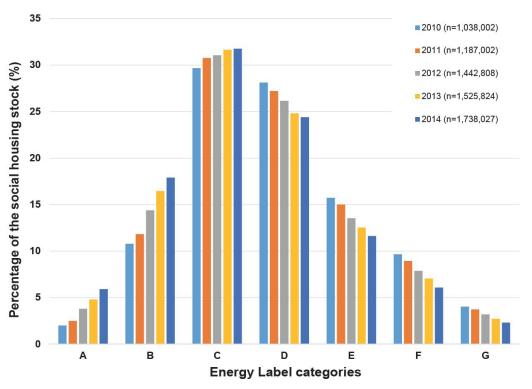
Discussion and conclusion

- UBEM in general
 - Calibrating with higher spatial-temporal resolution energy data might help to reduce more parameter uncertainties in UBEM.
 - Following the same methodology, developing the UBEM for other cities based on same or different simulation engines is possible.



UBEM in practice

"Base on the renovation rates achieved since 2010, attaining the short term goals of achieving an average energy label B in the non-profit Dutch housing stock by the end of 2020 is not probable..." (Filippidou, 2018)



Energy label distribution in the non-profit housing stock 2010-2014 (Filippidou, 2018)



Reference

- [1]: https://www.npr.org/sections/goatsandsoda/2016/12/17/503994463/video-time-lapse-google-maps-show-how-the-world-is-changing?t=1540906680992 [October, 2018]
- [2]: Department of Economic United Nations and Population Department Social Affairs. *World Urbanization Prospects*, volume 12. 2014
- [3]: https://www.youtube.com/watch?v=OtY8DpA XNE [October, 2018]
- [4]: International Energy Agency. Transition to Sustainable Buildings Strategies and opportunities to 2050. 2013.
- [5]:|https://www.slideshare.net/ClimateXMIT/urban-scale-energy-simulation-modeling-current-and-future-building-demands-carlos-cerezo-davila [September, 2018]
- [6]: Thermostat setting:

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- [7]: U-value: https://www.centrawindows.com/blog/what-is-uvalue-part1 [October, 2018]
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