Urban Building Energy Models

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TOPICAL REVIEW

Urban building energy models: how can we improve the treatment of uncertainty for energy policy decision-making?

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Abstract

Urban Building Energy Models (UBEMs) are emerging as a powerful tool for cities and regions seeking to make decisions on the best pathways for increasing the energy efficiency of their buildings. As model results are used to inform critical policy decisions, it is essential to understand and communicate the limits of inference of model results and how sensitive they are to changes in inputs. In the absence of standard datasets and protocols for model validation, Uncertainty Analysis and Sensitivity Analysis (UASA) procedures offer vital insights. However, there is no consensus on how UASA should be applied to bottom-up building physics-based UBEMs, nor on how different use cases might influence the choice of UASA approach. This study uses a systematic review of the literature (2009–2023) to explore the procedures which are applied and assess their appropriateness. We find a need for a more holistic view of uncertainty to be taken, and present a decision framework for selecting the most appropriate form of quantitative sensitivity analysis, based on model form, data provenance and use case. We also propose a number of approaches to improve the application of sensitivity analysis in UBEM studies, including the importance of undertaking a complementary assessment of information quality.

1. Introduction

Global greenhouse gas (GHG) emissions from buildings were in 2019 at 12 $GtCO_{2\text{-eq}}$, equivalent to 21% of global GHG emissions that year. 57% of this total were indirect emissions from offsite generation of electricity and heat, 24% were direct emissions produced onsite and 18% were embodied emissions from the use of cement and steel (Cabeza *et al* 2022). In light of the climate emergency, there is an urgent need to transition cities to more sustainable environments, e.g. by improving building energy efficiency. As Hong *et al* (2020) highlight: urban energy analysis is a complex, multi-scale, multi-sector challenge which demands a new breed of tools to support the rapid pace of decision-making. Urban Building Energy Models (UBEMs) are numerical simulations of the performance of groups of buildings, usually geographically co-located. UBEMs aim to assess the aggregated dynamics of the group of buildings and, to differing extents, to take account of the effects each building has on its surroundings (Langevin *et al* 2020). These models have a wide range of applications, including:

- Prioritisation and optimisation (size and scale) of retrofits to address inefficient and carbon-intensive building types (for example Liddiard *et al* 2021).
- Evaluating the potential for renewables and demand-side response strategies (Aduda *et al* 2016).

- Assessment of policy impacts on specific communities, an important consideration in addressing fuel poverty (Bienvenido-Huertas *et al* 2021) and avoiding unintended consequences.
- Assessment of the impacts of urban morphology on energy consumption of new developments (Godoy-Shimizu *et al* 2021).
- Modelling of indoor and outdoor air pollution (Schwartz *et al* 2021)
- Parametric design or optimisation of urban morphology (Wang *et al* 2021)

The range of applications continues to expand as UBEMs are increasingly coupled with other models, for example in urban metabolism and life cycle analysis as envisaged by González-García *et al* (2021) or integrated with digital twins of infrastructure systems and networks (Gürdür Broo *et al* 2021). Langevin *et al* (2020) highlight the increasing complexity of the field and propose a new taxonomy of models. The focus of this article is on bottom-up building physics-based models.

As an emerging field, existing reviews of UBEMs have focused on defining the field and understanding the tools used, for example Ferrando *et al* (2020), who provide a detailed analysis of a selection of models. Other reviews have focussed on how UBEMs account for specific inputs, for example Dabirian *et al*'s (2022) review of approaches to modelling occupant presence at the urban scale. However, although the need to account for uncertainties in UBEMs in the interests of transparency was highlighted by Kavcic (2010) over a decade ago, the topic has received only limited attention in the literature as we will show in this contribution.

Although standard methods have existed for some time for assessing the outputs of individual Building Energy Models (BEMs) based on inter-model comparison (Judkoff and Neymark 1995), no such standard exists for models of multiple buildings. While work is ongoing to develop equivalent methods for district-scale models (Johra *et al* 2022), methods for urban scale models remain to be developed. The scale of this task should not be under estimated since it presents two important challenges: Firstly, establishment of a validation dataset requires either overcoming the privacy challenges inherent in collecting highly granular information on real buildings and their energy consumption or the creation of an agreed test data set, the specification of which requires careful design. Secondly, development of a set of agreed tests requires the co-operation of research teams across many countries with no single source of funding.

The scarcity and lack of accessibility of detailed and comprehensive historical energy consumption data means that where validation has been attempted of a UBEM, it is generally limited to comparison with aggregated annual consumption. Davila, Carlos (2017) reported errors in the range 1%–19% for aggregate annual energy consumption but up to 99% for individual building energy consumption. The increasing range of applications of UBEMs, many of which focus on highly granular outputs, (e.g. buildings to grid integration) means that this level of validation is far from sufficient and there is a pressing need for quality assurance of the outputs of these models. In the absence of validation data or established inter-model comparison procedures, Uncertainty Analysis (UA), which explores the distribution of possible output values for a model, and Sensitivity Analysis (SA), which examines the influence that individual model inputs have on the output (Saltelli *et al* 2019), are important tools. Both UA and SA are concerned with understanding the full range of model outputs.

Tian (2013) provides an in-depth review of Uncertainty Analysis and Sensitivity Analysis (UASA) in the context of individual building performance analysis, outlining several methods and their applicability to various problems. However, while BEMs are based on detailed data for the individual building case, incomplete data is the norm for UBEMs where a key part of the workflow involves addressing unstructured and incomplete data for individual buildings. UBEMs may also use data on stock turnover, renovation rates and population trends which are not present in BEMs. In addition, the relative sensitivity of individual building parameters within a stock will be affected by the distribution and combination of inputs, including how they interact with geometry and location.

Consequently, while UA and SA of individual BEMs give detailed insights for those specific cases, they do not capture the stock-level sensitivity. Naber *et al* (2017), reviewed 19 models from district to national scale. They highlighted the potential for sensitivity analysis to be used to focus data collection efforts on the most influential inputs but note that this is impeded by a lack of transparency which means that only selected uncertainties are reported. Lim and Zhai (2017) undertook a detailed review of the application of stochastic methods to bottom-up engineering models of building stocks and identified six key challenges, also establishing a framework that we follow in this paper: computational time, input data scarcity for representative buildings, incorporating occupant-related uncertainties, availability of energy data for calibration and validation, calibration processes and results and approaches to aggregating from individual buildings to stocks. A sampling review was undertaken by Fennell *et al* (2019) who concluded that UASA are not common practice in urban building energy modelling and made recommendations for the future of the field.

Although the above-mentioned studies provide valuable insights on varying key aspects of the use of UASA in BEMs, there is no consensus on how these methods can be applied to UBEMs, or to what extent they are applied. These last two studies are focused on a small number of works, and their findings require validation.

The aim of our study is to comprehensively map the current applications of UASA procedures to UBEMs, and ultimately interpret the findings in terms of utilisation for strategic decisions towards energy and climate targets. To this end, we use a systematic review methodology, set out in section 2. Section 3 presents the results of the study, including an analysis of the types and sources of uncertainty, descriptions of the UA and SA methods which are applied and a critical assessment of their appropriateness and the influence of model form. The discussion in section 4 focuses on the challenges that remain in applying UA and SA to UBEMs and how these could be addressed, to facilitate communication of the results for decision-making.

2. Methods

The review followed a systematic approach, based on the PRISMA method, (Page *et al* 2021) that consists of identification, screening, synthesis and presentation of the results, was conducted using the Scopus database to explore UASA approaches employed to date in UBEMs. Given the relatively recent emergence of UBEMs, the period of review was limited to publications from 2009 to 2023, and titles in English. The use of additional databases could result in retrieving quite a different number of studies (Cabeza *et al* 2020, Konno and Pullin 2020), a limitation that is considered when discussing the studies identified and their implications.

A title, keyword and abstract search was undertaken in the Scopus database for the following terms: (energy AND building AND model) AND (uncertainty OR sensitivity OR probabilistic OR stochastic) AND (city OR building stock). A variety of search terms were assessed, and results were screened to ensure that previously identified publications on the subject were found, prior to the selection of the final search string. Journal articles, conference papers and book chapters were included in the search. A total of 2168 publications were identified, and these records were subjected to a sequential screening process (Fennell 2024). Details of the screening process can be found in appendix.

3. Current approaches to treating uncertainty

3.1. Types of uncertainty

A range of different schemas have been developed to classify sources of uncertainty (Oberkampf *et al* 2000, Walker *et al* 2003, Booth *et al* 2012, Coakley *et al* 2014). In principle, a formal framework for uncertainty classification would facilitate systematic approaches to the identification and assessment of uncertainty. While there has been little consensus on the detail of classification or terminology (Refsgaard *et al* 2007), Langevin *et al* (2020) suggest that categorising the source of uncertainty according to the point in the modelling chain in which it occurs provides a high-level classification which fits well with a range of different schema. In this categorisation, the model is broadly defined as the mapping process between input and output and the different types of uncertainty are related to either inputs, model, or outputs:

- Input-related
  - Aleatory (or stochastic) uncertainty: Uncertainty due to inherent or natural variation of the system under investigation.
  - Epistemic uncertainty: Uncertainty resulting from imperfect knowledge; can be partially quantified and in principle reduced.
- Model-related
  - Model structural uncertainty: Epistemic uncertainty that arises from a lack of sufficient understanding of the system (past, present or future) that is the subject of the analysis, including the behaviour of the system and the interrelationships among its elements.
  - Model technical uncertainty: The uncertainty generated by software or hardware errors.
- Output-related
  - Model outcome uncertainty: The quantified uncertainty on the model simulation (so endogenous rather than exogenous as the other categories).

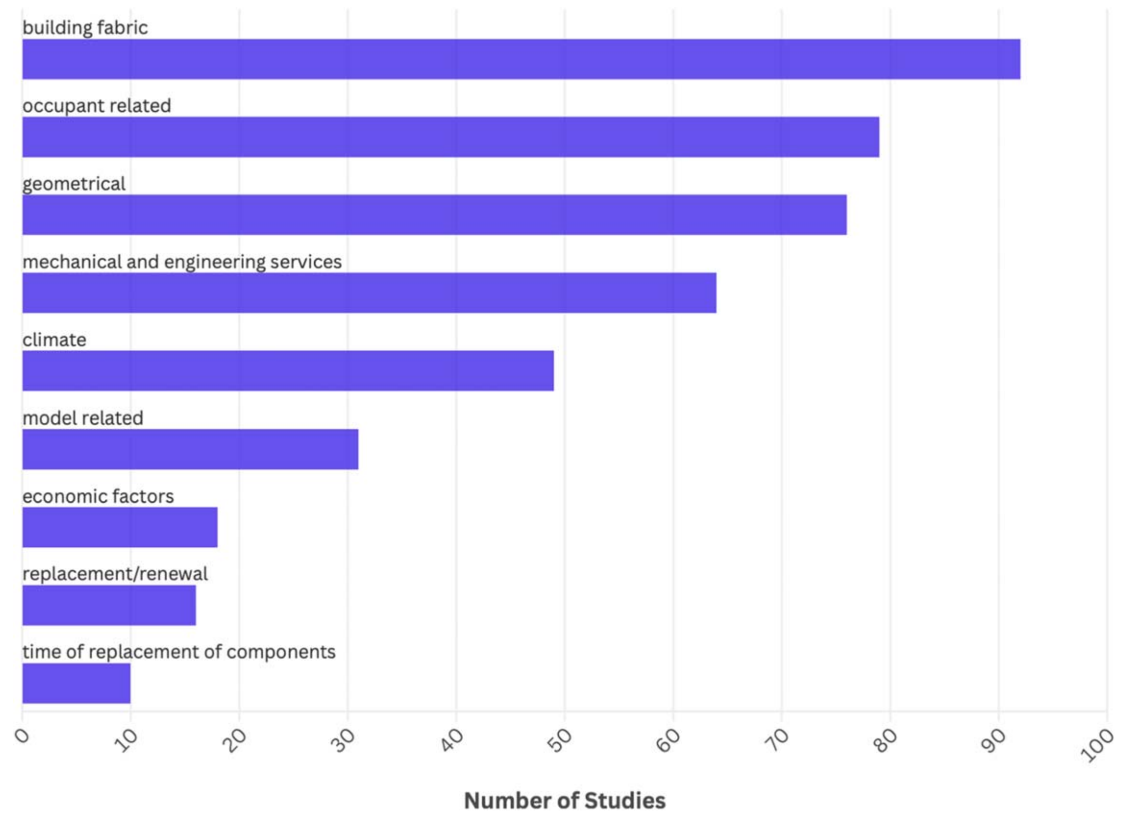

Figure 1. Number of studies exploring different sources of uncertainty.

- o Linguistic uncertainty: Uncertainty arising from language issues when communicating the findings; can be quantified and reduced.

3.2. Sources of uncertainty

The sources of uncertainty listed in each of the retained studies were recorded and categorised. In total, 9 broad sources of uncertainty were found as shown in figure 1: 8 different sources of input uncertainty, plus model technical uncertainty.

The dominant sources of input uncertainty are closely linked to the model use case:

- Prioritisation and optimisation of retrofits requires models which can represent the aggregate energy consumption of the stock. These models require an accurate geometric representation of the building stock and focus on uncertainties in thermophysical properties.
- Evaluating the potential for renewables and demand-side response strategies requires greater temporal resolution than prioritisation of retrofit measures, consequently, occupant related uncertainties are particularly important in these models. Some models may also consider uptake over time, introducing a significant additional source of uncertainty.
- Assessment of policy impacts on specific communities, these models have similar demands to those examining retrofit performance but may also require more detailed modelling of occupant behaviours and consideration of the impacts of future weather conditions.
- Assessment of the impacts of urban morphology on energy consumption of new developments, while the underlying geometry of the building stock is not treated as uncertain in models which focus on the existing stock, geometry is a source of uncertainty in these models.
- Modelling of indoor and outdoor air pollution requires high temporal resolution and introduces additional data requirements for pollutant sources.

The most studied sources of input uncertainty are building fabric, occupant-related, geometry and building services. In particular, 43% of the studies (n = 92) included building fabric parameters in the uncertainty analysis, i.e., the characteristics of the building envelope in terms of materials or thermal properties such as last renovation, infiltration rate, thermal transmittance, emissivity, solar absorption, heat capacity, thickness and density of fabric layers, solar heat gain coefficient of windows, shading and frame coefficient of windows. 37% of the studies (n = 79) considered occupant-related uncertainties, such as occupancy schedules and presence in different rooms, use of lighting and appliances, window operation and Heating Ventilation and Air Conditioning (HVAC) control preferences, metabolic rate, as well as household composition in terms of occupational status and age. These are studied in different units, e.g., per household, square metre or person, depending on how they are represented in the model. The model methodology and related data-simplification strategies had a significant impact on the uncertainties considered, for example while some studies treated parameters such as floor area or height as uncertain parameters, these were measured parameters in other studies. In total, uncertainty in terms of geometrical building parameters was quantified in 36% of the studies (n = 76). Examples of such parameters include the form ratio, window to wall ratio; gross and heated floor area, footprint, height, number of floors, and areas of external façade, roof and windows. Orientation was also included in this category. More recent studies show increasing interest in morphological study of districts exploring optimal arrangements for new districts or cities, typically in China, for example (Wang *et al* 2021).

30% of the studies (n = 64) investigated uncertainty parameters related to mechanical and engineering services, such as the number of installed HVAC systems, their efficiency, and ventilation supply rates.

23% of the studies (n = 49) assessed uncertainty under different regional and/or global climate forecasting models. Finally, the least-studied sources of uncertainty included replacement and renewal of the building stock, time of replacement of building components, economic factors and other model-related issues. More specifically, 8% of studies (n = 18) explore economic factors, for example, Mohammadi and Mousavi's investigation of the feasibility of net zero energy residential buildings in Iran (2022). 7% of the studies (n = 16) look at replacement and renewal of the building stock (Burillo *et al* 2019, Glotin *et al* 2019, Martins *et al* 2019, and another 5% of the studies (n = 10) focus on the time of replacement of building components (Nemeth and Lindauer 2012, Schiefelbein *et al* 2019).

Before 2019, only two studies were found to address model-related uncertainty: air infiltration modelling approaches (Happle *et al* 2017) and estimating uncertainties in a sub-model (Lu *et al* 2013). Comparison of different types of modelling approach or sub-model has been seen more frequently in the more recent literature with a further 29 cases, for example, Li and colleagues (2023) compare two approaches to demand side response - a stochastic model and Distributionally Robust Optimisation model using a generative adversarial network based on the Wasserstein distance; while Liu *et al* (2021) explore the importance of including models of shading effects. In total 14% (n = 31) of studies include model-related uncertainties. These studies all consider model technical uncertainties—exploring how choices in sub-model impact on results. However, in all the studies considered, the model systems were assumed to be fully understood. Although the underlying building physics models are well tested, lack of knowledge about factors such as the activity undertaken in a building (is it a shop, office, dwelling or does it contain several of these activities?) can have a significant effect on model inputs but is seldom considered.

3.2.1. Covariance of uncertain parameters

UBEM input parameters are expected to show significant correlation, for example, thermal transmittance coefficients of different elements of the building envelope are likely to be dependent on age of construction and refurbishment status meaning that there will be some correlation between values for different elements of the building envelope. De Jaeger *et al* (2021) explored the performance of different sampling methods for reconstructing a data set based on Flemish EPCs and showed an eight-fold decrease in the mean-maximum discrepancy of parameter distributions compared with treating the parameters as uncorrelated.

Ignoring the covariance structure of the input data will impact the results of sensitivity analysis by producing biased figures. However, only one of the studies reviewed explicitly addressed the correlation structure between uncertain parameters, from which we infer that in all other studies, uncertain parameters were treated as independent and uncorrelated. The exception is the study by Oliveira Panão, Penas (2022), who apply the Gaussian copula method based on the work by De Jaeger *et al* (2021). Their evaluation uses multi-correlation among seven main parameters: opaque-to-floor area ratio, window-to-floor area, u-values (of window, external wall, and roof), glazing and shading g-values with the co-variance structure derived from analysis of the energy performance certificate database. Li *et al* (2023) use ridge correlation to accommodate the anticipated collinearity between parameters in their study.

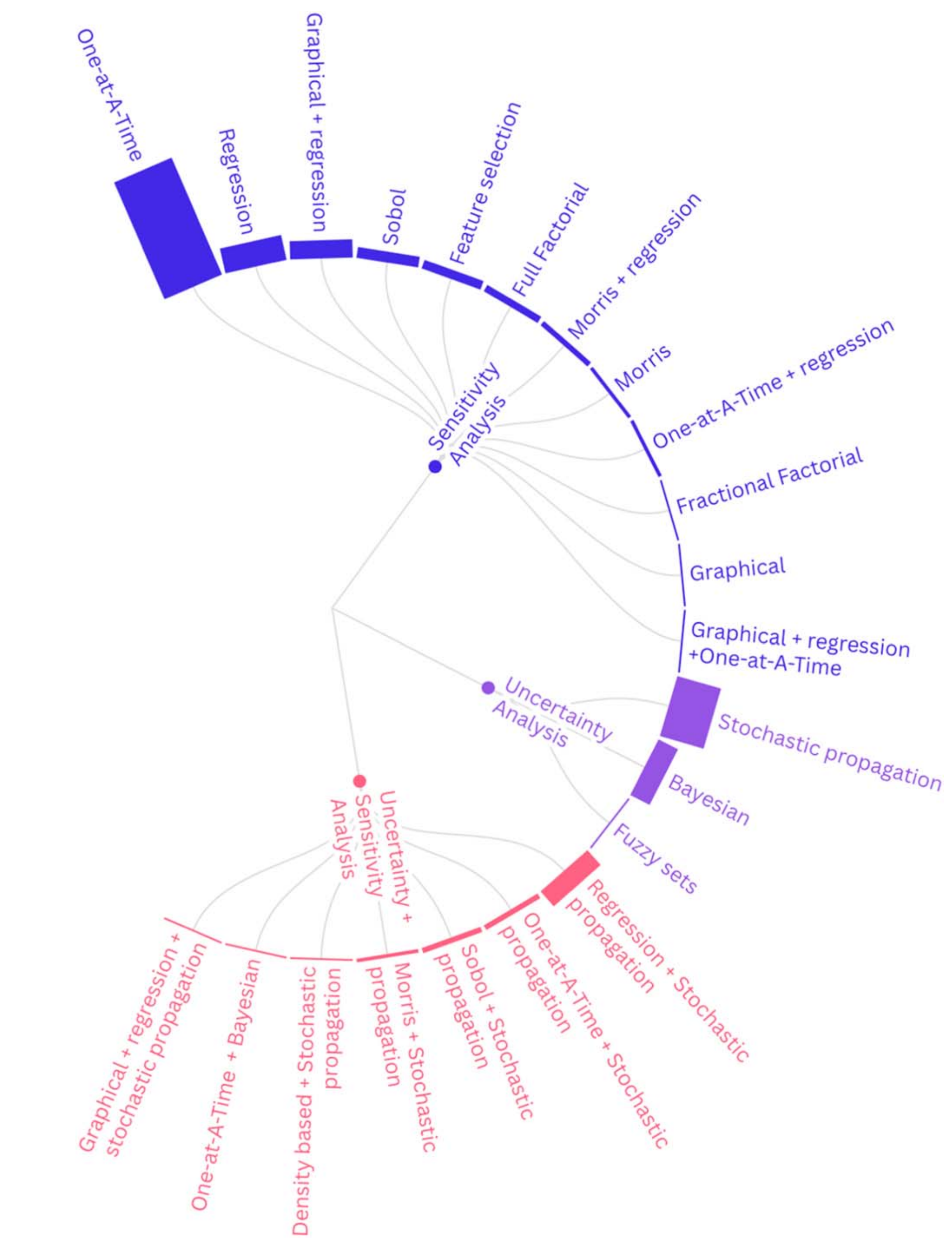

Figure 2. Methods found in the literature.

3.3. UA and SA methods in use in the literature

While Sensitivity and Uncertainty Analyses are distinct approaches with separate objectives as set out in section 1, the two are closely linked and SA is frequently undertaken to identify sensitive parameters for inclusion in a subsequent UA. The opposite approach can also be adopted: the level of uncertainty is firstly quantified in a UA, and then apportioned onto input parameters and assumptions via SA. During the data extraction phase, the methods used for UA and SA were recorded. The combinations found are presented graphically in figure 2.

3.4. Uncertainty analysis methods

214 articles were included in the retained records for data extraction. 64 (30%) of these articles included UA. SA were also conducted in a third of these studies. The complexity of UBEMs means that stochastic propagation methods are typically employed to investigate the uncertainties with one example (Lu *et al* 2013) using

arithmetic propagation methods to analyse the uncertainties and one example using fuzzy sets (Sharma *et al* 2018).

3.4.1. Monte Carlo methods

Monte Carlo methods dominate the literature. Monte Carlo processes typically involve random sampling from a defined input distribution before carrying out a deterministic calculation using the generated inputs and aggregating the results to establish a distribution of outputs. Monte Carlo methods were used to estimate the impact of uncertainties of input parameters on the uncertainties of outputs in 12% of the studies (n = 25). Jones *et al* (2015) conducted a Monte Carlo analysis to estimate the distributions of heating season infiltration and heat loss for apartment buildings in England. Kavgic *et al* (2015) used a simple Monte Carlo model to examine and calculate the uncertainties in predicting the energy consumption of the housing stock in Belgrade. Similarly, Lin *et al* (2017) followed the same approach to model 4000 typical layouts of residential dwellings in Taiwan. Benchmark values of EUI were calculated based on the simulation and uncertainty analysis.

Latin hypercube sampling (LHS) is a subset of Monte-Carlo methods using a stratified sampling approach. In this method, samples are drawn from areas of equal probability Helton and Davis (2002). This avoids the possibility of clustering of samples in one region of the input space which can occur with random sampling and as a result offers better coverage of the input space for a smaller number of samples, an important consideration for high dimensional models. Ascione *et al* (2016) used this method to generate the approximate probability distributions of different parameters including the geometry, building envelopes and HVAC system efficiencies and types of the building stock in Italy. Escandón *et al* (2019) followed the same approach to predict the thermal comfort for social housing multi-family buildings in southern Spain.

3.4.2. Monte Carlo markov chain (MCMC) processes

In contrast to Monte Carlo processes in which each draw is independent, in MCMC processes the next sample drawn is dependent on the current sample. This makes them more appropriate for creating time series of inputs, for example, for modelling occupant behaviour. An *et al* (2017) used Markov Chain to simulate the stochastic nature of occupant behaviours. The stochastic movement process of occupants is simulated using a large-scale residential survey in China with 1426 responses.

3.4.3. Bayesian inference

Bayesian inference improves the outcomes of the Monte Carlo and MCMC simulations by calculating a global probability distribution for all the relevant values, observing, and updating the values, and recalculating the conditional distribution of the remaining values given the observations (Brooks *et al* 2011). Choudhary (2012) applied Bayesian inference using Gibbs sampling to evaluate the influence of district features on energy consumption in non-residential buildings in Greater London. In this study, Bayesian inference is applied to define the prior estimates of the national Energy Use Intensity (EUI) per primary type of non-domestic building EUI is estimated for 11 categories of buildings. Heo *et al* (2012) and Zhao *et al* (2016) followed a similar approach to generate energy consumption data and derive energy-saving opportunities for office buildings in the UK and Chicago, respectively.

3.4.4. Bayesian networks

A Bayesian Network (BN) is a graphical model that consists of nodes and arrows showing causal relations between the nodes. BN explains probabilistic relationships among the variables of interest and, automatically overcomes the problems of missing data by indicating dependencies between variables. Sokol *et al* (2017) developed an urban building energy model considering incomplete information about the buildings. The authors used BN and Bayesian calibration approach to model six highly uncertain parameters of infiltration, thermostat set points (heating and cooling), occupant density, plug load and lighting power density, and the domestic hot water flow rate. Uniform distributions were assigned to characterise these parameters in the model. Dotzler *et al* (2018) report using a Bayesian Network to improve the accessibility of results for a retrofit planning tool for estate managers.

Evaluation of the different methods here.

3.5. Sensitivity analysis methods

Saltelli *et al* (2004) identify four distinct types of insight which are of value to UBEMs:

- Parameter ranking—identification of the parameter(s) which have the greatest effect on variance in the model output. Combined with knowledge of the confidence in the parameter ranges this enables the degree of confidence in model outputs to be assessed. Quantitative and semi-quantitative methods can be used.

- Parameter screening—identifying non-influential parameters allows them to be fixed, reducing the number of model evaluations required for uncertainty analysis in future work. Quantitative methods can be used.
- Variance reduction—if a model is to be used for decision-making it may be desirable to reduce the uncertainty in its outputs to a specified level by identifying parameters for which more data can be collected.
- Parameter mapping—SA can be used to identify combinations of parameters which result in extreme values, this can be useful for assessing resilience to extreme weather for example.

Although Saltelli *et al* (2004) highlight the importance of identifying the type of insight which is sought before choosing an SA method, this step is generally not discussed in the literature. In total, 137 articles in the final set (64%) included some form of sensitivity analysis. Sensitivity analyses were classified as either local (One-at-a-Time, OAT) analyses which consider the sensitivity of the model to perturbations of one parameter at a time away from its base-case value or global analyses (GSA) which consider variation across the whole input space of the model. 76 of the 137 (55%) included an OAT while 62 (45%) contained a global sensitivity analysis, two studies included both.

3.5.1. Local sensitivity analysis

OAT methods or differential sensitivity methods investigate local sensitivity about the base values. The number of simulations required is $1+2k$ where k is the number of uncertain parameters, meaning that the computational cost of the analysis is low. Five studies use OAT analysis as a preliminary step to identify influential parameters before undertaking further analysis. Cerezo Davila *et al* (2015, 2017) used OAT to identify influential parameters for inclusion in a Bayesian calibration technique for archetype parameters. Yamaguchi *et al* (2013) also used OAT to identify parameters for inclusion in a Bayesian calibration of a model for supermarket buildings' energy consumption in Hyogo prefecture, Japan. Kavgic *et al* (2015) used OAT analysis to investigate which segments of the Belgrade housing stock had the greatest impact on city-level consumption. Zheng *et al* (2017) used OAT to identify influential parameters for inclusion in an optimisation study of a Chinese industrial park. In seven studies, OAT was employed as part of a process of model testing and development, typically, proof of concept (Choudhary 2012, Marique and Reiter 2012, Arababadi *et al* 2015, Samuelson *et al* 2015, Happle *et al* 2017, Nouvel *et al* 2017, Müller *et al* 2019). 15 studies used OAT analysis to identify most influential parameters to guide policy development (Cheng and Steemers 2011, Nouvel *et al* 2013, Biere *et al* 2014, Zhao *et al* 2015, Dineen *et al* 2015, Osterbring *et al* 2016, Azar, Al Ansari 2017, Soufiane and Ewa 2017, Oregi *et al* 2018a, Oregi *et al* 2018b, Martins *et al* 2019, Popovski *et al* 2019, Rouleau *et al* 2019).

Two studies combined both OAT and GSA methods: Neves *et al* (2019) compared OAT, Morris and Monte Carlo methods for a sample of buildings in Sao Paulo, Brazil, their results highlight the inability of OAT methods to capture interactions between parameters, for example, although increasing window to wall ratio increased solar gains, it also resulted in increased opening areas which resulted in greater ventilation rates, when combined with increased shading which reduced solar gains, the net effect was a reduction in cooling demand. Arababadi *et al* (2015) compared the performance of OAT and stepwise regression methods and found similar results for both with independent and uncorrelated parameters.

It is clear from the broader literature that the principal failure of OAT analyses is the lack of coverage of the whole input space as demonstrated by Saltelli and Annoni (2010). This is a concern for Building Energy Models which typically result in nonlinear, multi-modal, discontinuous outputs (Nguyen and Reiter 2015). The limitations of OAT analysis for a UBEM were explored by Cheng and Steemers (2011) who demonstrated that the results were only valid locally. As a result, the sensitivity analysis was of limited predictive value since it did not apply to the full range of likely or valid values for each input parameter. This raises concerns about relying on the results of OAT for policy recommendations as applied in the large body of work identified here.

3.5.2. Global sensitivity analysis (GSA)

The key difference between GSA methods and OAT methods is that other parameters are not held constant while the influence of the parameter of interest is assessed. Consequently, these methods can accommodate non-linear and sometimes non-monotonic model outputs. The number of model evaluations required to allow the effects of variation of a single parameter to be assessed is much higher and a key challenge with these methods is access to sufficient computational power to undertake analysis of more than a handful of parameters.

3.5.2.1. Graphical methods

Scatterplots of model outputs are plotted against model inputs allow relationships between inputs and outputs to be visualised. Although graphical methods are not a quantitative method, if all inputs are varied simultaneously they meet the definition of a global sensitivity analysis method. However, the use of scatterplots with more than a handful of variables quickly becomes unviable. Lu *et al* (2009) utilised scatter plots to explore the relationship between different temperature series and heating and cooling loads for cities in the USA and Canada. Jones *et al* (2015) used a similar approach to examine the relationship between 8 inputs and outputs for the DOMVENT model for the UK housing stock.

3.5.2.2. Regression methods

Regression methods use a sampling approach such as LHS to generate a large number of sets of inputs which are then simulated, and regression analysis is then used to uncover the relationship between inputs and outputs. Regression is often combined with graphical methods. However, linear regression analysis is only able to explain linear relationships between inputs and outputs. Jones *et al* (2015) used both linear regression and rank regression which does not require a linear model, while Tian and Choudhary (2011, 2012) used SRC and Multi-Adaptive Regression Splines (MARS) which also does not assume a linear model. Both groups found very similar orders of sensitivity for the parameters in both approaches.

3.5.2.3. Morris method

The Morris method (Morris 1991) uses a design of experiments approach to maximise the coverage of the input space at as small a computational cost as possible. The approach is very similar to an OAT design which is repeated at different points in the input space and averages the results from each point. Campolongo *et al* (2007) introduced an improvement to the calculation of the mean of the elementary effects in the Morris method by using the absolute value of the output differences to ensure that positive and negative variations do not cancel each other out as in the original Morris Method. Campolongo *et al* also introduced a revised sampling strategy based on radial sampling about the original point; this approach (Elementary Effects—Radial or EER) offers better coverage of the input space. The number of model evaluations required depends on the desired number of estimates for each parameter; between 10 and 20 estimates are common, and each estimate requires k+1 model evaluations (one for the starting point and one for each of the k variable parameters). The Morris method has been commonly applied as a first step to reduce the number of input parameters for uncertainty analysis or global sensitivity analysis. For example, Mastrucci *et al* (2017) used the Morris Method (elementary effects) to assess the most influential parameters before UA and development of a simplified model for the housing stock of Esch-sur-Alzette in Luxembourg.

3.5.2.4. Sobol method

Variance-based analysis or Sobol's method (Sobol 2001) is based on decomposing the variance in the model output into the fractions which can be attributed to the different input parameters. First-order effects are those attributable to variance in each input on its own. Higher-order effects are attributable to interactions between inputs. Total effects encompass first-order effects and all the interaction terms. Sobol is relatively computationally expensive, requiring N(k+2) evaluations for a model with k uncertain parameters where N may be in the hundreds or thousands. Mastrucci *et al* (2017) applied the Sobol method to identify key parameters following an initial step in which the Morris method was used to screen out insensitive parameters. Multiple Linear Regression was then used to generate simplified models based on the key parameters identified in the Sobol analysis. The simplified models were then combined to create a model of the whole stock. Saltelli *et al* (2010) highlighted that Campolongo *et al* (2007) extension of the Morris Method resulted in quantitative indices of a similar form to Sobol and proposed an alternative implementation of the Sobol method based on this approach. Stone *et al* (2014) used this implementation to explore the most sensitive parameters in a model of the English Housing Stock. This is the method implemented in the SALib Python library (Herman and Usher 2017) used by Mosteiro-Romero *et al* (2017) to identify the most influential parameters in a model of 284 buildings in Zurich using the City Energy Analyst model (Fonseca *et al* 2016). Along with OAT and Morris Method, these methods can be classed as Design of Experiments approaches since they depend on careful structuring of inputs to increase the computational efficiency of the method. Although the efficiency of these designs is very important, it comes with the downside that only the base case(s) is(are) independently selected and therefore can be reused, for example in an uncertainty analysis.

3.5.2.5. Feature Selection

Random Forests (Breiman 2001) are a non-parametric statistical method dealing with classification and regression problems. The method resorts to the construction of a multitude of decision trees at training time. The variable importance measure describes how important a feature is for the predictive performance of the model and is thus a form of SA. The resulting indices do not assume independence of the underlying variables (Antoniadis *et al* 2021). This leads to sensitivity indices whether the data are dependent or not since RF do not assume any kind of independence. Jin *et al* (2022) used feature importance analysis to select a reduced set of labels for an urban data set for New York City. Zhang *et al* (2021) we compared the feature importance scores from various machine-learning algorithms finding that decision tree scores were closest to the expected results.

3.5.2.6. Other global sensitivity analysis methods
Froemelt and Hellweg (2017) took a different approach to the design of experiments methods, using Borgonovo's moment independent δ which can be used to derive global sensitivity indices from given data. Moment-independent methods define sensitivity measures by considering the entire output distribution rather than focussing on just one moment, variance. If model outputs are normally distributed, then the parameter influencing variance most likely will also be the one which influences the whole distribution most. If the output distribution exhibits significant skewness or kurtosis this will not necessarily be the case (Razavi *et al* 2020). Martins *et al* (2019) used a fractional factorial analysis to understand the sensitivity of multi-scale urban design parameters for three districts in Toulouse, France. In a factorial design, each input factor (parameter) is sampled at predefined intervals from its probability distribution. A full factorial design includes all combinations of the input samples, a fractional design, and a set proportion of the input samples, which was 50% in Martins *et al* (2019) case. The underlying search grid is relatively coarse (8 samples per factor) so this approach results in a relatively small number of model evaluations, spread across the input space.

The spatial component of UBEM input data is typically only considered as part of the geometric model which might be used to calculate shading etc. However, as Nyangon and Byrne (2021) highlight, spatial sensitivity may be an important factor in explaining the relationships between different building characteristics and merits further exploration.

3.5.2.7. Choosing the most appropriate SA method
The choice of SA methods in the studies assessed here has often been governed by a combination of computational burden and ease of application (typically through the application of open-source packages such as SALib in python). However, more fundamental factors should also drive the choice of method:

- Form of the model—OAT and linear regression methods assume linearity which is unlikely to be the case for bottom-up physics-based models.
- The form of insight sought—not all SA methods can provide all four types of insight or setting identified by Saltelli *et al* (2004). In particular, methods which do not account for interactions between parameters cannot be used for parameter mapping and methods which do not provide a single measure of parameter influence cannot be used for variance reduction.
- Underlying sampling approach - methods which use structured Design-of-Experiments approaches to create input samples do not result in an input sample which can be readily extended by adding additional samples, nor can the full set of samples be reused, for example for an uncertainty analysis. This also means that they cannot be used with given data which may have been the result of previous experiments.

Figure 3 below shows a proposed decision structure to assist in choosing the most appropriate method.

4. Recommendations for improving UASA practices

4.1. Dealing with computational burden
While the number of studies employing global sensitivity analysis approaches is increasing and fewer of the more recent studies are using OAT methods, the inclusion of relatively small numbers of variable parameters suggests that one of the key challenges highlighted by Lim and Zhai (2017) continues to impede robust analysis - the curse of dimensionality is intrinsically linked to the issue of computational burden. High performance computing and cloud computing offer access to much greater computational power. However, these come with a financial and energy cost and may require researchers to develop new skills to work with such resources. Reductions in computation time can also be achieved through the use of meta-models for sensitivity analysis, a well-established approach in the literature (Sudret 2008). However, although these solutions have been available for some time (Sudret 2008) they do not yet appear to have resulted in significantly greater uptake of methods. The popularity of the open source SA-Lib python toolbox and the R package 'sensitivity', as a resource for SA might provide a template for making meta-modelling approaches more accessible to the research community.

Related work in the field of Life Cycle Analysis by Lo Piano and Benini (2021) proposes a possible solution by breaking the assumption that all variable parameters are uncorrelated, allowing the dimensionality of the problem to be reduced. They highlight the techniques developed by Kucherenko *et al* (2012) and Iooss, Prieur (2019) for dealing with correlated variables. Using these methods requires an assessment of the correlation

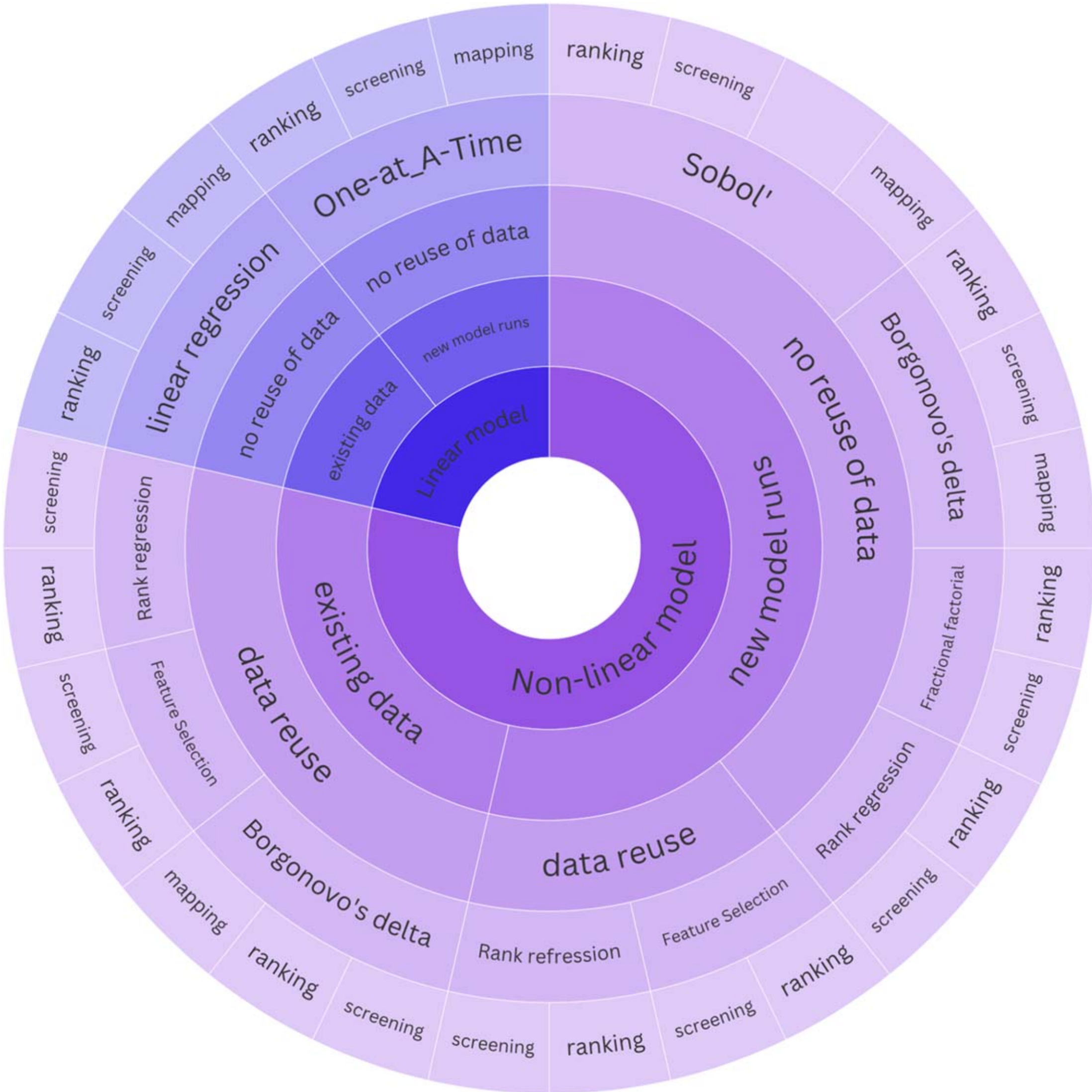

Figure 3. Decision framework for SA method selection.

structure of variable parameters. While this additional information requirement is perhaps a key reason why the studies reported here have treated variable parameters as completely independent, this is a significant shortcoming in the reported studies.

4.2. Understanding the approach to aggregation

The challenge of conducting a sensitivity analysis of a whole building stock is closely linked to how that stock is modelled, in particular, the degree to which individual units in the stock are modelled independently. The use of data archetypes is a common approach to this; individual buildings are assigned to a class or archetype typically based on use and age/construction period with a common set of inputs for each archetype. Archetypes can be complete (containing all details for individuals within the set) in which case they are simply scaled according to their representation in the stock or partial, in which case individuals are simulated individually but with common values for used particular inputs (e.g., construction materials and properties based on building age). While models vary in the degree of independence, all stock models contain some degree of data aggregation to render them computationally feasible. In archetype-based models, this is most apparent (Mauro *et al* 2015, for example), where all examples of a particular class are assumed to be represented by a single unique value for each parameter. In partial archetype approaches some input parameters for each example are derived from the archetype (typically building fabric) and some (typically geometric parameters) are specified independently. In these models, parameters are often assumed to vary independently (Ghiassi, Tahmasebi, and Mahdavi 2017, for example). Booth *et al* (2012) propose an alternative approach in which the heterogeneity of the members of a class is explicitly considered. None of the studies reviewed in this work discussed the impact of this aspect of model structure on uncertainty.

4.3. Applying sensitivity analysis to the whole model

When archetypes are used, SA may be applied to the archetype itself (SA of an individual reference building) or to the whole model output. Detailed analysis of the included studies revealed many cases in which SA was applied at the archetype level i.e., for individual buildings, rather than at the whole stock model level. Application at the archetype level is analogous to the SA of an individual building and strictly does not meet the definition for inclusion in this study. More recent approaches to archetype models which establish data-driven archetypes which may be implemented stochastically (for example, Borges *et al* 2022) represent an attempt to bridge this gap. Of the 62 studies which included GSA methods, 43 applied it at the model output level, mostly in machine learning based modelling approaches reflecting the challenge of computational time highlighted by Lim and Zhai (2017). This result is particularly striking taken in tandem with the findings discussed earlier about the unsuitability of OAT methods for these types of Models: of 137 studies which applied sensitivity analysis to a large-scale UBEMs, only 43 (31%) could be classed as robust, global analysis covering the full input space. Of these 43 studies, 27 involve less computationally intensive methods, either machine learning, or reduced order methods (Quasi-steady state: for example, (Froemelt and Hellweg 2017), for example, Resistor-Capacitor: (Martins *et al* 2019), with 11 applying GSA to various types of dynamic simulations (Protopapadaki and Saelens 2017, Neves *et al* 2019, Xu *et al* 2020, Fennell *et al* 2021).

4.4. Incorporating qualitative assessment alongside quantitative

Notably, the studies reviewed in this work take a predominantly quantitative approach to SA of a relatively small number of parameters, in many cases selected for convenience rather than because of the degree of influence they might be expected to have on model outputs. This is often driven by the data availability challenge identified by Lim and Zhai (2017). Consequently, there is a strong likelihood that the results of the SA will be of limited use unless they include a broader assessment of uncertainty. The approach to the management and communication of uncertainty proposed by Funtowicz and Ravetz (1990) and implemented by Pye *et al* (2018) provides a structured framework for assessing the confidence in inputs which can be combined with the influence of the parameter on the model output in diagnostic diagrams to assess of the importance of the stochastic and epistemic uncertainty in the parameter values. For local and national decision-makers seeking vital insights from UBEMs for urgently needed decarbonisation policies, the lack of uncertainty and sensitivity analysis is a key risk. The parameters identified as sources of uncertainty in most of the studies (figure 1) are related to key policy interventions or structural dynamics of the transformation of the urban built environment. For instance, *building fabric* and *geometry* determine energy use through their thermal properties and form factor, and are typically a key target of building energy codes; *occupant related* issues relate to behaviour, comfort, and interventions for active and passive management and operation that have since long been the object of energy saving programs, and, more recently, the core of so-called low demand scenarios; assumptions on *replacement and renewal of components* are essential to determine building renovations rates, when renovating existing buildings to low energy and carbon standards is the action with most climate mitigation potential in developed countries. Understanding the relationship between policy interventions and most significant model drivers, as the above exemplified, could contribute to the identification of trade-offs, prioritisation and targeting of local and national building stock decarbonisation policies that accelerate the achievement of climate, social and economic goals.

4.5. Communicating uncertainty

Effective communication of uncertainty is critical if it is to be embedded within decision-making. However, for non-experts, traditional approaches to communicating uncertainty such as error bars and violin plots are difficult to interpret (Wilke 2019). An alternative approach, proposed by Hullman *et al* (2015) is to use dynamic representations of possible outcomes, termed Hypothetical Outcome Plots. The authors report higher levels of accuracy in interpreting results for non-expert users. While this approach has not previously been applied to UBEM outputs, previous work by Ehlschlaeger *et al* (1997) has suggested that animation is helpful in communicating spatial uncertainty.

5. Conclusions

In this study, a comprehensive and systematic review was undertaken of UBEMs to examine the application of uncertainty and sensitivity analysis methods. From a total set of 2,168 records identified with a targeted search query in Scopus, 259 UBEM studies were identified after full-text screening. Although all contained some discussion of Uncertainty or Sensitivity Analysis, formal analysis was only included in 179, with the remainder either including a general discussion or scenario analysis.

Detailed analysis of the full-text records highlighted a focus on input uncertainties rather than model uncertainties. Building fabric-related uncertainties were considered in almost all studies with a slightly smaller number considering occupant-related factors. 85% (n = 179) of the studies considered 3 or fewer sources of uncertainty 54% (n = 115) of the studies performed a standalone Sensitivity Analysis, 10% (n = 22) undertook Sensitivity Analysis as a precursor to an Uncertainty Analysis while 20% (n = 42) undertook a standalone Uncertainty Analysis, sometimes as part of a Bayesian calibration exercise. One-variable-at-a-time sensitivity analysis (OAT) remains the most common form of Sensitivity Analysis despite clear warnings in the literature about its inadequacies. Regression methods are the most popular form of GSA method. Although uptake of GSA methods seems to be increasing over time, closer review revealed this to be driven in large part by the application of GSA methods to individual building archetypes rather than model outputs at stock level suggesting that computational limitations remain a considerable barrier. This finding also highlights the need for explicit consideration of the implied correlation structures within a stock model. Even though research within the GSA field generally has increasingly turned to the challenge of dealing with correlated inputs, only one study was found using a moment-independent method capable of dealing with correlations between inputs. The use of methods for dealing with correlated inputs would also reduce the dimensionality of the problem and the computational burden.

For local and national decision-makers seeking vital insights from UBEMs for urgently needed policies to achieve energy and climate targets, the lack of UASA presents a risk for misunderstanding and under-exploitation of the modelling results. We recommend that Uncertainty and Sensitivity Analyses are integrated from the very conceptualisation of the experimental design in UBEMs and within the reporting process as a cornerstone of model quality assurance. Quantitative model analysis should be undertaken in tandem with an assessment of information pedigree to allow key knowledge gaps and uncertainties to be highlighted and their impact on any policy recommendations carefully considered. Understanding the most significant drivers of model uncertainty will enable the identification of trade-offs, prioritisation and targeting of local and national building stock decarbonisation policies.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://public.tableau.com/views/UASAdashboard/Dashboard1?:language=en-GB&:sid=&:redirect=auth&:display_count=n&:origin=viz_share_link.

Appendix. Screening process

The screening process was undertaken manually using the EPPI reviewer tool (Brunton *et al* 2010) to assign records between the reviewing team and manage the moderation process. A sequential screening process was undertaken as illustrated in figure A.1 which also includes details of the exclusion criteria. Records were allocated randomly between the first three authors for the abstract screening step and between the full author group for the full text screening and data extraction. Spot moderation was undertaken at each screening step to verify consistent application of the screening criteria by the reviewing team.

A manual data extraction exercise was undertaken on each of the retained records. In this process model form (type of energy calculation), purpose, location were recorded, as well as the type of UA and SA, where available.

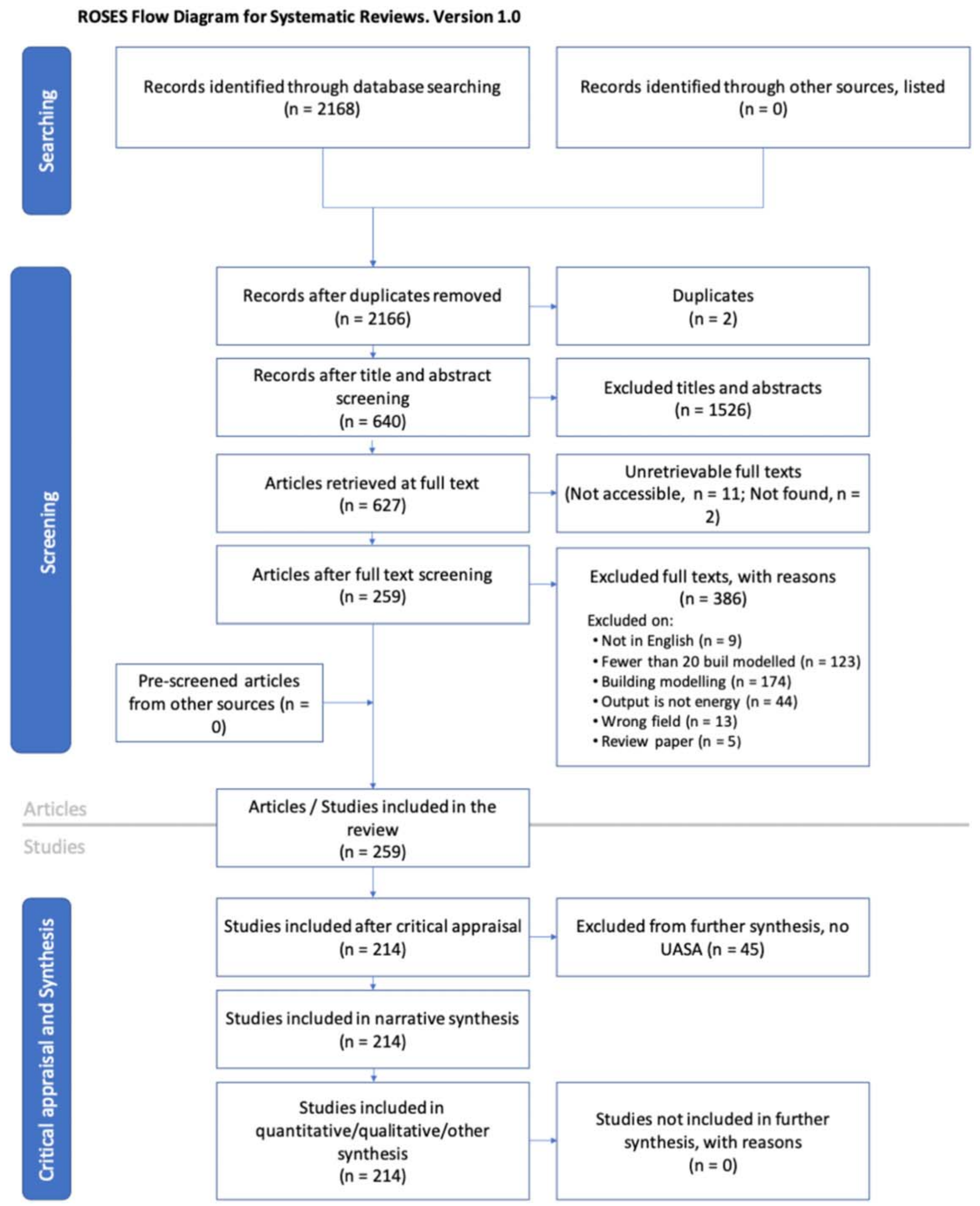

Figure A.1. Sequential screening process, diagram based on Haddaway *et al* (2017) .

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