Article
Partitioning Climate, Users, and Thermophysical Uncertainties from Building Energy Use: A Monte Carlo & ANOVA Approach
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Abstract: Buildings are subject to many uncertainties ranging from thermophysical performance to user activity. Climate change is an additional source of uncertainty that complicates building performance evaluation. This study aims to quantify the share of uncertainties stemming from building factors, user behavior, and climate uncertainty from boilers, chillers, fans, pumps, total HVAC systems, and total site energy use. A novel method combining Monte Carlo analysis and ANOVA is proposed to partition uncertainties from building energy simulation results under different climate change scenarios. The Monte Carlo method is used to generate distributions of building and user factors as building simulation inputs. Then, simulation results under current and future climate conditions are post-processed using a three-way ANOVA technique to discretize the uncertainties for a reference office building in Philadelphia, PA. The proposed method shows the share in percentages of each input factor (building, user, and climate) in the total uncertainty of building energy simulation output results. Our results indicate that the contribution of climate uncertainty increases from current conditions to future climate scenarios for chillers, boilers, fans, and pumps’ electricity use. User parameters are the dominant uncertainty factor for total site energy use and fans’ electricity use. Moreover, boiler and HVAC energy use are highly sensitive to the shape and range of user and building input factor distributions. We underline the importance of selecting the appropriate distribution for input factors when partitioning the uncertainties of building performance modeling.

Keywords: climate change; building and user factors; partitioning uncertainties; Monte Carlo; ANOVA

1. Introduction
In the United States, buildings are major consumers of energy, with commercial buildings accounting for 18% of the total national energy use [1]. The energy performance of commercial buildings is impacted by building thermophysical factors, occupant behavior, and exterior climate conditions [2–4]. To predict and reduce energy consumption in the building sector, simulation tools have been widely used across the industry [5], most of them applying deterministic approaches to evaluate building energy performance [6]. However, during the operational phase of a building, user behavior patterns, buildings’ physical characteristics, and climate conditions may change. The physical qualities of construction materials can deviate from the original design [7,8] due to natural decay, poor installation, changes in climate conditions, or imperfect manufacturing processes [9]. Furthermore, occupant behavior is dynamic and associated with many uncertainties [10]. Finally, the climate is changing, and evaluating building performance without taking the changing climate into account could yield unreliable assessments. The Intergovernmental Panel on Climate Change (IPCC) projects an increase in global mean surface temperatures in its emissions scenarios by the end of the century. Emissions scenarios provide snapshots of climate variability over time and are used as inputs for climate models [11]. However, these climate models are coarse in resolution and need to be downscaled before they
can be incorporated into building simulation tools [12,13]. In addition, climate models and emissions scenarios are uncertain in their nature [14] and downscaling them adds to this uncertainty [15], further complicating building energy modeling under uncertain thermophysical factors and user behaviors.

There are many examples of studies that have explored the uncertainty impacts of climate data [16–22], user behavior [23–27], envelope and material properties [28–30], and HVAC systems [31,32] on building energy use. Uncertainty analysis in evaluating building energy performance can be conducted following forward approaches (e.g., Monte Carlo (MC)), which propagate input uncertainties through energy models to observe energy use variations, in addition to inverse approaches (e.g., Bayesian methods) [3]. Sensitivity and uncertainty analysis can reflect the reliability of design inputs and show the dependency of model output on design parameters. Sensitivity analysis identifies how uncertainty in an output can be allocated to uncertainty in the input parameters of a process. Uncertainty analysis propagates the input uncertainty parameters to the model output. Uncertainty parameters are intrinsically non-static (e.g., mean occupant density) or deviate from the base design conditions (e.g., mean wall insulation conductivity). In building design studies, sensitivity analysis is commonly conducted following local sensitivity and global methods [33]. Local methods consider the impact of changing one factor while keeping all other factors constant, while global methods analyze variations in all input factors at once [34]. Many studies that compare the application of different sensitivity analyses on buildings question the reliability of building simulations in the absence of proper sensitivity and uncertainty analysis [35], both critical for improving design [36] and can lead to improved value and enhanced credibility of design [37] and verification procedures [38].

In addition, uncertainty analysis of building performance can be categorized using random sampling and scenario-based approaches. In the scenario-based approach, a distinction is made between categorical performance and operation levels of different buildings or user factors. For example, some studies have made a distinction between efficient, average, and intense energy users for uncertainty analysis in their building case studies [39,40]. Others followed scenarios determining uncertainty parameters for good, average, and poor building operations [41]; occupant behavioral scenarios [42]; low and high bounds of building thermophysical factors [43,44]; renovation levels [45]; or thermally efficient and inefficient buildings [46]. The scenario-based approach has the benefit of reducing computational needs when conducting uncertainty analysis and can be used when certain building and user factors are difficult to measure (e.g., occupant density). However, the method may not be able to capture the entire possible range of changes in input parameters, and the output results obtained from scenario-based approaches might only be reliable within the range of the scenarios identified. Random sampling methods can capture a broader range of uncertainty input factors.

Within global analysis techniques, a wide range of sampling methods are used, including MC and Latin Hypercube Sampling (LHS) methods [35], which are random and stratified sampling methods, respectively. LHS initially discretizes the parameters into equally probable areas prior to taking random samples [46,47], whereas the MC method can often develop data in regions that are otherwise not feasible (e.g., negative values of building factors). Some scholars argue that simple random sampling following MC with sufficient random numbers to provide data convergence can be the best combination for building applications [48,49], while some find LHS to be a better choice since it allows wider coverage of the entire probability distribution [50]. Another popular group among global sensitivity analysis methods is the ANOVA (analysis of variance) method, which enables evaluating the contribution of each input parameter to output variance. In building energy studies, ANOVA has been widely applied to identify sensitivity indices and key design factor uncertainties [51–53].

A major challenge of the random sampling method is identifying the distribution for input variables and determining the appropriate number of random samples for conver-
gence. In the literature, uniform and triangular distributions have been commonly used to reflect uncertainties in heat gain factors (occupant, light, or plug loads) or factors related to occupant/user behavior (density and setpoint temperatures), while normal distributions are mostly used for thermophysical characteristics. For the number of samples, some studies suggest that the minimum random numbers generated should not be less than $1.5 \times$ the number of input factors considered in the uncertainty analysis [33]. Others have relied on the work of Lomas and Eppel [54] to determine the total number of MC simulations [46] and recommend a minimum of 60 simulations to provide relatively acceptable convergence, which, however, could change on a case-by-case basis [55,56].

The research on uncertainty and sensitivity analysis in building applications is broad and varied. Still, the body of literature on the uncertainty of input building physical factors and user behavior is not extensive. The main reason is the lack of sufficient data [2,29,36] for both determining the appropriate distribution of the uncertainty factors [6,9] and identifying the possible range of discrepancies in the input factors [43]. Quantification of input uncertainty has been mostly based on measurements, estimates, expert judgment, physical bounds, simulation outputs, and analogies to similar simulation inputs [57,58]. For example, Varshney et al. [59] identified window U-factors within eight percent of those rated by the national fenestration rating system, and Madding [60] found thermal performance uncertainties from stud walls to vary between seven to twelve percent. Tables 1 and 2 show a summary of the input distributions used in whole building thermophysical and occupant/user factors in uncertainty analysis. Tables 1 and 2 were developed from the selected literature and referenced in the second row.

As shown in Tables 1 and 2, the literature suggests a wide range of input factor uncertainty distribution varying in their distribution type and parameters (e.g., mean and standard deviation). Identifying the exact level of uncertainty in building and user factors can be complex, and many scholars rely on assumptions to develop conduct and uncertainty analysis.

Developing methods capable of quantifying the share of uncertainties from building thermophysical factors, user behaviors, and downscaled climate models require closer attention. The objective of this study is to develop a method capable of quantifying the share of uncertainties coming from different building, user, and climate factors in building energy use, which can take into account any assumptions of input factor uncertainty distributions and provide unbiased results for the share of uncertainties.

Analysis was conducted for simulated boiler gas, chiller electricity, fan electricity, pump electricity, HVAC, and total site energy use, which are all highly influenced by discrepancies in input parameters [76]. To identify input uncertainties from building and user factors, we create scenarios that follow the literature (summarized in Tables 1 and 2) or assume a normal distribution for all building and user factor uncertainties. After identifying the input uncertainty distributions, an MC analysis was conducted, and random sampling data were developed for each building and user factor variable. The randomly generated input values of building and user factors were then propagated into a sample reference office building, and an EnergyPlus simulation was conducted for a set of 24 current and future weather files for the climate conditions of Philadelphia, PA. The output results were extracted for chillers, boilers, pumps, fans, HVAC, and total site energy use. In the next step, the results were sorted, and a three-way ANOVA was conducted on the data to decompose the uncertainties from each group of building, user, and climate factors and evaluate their variations from existing climate conditions to the end of the century. Main highlights of the paper are as follows:

- A new method for partitioning climate, user, and building uncertainties is proposed.
- The method combines Monte Carlo analysis and a three-way ANOVA approach.
- The method shows the share of uncertainty factors for building energy use categories up to the end of the century.
- The method exposes sensitivities to input distributions and the driving forces of energy use.
Table 1. Summary of the literature on identifying uncertainty distributions of input variables for office buildings.

| Case Study | Office Buildings |
|------------|------------------|
| Ref [61]   | [29,62] | [63] | [64] | [9] | [65] | [66] | [28] | [67] | [3] * | [68] |
| Location   | UK | ES | UK | NL | UK | HK | FR | FR | FR | CN | USA |
| Variables  | Unit | |
| Roof U-value | W/m²K | N (10%) | T | (±10.5%) | |
| Wall U-value | W/m²K | N | N | T | (±10.5%) | U | (±0.3) | U | |
| Material/Insl. Conductivity | W/mK | U (±25.7%) | N | [0.324] | N | (±10%) | |
| Win. U-value | W/m²K | N (10%) | T | (±28%) | N | T | (±10%) | N | TN | [0.03] | U | (±33.3%) |
| SHGC - | U | (±8.3%) | N | (±5%) | TN | [0.026] | U | (±43%) | |
| Infiltration | ACH | N (50%) | U (±33.3%) | N [0.102L⁻¹ Or 0.061T⁺¹] | N | (±10%) | U | U | (±14.3%) |
| Heating Eff. | - | N (20%) | T | (±1.5%) | U | (±11%) | |
| COP - | - | N | (±5%) | U | (±23%) | |
| Ventilation | 1/h ppl | T | (±20%) | T | [0.3,1,2,0.9] | |
| Heating SP °C | T | (±9%) | N | (±1 °C) | U | (±10%) | U | U | (±7%) | |
| Cooling SP °C | T | (±9%) | N | (±1 °C) | U | (±4%) | U | U | (±6%) | |
| Occ. H.G. | W/m² | T | (±23.8%) | U | N | [2.4] | T | (±40%) | |
| Equip. H.G. | W/m² | N (15%) | T | (±28.5%) | U | N [3.2] | U | (±29%) | T | [0.3,1,2,0.9] | U | U | (±15%) | |
| Lighting H.G. | W/m² | N (20%) | T | (±28.5%) | U | N [2.4] | T | (±15.3%) | T | [0.3,1,2,0.9] | U | U | (±16.5%) | |
| Occ. Density | ppl/m² | U | (±33.3%) | T | T | [0.3,1,2,0.9] | N (20%) | U | (±20%) | U | U | (±25%) | |
| Schedules h | N | (1 h) | |
| Metabolic R. | W/ppl. | N (50%) | Log | U | (±30%) | |
| Weather File | TMY | U | N | |

* Based on expert judgments for uniform ranges; probability. ¹—Loose Building. ²—Tight Building. Note 1: Summary of distributions: N—Normal, U—Uniform, T—Triangle, TN—Truncated Normal, Log—Lognormal, D—Discrete, B—Beta. Note 2: Values in parentheses () show the range of changes of variables considered in the literature. Values in brackets [] are actual parameters (e.g., standard deviations) used for the variable in the literature. If not defined, it was not applicable to this study due to different measurements of factors or different units.
## Table 2. Summary of the literature on identifying input variables uncertainty distributions for educational and residential buildings.

| Case Study | Educ. Bldng. | Residential Buildings |
|------------|-------------|-----------------------|
| Location   | UAE TR UK ES | CL UK BR NL Hot Cl. DK BE |
| Variables  | Unit        |                       |
| Roof U-value | W/m²K       | U (±30%)               | Log [1.332] U (±50%) |
| Wall U-value | W/m²K       | U (±30%)               | Log [0.942] N [0.018] |
| Material/Ins. Cond. | W/mK | U (±50%) | N | |
| Win. U-value | W/m²K       | U (±45%)               | N | |
| SHGC       | -           | U (±45%)               | B [20:13.33] N [0.01] |
| Infiltration ACH |       | U (±60%)               | N [0.005] U (±34%) T | N [0.0] U (±93%) |
| Heating Eff. | -           | N | U (±30%) | |
| COP        | -           | N [0.15]               | |
| Ventilation 1/h ppl. | | Log [0.222] N | |
| Heating SP °C | U (±2 °C) | U (±9.5%) | N [1.7] | N [0.7] |
| Cooling SP °C | U (±2 °C) | U (±4%) | N [1.7] | N [0.7] |
| Occ. H.G. W/m² |        | U | Log (±60%) | Log [0.312] N [0.25] U (5a) |
| Equip. H.G. W/m² |        | U | Log (±60%) | Log [0.312] N [0.53] U (5a) |
| Lighting H.G. W/m² |        | U | Log (±60%) | D ² |
| Occ. Density ppl./m² | D | U (±10%) | D ² | N (±5%) |
| Schedules h | D | U (±1 h, ±2 h) | D ² |
| Metabolic R. W/ppl. | TMY | D | |
| Weather File TMY | D | |

1—Airflow coefficient over cracks. 2—Differed for each zone. 3—Nominal boiler bower 4—Air flow.

### 2. Methodology

A sample reference building was suggested to reflect different operation conditions during the building use phase. The steps taken to partition the uncertainties of climate, user, and building factors were as follows:

I. Developing a database of current and future weather files;

II. Pre-processing: generating input user and building uncertainty factor distributions following an MC analysis, then developing stochastic iterations of the building and user factors to be run in EnergyPlus;
III. Conducting EnergyPlus simulations for building and user factor iterations and current and future weather files;

IV. Post-processing: sorting the output energy use data (denoted as “X” in Figure 1) associated with each input factor (i.e., building and user factors and weather files) and conducting an ANOVA to partition the uncertainties for current and future time slices.

Figure 1. Framework of partitioning climate, user, and building factor uncertainties following Monte Carlo and ANOVA.

Figure 1 shows the framework of the proposed uncertainty partitioning method for building applications ('U' and 'B' represent the group of randomly generated values for all user and building factors, respectively. The full list of abbreviations can be found in Abbreviations).

The proposed method is also novel in terms of considering downscaled climate model uncertainties along with building and user factor uncertainties and can partition all three factors from building energy use indicators. For example, when obtaining output energy use from a sample building energy simulation, the proposed methodology can quantify the share each input factor (e.g., window u-value, user behavior, etc.) has in the total output energy use uncertainty (in percentages).
2.1. Step I: Weather Files and the Case Study

The U.S. Department of Energy (DOE) large office reference building following the ASHRAE 90.1-2004 standard for the 4A climate category was used as the sample case study (Appendix A). All design parameters for the building were kept at base case for all simulations to reflect a building in the operational phase. Base case design conditions (including cooling and heating design capacity, designing outdoor airflow, maximum airflow rate and hot water flow rate of a VAV reheat system, maximum airflow rate of the fan, controller maximum and minimum outdoor air flow rate, noncoincident design day, and heating and cooling coil design parameters) were obtained from the sample office building simulation conducted under the TMY3 weather file for Philadelphia, categorized as a 4A DOE climate region. Current weather files were obtained from the existing database of typical meteorological year (TMY) files generated for different historical periods (Table 3).

Table 3. Sources of current TMY files used in this study.

| File  | Source                                      | Generation Periods |
|-------|---------------------------------------------|--------------------|
| TMYx  | Climate.OneBuilding.org                     | 2003–2017          |
| TMYxx | Climate.OneBuilding.org                     | 2004–2018          |
| ER    | European Energy Efficiency Platform         | 2005–2015          |
| Met1  | Meteonorm Base                              | 1961–1990          |
| Met4  | Meteonorm Base                              | 2000–2009          |
| TMY3  | National Solar Radiation Data Base          | 1991–2005          |

For the future weather files, weather generators were used to develop a series of future meteorological year (FMY) files from various emissions scenarios for the mid-century (2050) and end-of-century (2080) periods. The climate change world weather generator (CCWorldWeatherGen) [77,78] was used to morph the existing weather files presented in Table 3. The CCWorldWeatherGen is an excel-based generator that adapts the morphing technique [79] and creates future hourly weather files from existing TMY weather files following the IPCC A2 emission scenario. Meteonorm was used to develop future weather files from three IPCC emissions scenarios: A1B, A2, and B1. The advanced weather generator (AWE-GEN) [80,81], which is a MATLAB-based weather generator, was used as the stochastic weather generator to generate future weather files without considering any emissions scenarios. Appendix E summarizes details of the future weather files used in this study.

2.2. Steps II: Developing Input Distributions for Building and User Factors

In the next step, an MC random sampling method was applied to propagate input uncertainties into the building energy use. The input building and user factor distributions were selected based on the literature review (see Tables 1 and 2). The building uncertainty factors considered were the window U-value (Win), window solar heat gain coefficient (SHGC), wall insulation thermal conductivity (WL), infiltration rate (Inf), boiler efficiency (Boil), and chiller coefficient of performance (COP). The user uncertainty factors were light density (LD), plug load density (PD), cooling setpoint temperature (SPC), heating setpoint temperature (SPH), and occupancy density (OCC). Since identifying the exact value and distribution of building and user uncertainty factors can be complex and there is little data available in this regard, two separate scenarios were created for MC sampling. In the first scenario, the distribution of input factors was identified, drawing upon the literature. In other words, the most followed distribution and distribution parameters (e.g., standard deviation) were used for each variable. In the second scenario, normal distribution with a standard deviation of 5% was assumed for all input uncertainty factors. Figure 2 shows the process of generating EnergyPlus IDF files.

Since uncertainties from all factors could occur simultaneously, stochastic iterations of the building (B) and user (U) factors were aggregated into the EnergyPlus simulation to capture the random impacts of all uncertainty factors.
2.3. Steps III: Conducting Building Energy Simulation

The EnergyPlus simulation was conducted for all EnergyPlus IDF files, each corresponding to one iteration of the input uncertainty factor distributions (stemming from building and user factors). The simulations were conducted for current and future weather files (EPW weather files). A total of 14,400 simulations were conducted to capture the coupled building and user factors’ impact under current and future weather conditions for the uncertainty partitioning analysis.

Figure 2. Process of conducting Monte Carlo analysis and generating stochastic iterations for EnergyPlus simulations.

2.4. Step IV: Partitioning Uncertainties

The ANOVA approach captures the fraction of the model response variance explained by the model input(s) and can measure the contribution of input discrepancies to the output. It enables capturing between-group and within-group variations (residual variations) even in the presence of nonlinearities. To conduct the ANOVA test, first, the output results of the EnergyPlus simulations were sorted according to their iterations of building and user factors for all weather files (Appendix C). The uncertainties from input user and building factors under climate change were partitioned for the output results of chiller (electricity), boiler (gas), fans, pumps, HVAC (heating, cooling, fans, and pumps), and total site energy use. Normality assumptions for residuals and outliers were tested with scatter plots, and all measures complied. Details of the three-way ANOVA are presented in Equations (1)–(11), and the abbreviations are summarized in Table 4 [82]:

\[
SST = (SSA + SSB + SSC) + (SSAB + SSAC + SSBC + SSABC) + SSE
\]  
(1)

\[
SST = \sum_{i} \sum_{j} \sum_{k} (X_{ijkl} - \bar{X}_{....})^2
\]  
(2)

\[
SSA = JKL \sum_{i} (\bar{X}_{i..} - \bar{X}_{....})^2
\]  
(3)

\[
SSB = IKL \sum_{j} (\bar{X}_{..j} - \bar{X}_{....})^2
\]  
(4)

\[
SSC = IJK \sum_{k} (\bar{X}_{..k} - \bar{X}_{....})^2
\]  
(5)

\[
SSAB = KL \sum_{i} \sum_{j} (\bar{X}_{ij..} - \bar{X}_{i..} - \bar{X}_{..j} + \bar{X}_{....})^2
\]  
(6)

\[
SSAC = JL \sum_{i} \sum_{k} (\bar{X}_{i..k} - \bar{X}_{i..} - \bar{X}_{..k} + \bar{X}_{....})^2
\]  
(7)
where $SS$ is the sum of squares, and $A$, $B$, $C$, and $T$ represent user factors, building factors, weather, and total respectively; $i$, $j$, and $k$ represent the count for each of the factors $A$, $B$, and $C$; $I$, $J$, and $K$ represent the total number of observations for each factor $A$, $B$, and $C$, respectively; $L$ is the observation made with factor $A$ at level $i$, factors $B$ at level $j$, and factors $C$ at level $k$. In this case, they are all single observations for all factors and each run and, therefore, $L=1$, which simplifies the ANOVA formula. Table 4 summarizes the abbreviations used in Equations (1)–(11).

### Table 4. Summary of abbreviations used in Equations (1)–(11).

| Abb. | Description                         | Abb. | Description                                      |
|------|-------------------------------------|------|--------------------------------------------------|
| SS   | Sum of Squares                      | AB   | Interaction between user and building factors    |
| A    | User Factors                        | AC   | Interaction between user factors and weather files|
| B    | Building Factors                    | BC   | Interaction between building factors and weather files|
| C    | Weather Files                       | ABC  | Interaction between user, building, and weather files|
| T    | Total                               | F    | Fraction of the sum of squares of each factor to total |
| E    | Error                               | $\bar{X}$ | Average of observations in each subgroup          |

An example of how each $X$ can be extracted from the actual data set is provided in Appendix C for a sample output cooling energy use under current weather files. In the following section, the results of the proposed partitioning method are presented for the sample reference office building under Philadelphia climate conditions. First, the deterministic results of the weather file datasets (current and future) on the energy use indicators (heating, cooling, fans, pumps, HVAC, and total site energy use) are presented. Next, the results of a simple sensitivity analysis of the building and user factors on the energy use indicators are shown. Then, the input user and building uncertainty factor distributions following the MC approach are summarized. Finally, the results of the three-way ANOVA in partitioning the coupled effect uncertainties are presented.

## 3. Results

### 3.1. The Impact of Climate, Building, and User Factors

Future weather files developed from weather generators are uncertain in nature. This is mainly due to climate model uncertainties, emissions scenario assumptions, and downscaling processes. However, by creating an ensemble of future weather files, we were able to generate a range of possible snapshots of future climate conditions. Figure 3 summarizes the impact of the current and future weather files that we used on the energy consumption indicators. The data are sorted based on the temperature in an ascending order since dry bulb temperature (DBT) is recognized as the main weather variable influencing building energy use.

The models indicate that boiler energy use decreases with time, while chiller energy use increases with the rise in dry bulb temperature. Higher temperatures yield reduced heating energy requirements and increased cooling energy needs. However, the impact of the changing climate (i.e., DBT) is of lower magnitude on fans and pumps' electricity use (pump energy shows a slight increase with rising temperature). HVAC energy use, on the
other hand, does not have a linear response to climate variables, which is expected since boiler gas use and chiller, fan, and pump electricity use all contribute to HVAC energy use. Figure 4 shows a summary of the sensitivity analysis of the building and user factors on energy use indicators. The sensitivity analysis follows a 5% and 10% change in input factors and shows the percent change in output energy use.

The 5% and 10% change in input factors were only considered in the sensitivity analysis to reflect potential nonlinearities. However, the uncertainty partitioning analysis follows a first scenario based on the literature and a second scenario based on only a 5% change in input parameters following a normal distribution. The results of the sensitivity analysis indicated that user factors generally have a greater impact on a boiler’s gas use and fans, pumps, and total site energy use. From Figure 4, user factors had a significant effect on fan and pump electricity usage compared to building factors. This could be explained by setpoint temperatures being the main driver of fan and pump energy use. A similar effect was seen for total site energy use since users have primary control over lighting and equipment use patterns. Boiler gas use and chiller electricity use were highly impacted by the heating setpoint and chiller efficiency, respectively. In this case, changes in the cooling setpoint temperature also influenced the boiler’s gas use because the reference office building had a VAV reheat system with the possibility of simultaneous heating and cooling, which is highly sensitive to setpoint temperatures. The same effect was observed for the chiller’s electricity use, where changes in the heating setpoint temperature yielded changes in cooling energy demands. For HVAC energy, both building and user factors had relatively significant impacts on the output energy use (with the heating setpoint temperature having the highest impact).

### 3.2. The Impact of Input Uncertainty

MC sampling was conducted to develop and propagate the probability density functions of input factors into the EnergyPlus simulation. The input distributions were developed following two scenarios. For the first scenario, recommendations in the literature were followed to create distributions of input user and building factors. For the shape of the distribution, the most common distributions used for each factor were selected, and for the measures of spread for each factor (e.g., standard deviation), similar case studies were sought. Under the second scenario, a normal distribution was assumed for all building and user factors with a standard deviation of 5%. Table 5 summarizes input variables distributions for building and user factors.
Figure 3. Summary of the impact of current and future weather files on all energy use indicators. The models indicate that boiler energy use decreases with time, while chiller energy use increases with the rise in dry bulb temperature. Higher temperatures yield reduced heating energy requirements and increased cooling energy needs. However, the impact of the changing climate (i.e., DBT) is of lower magnitude on fans and pumps’ electricity use (pump energy shows a slight increase with rising temperature). HVAC energy use, on the other hand, does not have a linear response to climate variables, which is expected since boiler gas use and chiller, fan, and pump electricity use all contribute to HVAC energy use.

Figure 4. Summary of the sensitivity analysis on six output energy use indicators following a 5% and 10% change in input building and user factors. The sensitivity analysis follows a 5% and 10% change in input factors and shows the percent change in output energy use.

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3.3. Partitioning Uncertainties following Three-Way ANOVA

3.3.1. Distribution Scenario I

A three-way ANOVA was conducted on the results for each energy use category. Figure 5 presents the uncertainty partitioning results for chiller gas use and boiler electric use and shows the share of uncertainty from each building, user, and climate factor on the output energy use uncertainty for the entire century (from current weather files up to the end of the century), current conditions (existing TMY files), mid-century (future TMY files of 2050), and end-of-century (future TMY files up to 2080). It should be noted that the entire century (Entire Cent.) category compares the uncertainties when the entire weather dataset (current and future) are considered regardless of time. Results for all energy indicators showed a relatively small share of interaction factors, and therefore, only the sum of the entire interactions and errors are graphed. The interaction terms reflect whether a change in one factor (e.g., a building factor) results in changes in the value of other factors (e.g., climate or user factors). The interaction levels in this study are relatively small compared to the main effects.
to the main effects and were considered unimportant in the modeling process. The results of the three-way ANOVA uncertainty partitioning presented hereafter do not present the absolute magnitude of the impact of factors but show the relative contribution of building, user, and climate uncertainties to the output energy use distribution.

Table 5. Results of the input distribution for building and user factors used for the uncertainty partitioning analysis (Appendix B).

| Factors | Based on Literature (Scenario 1) | Ref. for Magnitude of Uncertainty | Normal Dist. w/5% (Scenario 2) |
|---------|---------------------------------|---------------------------------|---------------------------------|
| Building Factors | | | |
| Win | N (3.23646,0.258917) | [59] | N (3.23646,0.161823) |
| WL | N (0.049,0.014) | [63] | N (0.049,0.00245) |
| SHGC | U [0.3588,0.4212] | [62] | N (0.39,0.0195) |
| Inf | N (0.000302,0.00010268) | [37] | N (0.000302,0.0000151) |
| Boil | U [0.6942,0.8658] | [68] | N (0.78,0.039) |
| COP | U [4.235,6,765] | [68] | N (5.5,0.275) |
| User Factors | | | |
| SPH | N (21,1) | [66] | N (21,1.05) |
| SPC | N (24,1) | [66] | N (24,1.2) |
| PD | U [9.146,12,374] | [61] | N (10.76,0.538) |
| LD | U [8.608,12,912] | [61] | N (10.76,0.538) |
| OCC | T [5.574,22,296,16,722] | [65] | N (18.58,0.929) |

Notes: Normal (mean, standard deviation), Uniform [min, max], Triangle [min, max, mode].

From Figure 5, the share of climate uncertainty increases for the future conditions (from the current time to the end of the century) of both chiller electricity and boiler gas use. This is expected considering the uncertain nature of climate models and emissions scenarios (Climate S/M). This is consistent with the findings of previous studies [13,83–86], which have identified that the role of emission scenario uncertainty grows more significant with time. Emissions scenarios are based on assumptions, and climate models only capture snapshots of what the future may look like. Therefore, while we might have a relatively better understanding of near future climate conditions, assumptions made for future time slices are highly uncertain, and this uncertainty is propagated to building energy use.

Figure 5. Results of uncertainty partitioning for chiller electricity use and boiler gas use.
For chiller electricity use, users have the smallest contribution to the overall uncertainties compared to building factors in all time periods. For current conditions, building factors are the dominant uncertainty factor for chiller energy use. This, however, changes by the end of the century when the share of building factor uncertainty becomes similar to climate uncertainties, and again when comparing the entire century, the climate becomes the dominant uncertainty factor. The small share of user factor contributions to chiller electricity consumption uncertainty could be potentially linked to the fixed HVAC operation schedules. In this case study, no major changes to HVAC operation or user schedules were considered that would have required deeper scrutiny of an occupant-centric design and would fall beyond the scope of the study. For boiler gas use, however, a different pattern emerged. User factor uncertainty showed a relatively large contribution to boiler gas use uncertainty compared to chiller electricity use. As noted in Figure 5, based on the designated distribution assumptions for building and user uncertainties, both user and building factor uncertainties have a relatively high contribution to boiler gas use uncertainty with a share of 41% and 47%, respectively. However, their share reduces towards the end of the century, as climate uncertainty rises as the dominant uncertainty factor. Looking throughout the entire century, both user and building factors have a similar share of the contribution to the total uncertainty, while climate is the dominant uncertainty factor.

Figure 6 shows the uncertainty partitioning results for fan and pump electricity use. Similar to chiller and boiler energy, the share of climate uncertainty increases from current conditions to the end of the century for both fan and pump electricity use. In general, changes in the share of uncertainty across time are mostly due to climate change uncertainty. For fan electricity use, user factors are the dominant source of uncertainty for all time slices, while building factors have a very small contribution to the total uncertainty. A similar trend can be seen for pump electricity use, where users have a higher contribution compared to building factors for all time slices. This can be attributed to the users’ direct control over fan and pump energy use. Nevertheless, despite the user factors’ higher contribution to uncertainty compared to building factors, the dominant uncertainty factor for all time slices remains the climate with a share of 88% for the entire century.

Figure 7 shows the uncertainty partitioning results for HVAC and total site energy use. The most notable change in the share of uncertainties in HVAC and total site energy use compared to all other factors is the contribution of climate uncertainty. Climate has a minor share of the uncertainty for both HVAC and total site energy use categories, unlike

![Figure 6](image-url) **Figure 6.** Results of uncertainty partitioning for fan and pump electricity use.

![Figure 7](image-url) **Figure 7.** Results of uncertainty partitioning for HVAC and total site energy use.
fan, pump, chiller, and boiler energy use. In addition, a large portion of the total site energy use is lighting and equipment electricity use (interior and exterior), which are directly controlled by users and, therefore, highly sensitive to user uncertainties. Both user and building factors have a relatively significant share in HVAC energy uncertainty, with building factors having the higher portion for the entire century. Results of partitioning the HVAC energy use uncertainties for the designated distribution assumptions indicate relatively high contributions from both user and building factors with shares of 30% and 56%, respectively, to the total uncertainties for the entire century.

Figure 6. Results of uncertainty partitioning for fan and pump electricity use.

Figure 7. Results of uncertainty partitioning for HVAC and total site energy use.

3.3.2. Distribution Scenario II

The uncertainty partitioning method explained is based on the input variable distributions extracted from the literature. However, the results could be different if the input uncertainty assumptions change. Indeed, the model can only be as rigorous as its underlying assumptions. To explore the sensitivity of each energy use indicator to the input building and user factor distributions, a second analysis is conducted, assuming a normal distribution with a 5% standard deviation for the input building and user uncertainty factors. The uncertainty partitioning results under the second scenario are presented in Figure 8.

The results show that the share of uncertainty contributors for fans, pumps, and total site energy use is similar to the initial input uncertainty scenario (presented in Figures 5–7). Comparing the results of the two scenarios, regardless of the building and user input factor distributions, pumps and fans are highly sensitive to user factors, and as such, users are the dominant uncertainty parameter. Under the second scenario, building factors still have a higher contribution than user factors to chiller electricity use uncertainties, as shown by the uncertainty partitioning. However, this could be potentially linked to the fixed HVAC operation schedules in the model since changes to the operation schedules could alter the share of contributors to chiller electricity use uncertainties. For boiler gas use, uncertainties shift from an equal share of building and user factor contributions (Figure 5) to a more user dominant uncertainty in the second scenario (Figure 8). Under the second scenario, similar to the first scenario, the share of climate uncertainty increases for chiller electricity and boiler gas from current conditions to the end of the century. Regarding HVAC energy use, significant changes can be seen in the share of uncertainties where users become the dominant factor compared to the initial scenario. The shifts in the share of contributors to boiler gas use and HVAC energy use uncertainty indicate high sensitivity
to input distribution assumptions for these consumption categories. The results for fans, pumps, and total site energy use showed higher sensitivity to their main driving force and were less sensitive to the input distribution assumptions.

3.3.2. Distribution Scenario II

The uncertainty partitioning method explained is based on the input variable distributions extracted from the literature. However, the results could be different if the input uncertainty assumptions change. Indeed, the model can only be as rigorous as its underlying assumptions. To explore the sensitivity of each energy use indicator to the input building and user factor distributions, a second analysis is conducted, assuming a normal distribution with a 5% standard deviation for the input building and user uncertainty factors. The uncertainty partitioning results under the second scenario are presented in Figure 8.

Figure 8. Results of uncertainty partitioning for chiller, boiler, fans, pumps, HVAC, and total site energy use following the second scenario in developing input uncertainty distributions.

4. Conclusions

Given the many layers of uncertainties in building thermophysical characteristics and user behaviors, evaluating building performance without considering the uncertainties could yield unreliable results. Climate change uncertainties add to the complexity of building performance evaluation, and considering the combined impact of building, climate, and user uncertainty is becoming increasingly important. Building simulation models are not capable of capturing the many layers of uncertainty and are simplified...
representations of actual performance. Therefore, accounting for uncertainties is crucial for reducing the gap between design and measurements and providing accurate outcome estimates. However, our understanding of the share of uncertainty factors in the total uncertainty needs to improve.

The major portion of building energy consumption occurs during the operational phase, which highly depends on climate conditions, user behavior, and building thermophysical characteristics. In this study, the share of uncertainties stemming from building factors (window U-value, SHGC, wall insulation, infiltration, and chiller and boiler efficiency), user factors (occupancy density, lighting and plug load density, and heating and cooling setpoint temperatures), and climate uncertainties (climate models, emissions scenarios, and downscaled weather files) were partitioned. A novel method was used combining Monte Carlo analysis and a three-way ANOVA approach to discretize the uncertainties of the output boiler gas use; chiller, fan, and pump electricity use; HVAC, and total site energy use to their sources for a sample reference office building in Philadelphia, PA. Two separate scenarios were developed with regard to the distribution of each input uncertainty factor. The results from the proposed uncertainty partitioning method suggest that energy use categories show different levels of sensitivity to the uncertainty distribution shape and range of the input factors or to the main drivers of energy use, which can change with time:

- The share of climate uncertainty increased from current conditions to future time slices for chiller electricity use, boiler gas use, and fan and pump electricity use. Climate uncertainty is the dominant uncertainty factor for the chiller and pump’s electricity use throughout the entire century, while it has a smaller share in HVAC and total site energy use uncertainty.
- Chiller electricity use is relatively sensitive to input uncertainty factor distribution, for which building factors have a higher share than user factors, regardless of the input factor distribution.
- Boiler gas use uncertainty is highly sensitive to the shape and range of the input uncertainty factor distribution, with user factors either having an equal or higher contribution compared to building factors, depending on the distribution scenario.
- Fan and pump electricity consumption and total site energy use are less sensitive to the shape and range of the input factor distribution. User factors are the dominant uncertainty factor for total site energy use and fan electricity use. The contribution of climate uncertainty to fan and pump energy consumption uncertainty increases with time.
- HVAC energy use shows the highest sensitivity to the user or building uncertainty factors depending on the input distribution scenario.

In general, this uncertainty partitioning method heavily relies on the type and range of input uncertainty distributions and/or the energy use indicators’ main driving forces. We have a good understanding of the main driving forces, and sensitivity analysis could further clarify the crucial factors influencing energy use estimates. However, there is still little consensus on the shape and range of the input distributions. For example, the HVAC energy use indicator did not show a strong linear correlation with dry bulb temperature in the sensitivity analysis. The results of the uncertainty partitioning also showed that the share of climate model uncertainty in HVAC energy use was very low and less significant than the share of user and building factors. In addition, the uncertainty partitioning model for HVAC under both input scenarios showed the model was highly sensitive to the input user and building factor distribution assumptions. This suggests that HVAC energy use estimates are more likely to be sensitive to input distribution assumptions. However, for pump electricity use, for instance, even though the sensitivity analysis did not reveal a strong linear relationship between pumps’ electricity use and dry bulb temperature, the uncertainty partitioning model showed climate uncertainties as the dominant uncertainty factors compared to building and user factors. This indicates that pump electricity use is less sensitive to input building and user factor distributions, and climate was the dominant factor in the uncertainty analysis.
Normalizing the input uncertainty parameters or using effective mean and standard deviation values was examined in this study. However, the parameters of the input variables to the MC analysis in some cases fell beyond the feasible range (some in the negative value range), and therefore, normalizing was not further investigated. Developing a method to partition uncertainties compatible with the normalizing of input parameters could complement this analysis in the future. In addition, current and future weather files were developed following the methods and resources available to develop the maximum number of weather files. We did not analyze whether the data were oversaturated or did not reach convergence. Methods such as the Fisher Exact matrix could identify the saturation point for the number of weather files needed. Oversaturation would not change the results of the uncertainty partitioning since the model accounts for all maximum discrepancies. However, if the number of future weather files was not sufficient to reach convergence, the contribution of climate uncertainty could change.

The building case study reflects an existing office building and its performance under building, user, and climate uncertainty. Therefore, all design parameters of the building were held constant at the base case (simulations following TMY3 conditions). Otherwise, changing factors, such as setpoint temperature, could change fan and pump sizing. To develop setpoint temperature uncertainty distributions, MC analysis was conducted for temperature only during occupied hours. The unoccupied hours’ setpoints were manually changed after the MC analysis to reflect the changes to the base case proportionally. This was because our initial investigations (Appendix D) showed that not changing unoccupied setpoints proportional to the changes during the occupied hours could result in heat build-up, especially throughout changes in cooling setpoint temperature, yielding higher cooling energy use even when the occupied cooling setpoint temperature was increased.

With regard to future steps, the proposed partitioning method can be applied to the full list of DOE building prototypes to represent the entire domain of building types. In addition, occupant-centric approaches and operation schedules can be included as user uncertainty factors to provide a more comprehensive understanding of occupant uncertainties. In this study, we only examined energy indicators that can be further expanded by partitioning uncertainties from occupant comfort and building hygrothermal properties to their sources. This study relied on the literature to identify input variables’ uncertainty distributions for building and user factors, and therefore, developing a method to partition uncertainties compatible with normalizing input parameters could serve to complement this analysis and potentially enhance confidence in developing the distribution of appropriate input variables. Identifying the saturation point for the number of weather files needed to conduct the uncertainty analysis could also be an addition to this work.

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## Appendix A. Thermophysical Description of the Large Office Reference Building Case Study

| Parameter                  | Unit       | Value       |
|----------------------------|------------|-------------|
| Wall                       | U-factor   | 0.857       |
| Wall Insulation            | Conductivity | 0.049      |
| Roof                       | Type       | IEAD 1      |
|                            | U-factor   | 0.365       |
| Floor                      | Type       | Slab        |
|                            | U-factor   | 2.193       |
| Window                     | U-value    | 3.241       |
|                            | WWR2       | 40.00       |
|                            | SHGC3      | 0.385       |
| Infiltration               | m³/s·m²₂   | 0.302 × 10⁻⁴|
| Heating Setpoint           | Occupied h.| °C          | 24          |
|                            | Unoccupied h.| °C   | 26.7        |
| Cooling Setpoint           | Occupied h.| °C          | 21          |
|                            | Unoccupied h.| °C | 15.6        |
| Outdoor Air Requirement    | m³/s-person| 0.0125      |
| Occupancy Density          | m²/person   | 18.58       |
| Interior                   | W/m²       | 10.76       |
| Pump Control Type          | -          | Variable Speed |
| Control Type               | %          | 88          |
| Fan Efficiency             | %          | 60          |
| Heating Type               | -          | Boiler      |
| Efficiency                 | %          | 78          |
| Cooling Type               | -          | Chiller     |
| Efficiency COP             |            | 5.5         |

¹—Insulation Entirely Above Deck. ²—Light Power Density. ³—Plug Load Density. ⁴—Variable Air Volume with reheat.
Appendix B. Shape and Size in Input Uncertainty Factors Distributions: (A) Based on the Literature, (B) Following Normal Assumption with a Standard Deviation of 5% of Mean Values

(A)
(B)
Appendix C. Sample Legend on Identifying Factors for ANOVA Analysis. Data Are a Snapshot of the Chiller Electricity Energy Use for Current Weather Files. Data Are Results of EnergyPlus Runs Due to Iteration of Each User Factor (U) and Building Factor (B). Uncertainty Distribution for Existing Weather Files (TY3, Met1, etc.)
Appendix D. Sample Results of Indoor Temperature of the Case Study for the Month of July. Results Present Before and After Corrections Made to Unoccupied Hours Setpoint Temperatures

Appendix E. Summary of the Future Weather Files Developed Following Weather Generators

| Weather Files | Generation Method          | Projected Year |
|---------------|----------------------------|----------------|
| AWE50         | AWE-GEN                    | 2050           |
| B1-50         | Meteonorm B1 Scenario      | 2050           |
| A2-50         | Meteonorm A2 Scenario      | 2050           |
| A1B-50        | Meteonorm A1B Scenario     | 2050           |
| Met1-50       | Morphed Meteonorm Base File M1 | 2050       |
| TY3-50        | Morphed NREL TMY3          | 2050           |
| ER2-50        | Morphed ER2 File           | 2050           |
| TYx-50        | Morphed OneBuilding TMYx File | 2050     |
| Met4-50       | Morphed Meteonorm Base File M4 | 2050       |
| AWE80         | AWE-GEN                    | 2080           |
| B1-80         | Meteonorm B1 Scenario      | 2080           |
| A1B-80        | Meteonorm A1B Scenario     | 2080           |
| A2-80         | Meteonorm A2 Scenario      | 2080           |
| Met1-80       | Morphed Meteonorm Base File M1 | 2080     |
| TY3-80        | Morphed NREL TMY3          | 2080           |
| ER2-80        | Morphed ER2 File           | 2080           |
| TYx-80        | Morphed OneBuilding TMYx File | 2080     |
| Met4-80       | Morphed Meteonorm Base File M4 | 2080       |
Abbreviations

| Abb. | Description |
|------|-------------|
| ANOVA | Analysis of Variance |
| IPCC | Intergovernmental Panel on Climate Change |
| HVAC | Heating, Ventilation, and Airconditioning |
| MC | Monte Carlo |
| LHS | Latin Hypercube Sampling |
| X | Output Energy Use Indicator |
| U | User Factors |
| B | Building Factors |
| DOE | Department of Energy |
| ASHRAE | American Society of Heating, Refrigerating, and Air-Conditioning Engineers |
| VAV | Variable Air Volume |
| TMY | Typical Meteorological Year |
| FMY | Future Meteorological Year |
| CCWeatherGen | ClimateChangeWorldWeatherGenerator |
| AWE-GEN | Advanced Weather Generator |
| SS | Sum of Squares |
| Met | Meteonorm |
| ER | European Energy Efficiency Platform |
| DOE | Department of Energy |
| GJ | Giga Joule |
| Win | Window U-Value |
| WL | Wall Insulation Thermal Conductivity |
| SHGC | Solar Heat Gain Coefficient |
| Inf | Infiltration Rate |
| COP | Coefficient of Performance of Chiller |
| Boiler | Boiler Efficiency |
| LD | Light Density |
| PD | Plug Load Density |
| OCC | Occupancy Density |
| SPC | Cooling Setpoint |
| SPH | Heating Setpoint |
| UK | United Kingdom |
| ES | Spain |
| NL | Netherlands |
| HK | Hong Kong |
| FR | France |
| CN | China |
| USA | United States of America |
| UAE | United Arab Emirates |
| TR | Turkey |
| CL | Chile |
| BR | Brazil |
| DK | Denmark |
| BE | Belgium |

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