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Application of Epistemic Uncertainty Analysis and Sensitivity Analysis in Green Construction Design

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Abstract

Building performance is often expressed according to primary energy use; however studies should also include environmental load. To mitigate the effects of increased CO2 emissions, green building designs are now increasingly popular options for stakeholders. In contrast, impacts of green design parameters, building performance assessment, and design optimization objectives are not addressed sufficiently for American infrastructure. Designing low-energy architecture to minimize carbon emissions requires thoughtful articulation of green building design alternatives. A common barrier for green building design in the U.S. is the time needed to identify and evaluate alternatives. Modeling energy consumption in buildings is essential for different applications, including building energy management and establishing baselines for sustainable building performance codes. This paper proposes a new optimization objective, which considers annual carbon emissions for multi-family construction in Florida. A multi-step sensitivity and epistemic uncertainty approach are proposed to identify the critical design parameters during the early stages of sustainable building design. Building simulation software was utilized to model green building configuration for carbon emission values, further analyzed using Monte Carlo and Morris Method sensitivity analysis techniques. The present study considered green building design alternatives as variables since carbon emission reduction potential is sensitive to these variables. Results indicate that PV panel efficiency, PV payback limit, lighting efficiency, plug load efficiency, and solar heat gain coefficient are highly influential parameters. The methodology is presented, and an example is applied to a new construction multi-family apartment design in Tallahassee, FL. This uncertainty and sensitivity analysis improved the design efficiency, while emphasizing usefulness in the green building optimization process.

Keywords
Monte Carlo simulation; epistemic uncertainty; green building; sustainability

1. Introduction

Climate change can be attributed to the ever-increasing effects from the built environment, impacting structural resilience and sustainability. A comprehensive meta-analysis of climate change impacts for Florida specifically, predicted annual precipitation changes of up to +30%, an indicator of the severe shifts in Floridian climate change [1]. This study displays the importance of sustainable infrastructure, promoting environmental synergy, since construction management, adaptation, resilience, and climate change mitigation, are areas of interest addressed through green infrastructure adoption. Green construction possesses many benefits, including cost-effectiveness, natural resource conservation, and creating a healthier balance with the environment.

Energy use and related emissions is substantially increasing due to several key trends including, demand for adequate housing options, leading to increased strain on urban ecosystems due to inextricable connections between emerging infrastructure and the environment. This is led by population growth, exponential urbanization, modernization, accompanied by increasing lifestyle demands globally, contributing factors for significant building energy use. New construction in developed nations represents a climate risk and opportunity from a mitigation perspective. According to Construction Permit Data Northeastern Florida construction has spiked by approximately 38% in the past year, with an additional 24,274 permits submitted [2]. Energy usage of buildings and the resulting carbon emissions can be addressed through a low-carbon pathway approach associated with robust decision-making design methodologies.

Green infrastructure strategies utilize ecosystem services and natural systems for adaptation and resilience. A range of environmental issues is impacted by the built environment, including natural resource use, solid waste generation, ozone depletion, coastal zone effects, and global warming [3]. It is necessary to establish building codes and regulations for new buildings, that consider climate change, while enforcing energy savings, and CO_2 emission reduction, however building commissioning data reveals millions of inefficient buildings will remain until 2050. Design decisions, impacting the residential structure's life cycle, must consider operational carbon emissions and energy usage, during its service life, to determine environmental impact and energy savings. Traditional thinking in this realm is dominated by thermal comfort and increasing energy usage, at the expense of the environment. A new way to evaluate systems and inform design teams for optimal design decisions includes Building Information Modeling and statistical analysis. Environmentally friendly design decisions will include the optimization of the building envelope including the implementation of PV Panel Systems, since most studies focus on HVAC systems, however more than half of total residential energy consumption is composed of additional building element factors. Solar electricity generation through PV systems estimate an energy savings of up to 19 to 30% relative to BAU (Business-as-Usual Emission Scenarios) in Florida (Intergovernmental Panel on Climate Change) [4].

1.1 Building Performance Simulation (BPS)

Building performance simulation (BPS) is a powerful analytical tool for building energy assessments and environmental impacts. Within green construction research, these tools address unprecedented design challenges that are likely to exist in the years ahead (e.g., adaptation to climate change impacts, increased urbanization, and additional complexities of technological system operations)[5]. [6] defined the main objective of BPS is to support this mission by providing a high integrity representation of the dynamic, connected, and non-linear physical processes that govern the different performance aspects dictating the future of green building innovation and their respective energy supply systems. Building simulations address challenges with the renderings of sustainable construction designs, but they also reveal gaps in energy usage over time. The energy performance gap causes significant discrepancies between real-time and calculated energy consumption of a building [7]. In building energy models, incorporating decision-making sensitivity analysis tools for use in design can be helpful, providing parameter impact insight while displaying the proposed objective [8]. [9] Results from simulations relying on erroneous parameter values can lead to highly unquantifiable inaccuracies with small perturbations to a sensitive variable, influencing the results significantly. In previous studies, the uncertainty associated with model parameters of a building using a solar thermal collector and the influence of associated parameters on solar fraction was quantifiable by using the Monte Carlo simulation technique [10]. [11] conducted a study utilizing a global design exploration in the late design phase with Monte Carlo Simulations, obtaining feasible solutions for the architects, and improving collaboration efficiency between stakeholders.

In addition, BPS requires detailed characterization of the green construction's envelope and operation. Similarly, sensible development of modeling approaches and definition of their outputs is necessary to keep models targeted to the objectives of the simulation study, which in this case would be harmful environmental impact reduction [6, 12, 13]. Furthermore, the adaptation of building design, combating climate change impacts is a primary challenge and central component of this research.

1.2 Uncertainty Quantification Methods

Uncertainty quantification (UQ) determines the effect of input uncertainties on response metrics of interest. These input uncertainties are characterized as aleatory uncertainties classified as irreducible variabilities inherent in nature. They are also classified as epistemic uncertainties, which are reducible uncertainties resulting from a lack of knowledge. [14] Based on uncertain inputs (UQ), determine the distribution function of outputs and probabilities of failure (reliability metrics). Epistemic uncertainties encompass several methodologies, including analytic reliability, Dempster-Shafer, second-order probability, and sampling, with research studies using multiple uncertainty quantification methods to reach the study's objective. Dempster-Shafer does not allow input specification by a probability distribution and input correlation studies, making this type only suitable for cumulative distribution functions. Second-order probability for inner loop analysis, analytic reliability, and sampling are methods used to express multiple common distributions while enabling a correlation analysis for input parameterization [15].

This research analyzes application of the second-order probability approach [16] through a multi-step epistemic uncertainty quantification methodology, complete with an outer level of epistemic uncertainty through interval frequencies while utilizing an inner level of aleatory uncertainty through probability distribution.

1.3 Morris Screening Method and Sustainable Building Design

Two approaches, both mathematical and statistical, were utilized to produce many model evaluations, in order to pinpoint the most impactful green parameters and then produce a ranking system of green building parameters.

The one-parameter-at-a-time (OAT) approach also known as a "mathematical approach," utilizes output calculations to determine parameter input within its possible range, consisting of the Morris methodology. The "statistical (or probabilistic) approach" involves running many model evaluations on a randomly generated input sample, with the capability of multiple inputs being varied at once [17]. The statistical methods allow quantifying the effect of simultaneous interactions among numerous parameters. The statistical approach includes methods using statistical indices: PEAR (Pearson product-moment correlation coefficient), SPEA (Spearman coefficient), SRC (Standardized regression coefficient), and SRRC (Standardized rank regression coefficient)[8, 18].

The Morris method, also known as the Elementary Effect (EE) method, utilizes a discrete approximation of an average Jacobian matrix value within respective input spaces. This methodology relies on the one-factor-at-a-time (OAT) experimental design mechanism, which allows assessment of random green building design effects, known as trajectories, on each defined output. The main advantage of Morris screening method utilization is assumption reduction on sustainable input parameters' monotonicity. [19] OFAT sensitivity analysis methods are straightforward to establish parameter dependency of the solutions and useful to study problems with a few uncertain parameters. Screening methods reduce computational cost in high-dimensional green building design models. In these methods, a sensitivity index is evaluated by the partial derivative average at different points in the input space, determining the significance of each input parameter.

1.4 Sensitivity Analysis (SA) in Building Performance Assessment (Sources)

[20] investigated the sensitivity of energy performance of office buildings in subtropical Hong Kong through parametric analysis of existing structures. [21] proposed a multi-output calibration of the building model undertaken, utilizing thirty-five parameters and ten outputs. The sensitivity analysis results revealed active model inputs and interactions that produce building performance predictions. [22] addressed the difficulties of obtaining SA data using detailed models with existing techniques and proposed a problem-solving methodology. The methodology consists of using a building model, defining uncertainties of input parameters, and calculating macroparameters resulting in statistical sensitivity indices. [23] developed a methodology to calibrate building models, including simulation of design days for thermal analysis and sensitivity analysis of input parameters related to heat gains/loss. However, these methods only explore the variation of energy performance with typical energy systems, therefore negating additional interactions amongst other design parameters.

[24] identified and analyzed input design parameters from the aspect of annual energy consumption, peak design loads, and building load profiles. Since the results from regression methods indicate a large proportion of the output variance is left unexplained, a meta-model sensitivity analysis is used to determine the most influential factors without running additional simulation runs. A common high computational energy model qualitative analysis method includes Morris method. Alternatively, a better choice is the meta-model sensitivity analysis quantifying output variance for every input, prompting an observational building energy performance study [26].

The global sensitivity approach evaluates the significance of an input factor, by varying other input factors, usually generating many model evaluations. [27] used two types of sensitivity analyses, noticing a benefit of sensitivity index and GSA (Global Sensitivity Analysis) inclusion since an individual building elements' performance alone differs from how it relates to other components. [28-30] noted that sensitivity analysis methodologies are beneficial to identify impactful building parameters across numerous construction types. [29] used a Monte Carlo Latin hypercube sampling technique to calculate the energy rating for a residential structure in Italy. [31] compared the performance of simple random, stratified, and Latin Hypercube sampling (LHS) when applied to a typical building simulation problem and established that fewer simulation runs are required for LHS and stratified, respectively.

1.5 Uncertainty Analysis in Building Performance Assessment

Design parameter uncertainty is described as design variations occurring during the planning process. Decision-makers fully determine them, causing green building design phase irregularities [32]. The main focus in current research is reducible epistemic uncertainty, characterized by utilizing building performance simulation tools. Table 1 displays basic descriptions of the Global Method used for this analysis.

Table 1 Global methods description chart [33].

Aim	Meant for the determination of uncertainty of a specific input parameter in relation to the overall output.

Input Parameters	The input parameters are sampled simultaneously
Correlation between input and output	A linear correlation is assumed between input and output of a model
Choice of distribution	In the input each variation/distribution is possible
Distribution of variables	Distribution of input is based on an assumed distribution of each parameter. Implying the insight in the behavior of the parameters

Quality assurance related to green building design options relies on analyzing these design uncertainties. In addition to physical uncertainty, epistemic uncertainty is an emerging research topic, observable when utilizing building performance simulation. Uncertainties belonging to an epistemic group arise from many different sources and can be divided into three groups caused by other parameters: physical, design, and scenario uncertainties [34]. The effective integration of UA/SA in BPS for information and quality assurance is critical for decision-making regarding the overall sustainable residential building design.

1.6 Hybrid Green Building Systems Parameters

According to the Energy Information Agency, the residential sector accounted for roughly 22% percent of the total U.S. energy consumption in 2020, or approximately 11 quadrillions (Btu). Less than three percent of total energy production came from renewable energy sources (U.S. Energy Information Administration, 2012).

Passive measures and renewable energy sources reduce long-term costs and the building's energy consumption. This research strongly suggests the need to increase renewable energy use within the residential building sector. Building energy performance parameter evaluation is complex, dependent on several factors related to the building characteristics, equipment and systems, green building options, local weather conditions, occupant schedule, and sociological influences [35, 36]. Although there has been a significant push from the federal government to incorporate renewable energy use in the U.S., there is substantial room for increased renewable energy dependency.

[17] A review of SA case studies noted that the most frequent input parameters are weather, building envelope I (e.g., walls, roof), building envelope II (e.g., windows), ventilation/infiltration, HVAC/mechanical systems, and occupant behaviors. The building/urban energy consumption and occupant thermal comfort are frequently studied outputs; however environmental impacts are not often-studied outputs. This research aims to utilize both the screening method and a global sensitivity analysis methodology for parameterized environmental impact determination of green infrastructure design elements.

1.7 Problem Statement

A primary aim of this UA/SA research study is to support the pre-construction process by providing a comparative analysis between green design parameter impact on carbon emissions and energy usage. In this case, the input variables are defined as continuous uniform or triangular distributions, respective to each parameter presented in Table 2 and Table 3 below. For example, sensitivity analysis is used to decide whether higher lighting efficiency is necessary compared to other energy-saving measures since stakeholders' additional construction costs are a concern. A detailed simulation to estimate how building energy performance and carbon emissions change with meteorological conditions and green building design parameters epistemic uncertainty will be produced. This study's global objective is sensitivity analysis method evaluation, with a focus on residential structures in sub-tropical climate conditions.

Table 2 Epistemic uncertainty properties in design variations.

	Parameter	μ	σ
X1	**Building Orientation**	58.0948	112.5
X2	**Lighting Efficiency**	0.7303	1.1
X3	**Plug Load Efficiency**	1.525	0.8302
X4	**Infiltration Factor**	1.0425	0.8947
X5	**Wall Construction Factor**	0.074	0.067
X6	**Roof Construction Factor**	0.0176	0.0255
X7	**Window Shading**	0.2367	0.335
X8	**Solar absorptance of external walls**	10.524	27.636
X9	**Solar absorptance of the roof**	41.87	52.51
X10	**Windows Glazing**	0.2202	0.33
X11	**Window to Wall Ratio**	0.0427	0.1563
X12	**Solar Heat Gain Coefficient**	0.1826	0.44
X13	**Panel Efficiency**	1.8257	18
X14	**PV-Payback Limit**	8.5391	18.75
X15	**PV-Surface Coverage**	33.2603	48.75

Table 3 Parameterization table: Building envelope parameters, distributions, and boundaries used in Monte-Carlo simulation.

#	DESIGN VARIABLE	ID	UNIT	LEVEL 1	LEVEL 2	LEVEL 3	LEVEL 4
1	Building Orientation	BO	Degrees (°)	45	90	135	180
2	Lighting Efficiency	LPD	W/sqft	0.3	0.7	1.5	1.9
3	Plug Load Efficiency	EPD	W/sqft	0.6	1.3	1.6	2.6
4	Infiltration Factor	INF	dimensionless	0.17	0.4	1.6	2.0
5	Wall Construction Factor (N, S, E, W)	WCF	W/m^{2}K	R38 Wood 0.026	R13+R10 Metal 0.17	R13 Wood 0.07	R13 Metal 0.03
6	Roof Construction Factor (N, S, E, W)	RCF	W/m^{2}K	R60 0.016	R38 0.026	R19 0.05	R10 0.1

7	Window Shading (N, S, E, W)	WS	dimensionless	0.1	0.25	0.33	0.66
8	Solar absorptance of the external walls	SAEW	dimensionless	0.2	0.4	0.6	0.8
9	Solar absorptance of the roof	SAR	dimensionless	0.2	0.4	0.6	0.8
10	Windows Glazing	WG	W/m^2K	0.12	0.27	0.29	0.64
11	Window to Wall Ratio (N, S, E, W)	WWR	dimensionless	0.1	0.15	0.175	0.2
12	Solar Heat Gain Coefficient (N, S, E, W)	SHGC	dimensionless	0.24	0.34	0.54	0.64

2. Methodology

2.1 Monte-Carlo Probability Analysis

Prior to relative sensitivity assessment of each input factor, a method must be selected based on the target function. Monte Carlo Analysis is the most commonly utilized method for UA/SA, while considering the total sensitivity due to input uncertainties. The Monte Carlo analysis (MCA) method is applied to analyze an approximate distribution of possible results based on probabilistic inputs displayed in the equations below:

$$E(Y) = \frac{1}{N}\sum_{i=1}^{N} y_i$$

$$E(Y) = \frac{1}{10000}\sum_{i=15}^{10000} y_{15}$$

$$V(Y) = \frac{1}{N}\sum_{i=1}^{N}[y_i - E(Y)]^2$$

where N = number of samples, and I = number of input parameters.

To run a carbon emissions model, an extensive set of inputs are pre-defined within Revit to specify the building geometry, internal loads, outdoor environment, equipment, and occupancy schedules. In conceptual design, only a small subset of these inputs, specifically, the building envelope, orientation, materials, and green building design alternatives, are considered. The remaining inputs required to run an annual simulation are fixed at default values based on the building type and composition of the base energy model presented in the pre-processing section. Initially, key green design parameters relevant to sustainable building construction are identified. Next, to sample the design space, Monte Carlo simulation is used to test combinations of parameter values within their defined ranges, producing a rich dataset determining standardized rank coefficients. Monte Carlo Latin hypercube sampling was utilized to assess annual carbon emissions and energy usage, while gaining a more comprehensive understanding of parameter impact on carbon emissions reduction, further outlined in Figure 1. This analysis focuses on the environmental impact of green building design options by considering solar power as an energy source.

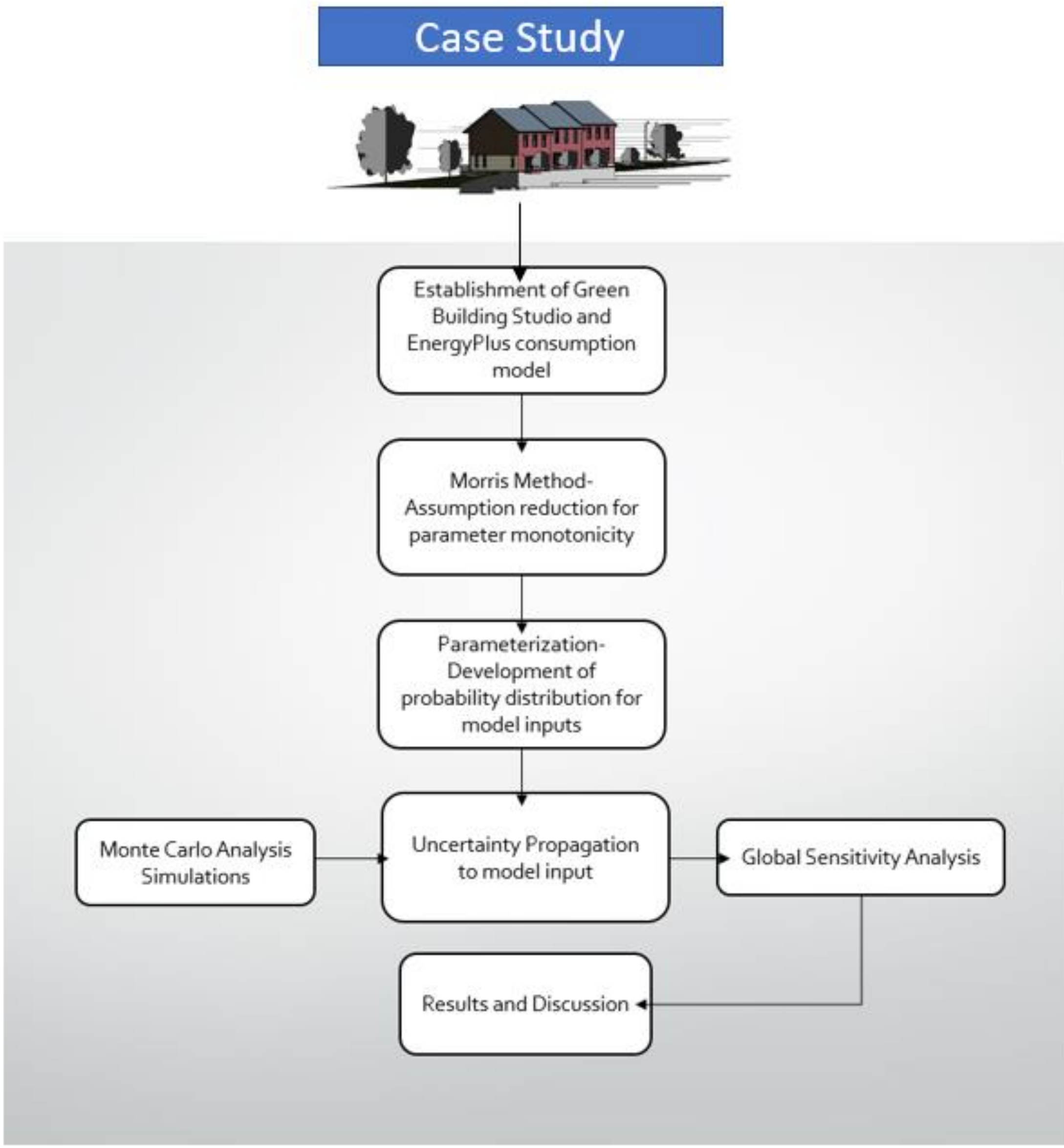

Figure 1 Global sensitivity analysis and epistemic uncertainty analysis framework.

1. The limit state function for the response metric of interest is defined, based on model outputs. Next, the reliability method of specified probability was illustrated above in Figure 2. A 95% confidence interval was chosen to display Monte Carlo Simulation results, for the estimate range of epistemic uncertainty parameter population values.

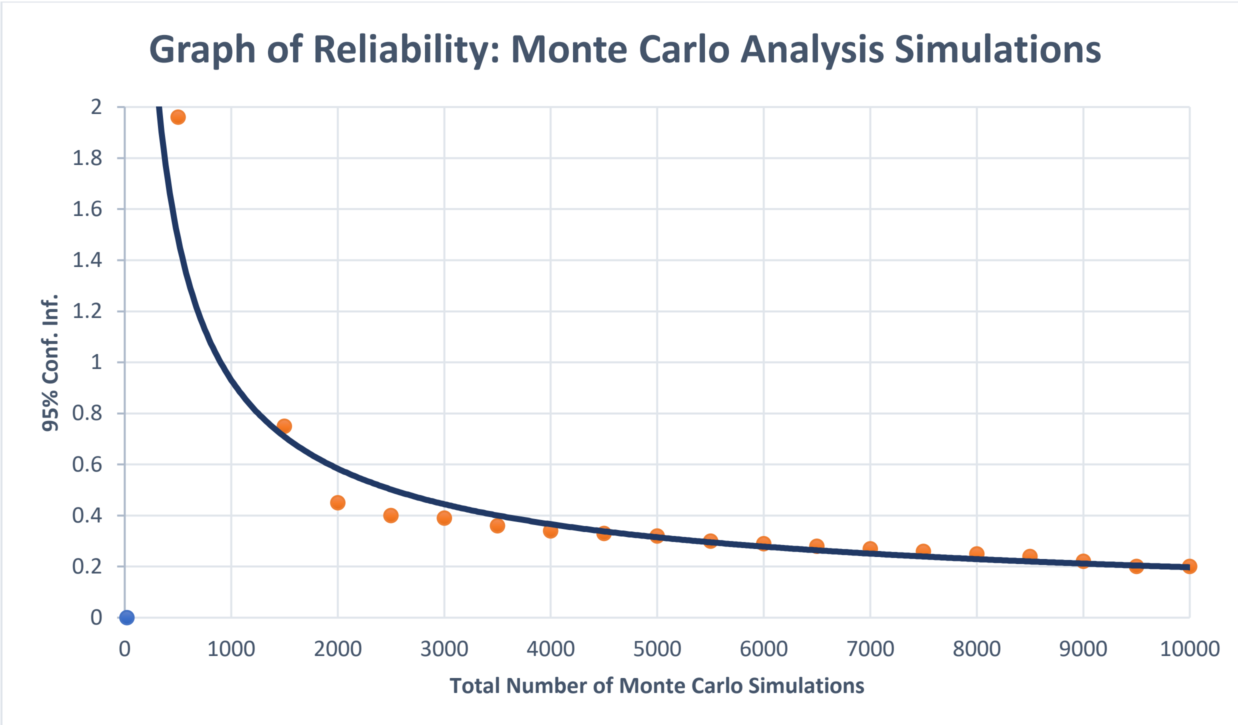

Figure 2 Graph of reliability.

2. The sensitivity analysis of environmental impacts should form an integrated part of the green building design decision-making processes, guiding the main objective of this study. Due to this observed phenomenon, a two-dimensional Monte Carlo method can be used in this case, considering respective output factors. Global sensitivity measures, also known as elementary effects are calculated by using the equation below, with x_1, x_2, x_i, x_k as input variables and Δ as the change in operational carbon emissions and energy usage:

$$EE_i = \frac{f(x_1, x_2, \dots x_i + \Delta, \dots x_k)}{\Delta}$$

3. Next, Figure 3 and Figure 4 display results of the Morris randomized OAT (one-step-at-a-time) design code runs to conduct parameter screening method, with outputs given as meta-model simulations for further evaluation [37]. Typically, a design parameter can be classified as sensitive, if its value can vary considerably; therefore, these parameters are selected for the initial screening with epistemic uncertainty properties shown in Table 2. Variation of the parameter results for considerable environmental impacts defined within the problem statement, are illustrated by the equation below.

$$\sigma = \frac{\mu\sqrt{r}}{2}$$

where sigma (σ) is the mean value of the elementary effect (tons/year), r is the number of elementary effects per design parameter, Mu (μ) is the standard deviation of the elementary effect (tons/year).

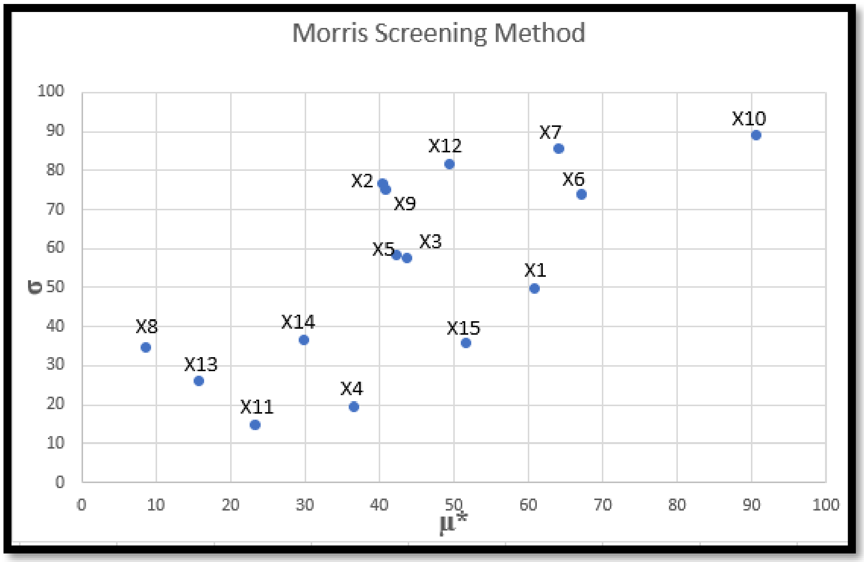

Figure 3 Annual carbon emissions Morris screening method.

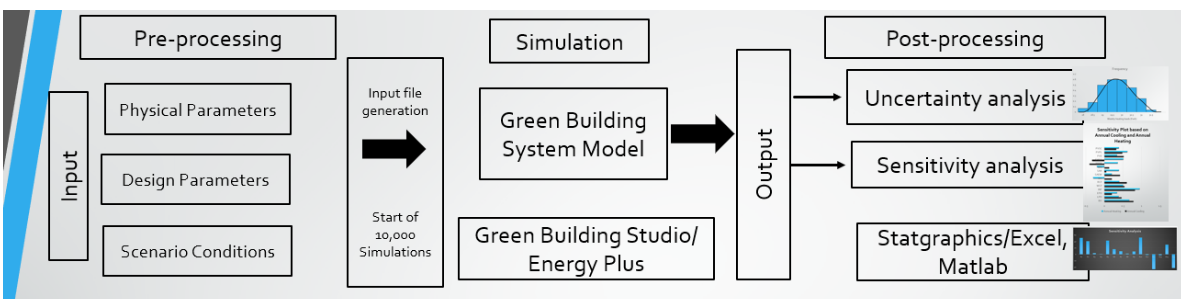

Figure 4 Three-phase epistemic uncertainty analysis methodology.

4. Due to the individual impacts, each element has on green building performance, the necessary design parameters are listed below in Table 4. The range of all green building input factors in the specified case study is determined before conducting the sensitivity analysis. The probability distributions of the inputs must also be defined when utilizing the Monte Carlo sensitivity analysis methodology.

Table 4 PV systems parameterization table.

Types of modules (Cell Material)	*Type of PV system (kW)*	*annual electricity production (kWh)*	*annual carbon emissions reduction (tons)*	*Panel Efficiency (%)*	*Surface coverage*	*Energy payback estimate*	*Ground Coverage Ratio*	*System Losses*

Multicrystalline-silicon	*10 kW*	*14100*	*10*	*17.2%*	*62.5 m^2*	*4*	*0.4*	*14%*
Thin-film	*10 kW*	*8207.5*	*5.8*	*10%*	*62.5 m^2*	*2*	*0.4*	*17%*

Next, probability density functions are assigned to each key parameter, utilized to quantify annual carbon emissions, which in this case is closely correlated to annual energy costs. Limit estimation for the design parameter variation identifies the most appropriate probability density function. Sensitivity analysis results generally are dependent on selected ranges. Uncertain inputs are assigned a continuous distribution, based on the approximate distribution of possible results. The Quasi-Monte Carlo technique derived from SIMLAB includes continuous distribution, maximizing data entropy with a calculated mean and standard deviation [25].

5. An input matrix was generated, based on the probability density functions of each parameter within Statgraphics™. Utilizing Building Information Modelling, an output parameter is created by a simulation model for each sample of design parameters.

2.2 Pre-processing Phase

During the pre-processing phase, simulations to obtain values for input parameters were conducted in Green Building Studio. Insight and Project Solon were utilized to obtain parameter ranges for Monte Carlo Latin hypercube sampling. The generated files were then transferred to Excel, and the Monte Carlo simulation output considered in energy consumption and carbon emissions. The generated values pass to Excel, and the simulation is started 10,000 times automatically. Figure 4 displays the three-phase epistemic uncertainty analysis. Advantages include: (i) understanding parameter relatability to environmental impacts, (ii) comprehension of how variations in the model input affect the output, and (iii) decision- making process support by providing a baseline for comparison within green building systems.

2.3 Case-Study

One realistic case study has been simulated adapting UA/SA and was implemented in this proposed framework on a new construction multi-family floorplan in Tallahassee, FL, considering green building design epistemic uncertainties. The multi-family home has three floors with a total area of 5846 ft^2. Based on 2D CAD drawings, a BIM model is developed using Autodesk Revit software. The various building envelope components are extracted from the model for utilization within Green Building Studio and Revit EnergyPlus. Based on the energy savings for each associated building envelope modification used in this model, maximum carbon emission reduction were analyzed for each defined green building design parameter.

2.4 Computational Model of the Case-study Building

The simulation software used was Revit™, which allows importing architectural drawings. Green Building Studio was then utilized to conduct a base run for the original model. Specifically, since the approach used is based on sensitivity analyses, a base case was needed as a reference against which green building design alternatives should be assessed. At the preliminary stage of sustainable design, choices must be made according to good engineering judgement criteria—constructive solutions, such as wall construction factor, roof construction factor, window to wall ratio, glazing, lighting efficiency, SGHC (solar heat gain coefficient), and the impact of renewable energy systems. Some of the initial choices included the weather file, present within Green Building Studio, a default occupant schedule of 24/7, and an air change rate set at 0.75 air changes/hour, a higher value than the natural infiltration rate, as demanded by the simulator.

2.5 Energy Model Creation

Autodesk Revit, a software package, allows the user to create an architectural template, define building geometry, thermal zones, and occupancy number, within the energy model. The model is then exported to GBS as a gbXML (green building eXtensible Makeup Language) file format for sustainable building performance analysis. Within Green Building Studio's web interface, a new project for Tallahassee, FL was created by specifying the project name, building type, operational schedule, and location.

2.6 Simulation Results

The simulations were organized to identify the influence on the building performance for green building design changes, including constructive elements and equipment. This sensitivity analysis methodology aims to identify the most impactful parameter for a robust and economical green building design. PV panel parameters collected from GBS and the solar panel efficiency estimation website are displayed below in Table 5:

Table 5 Default values assumptions chart.

Parameter	Default Value	Description
Ground Coverage Ratio	0.4	An array with wider spacing between rows of modules has a lower GCR than one with narrower spacing. A GCR of 1 would be for an array with no space between modules, and a GCR of 0 for infinite spacing between rows.
DC System Size	2.75	The default 10 kW system has an array size of 10 DC kW and an inverter size of 3.62 AC kW.

System Losses	14%, 17%	System losses account for performance losses expected in a real system and were assumed for each module type according to corresponding efficiency. Default value of system losses is assumed to be 14% and 17% respectively for each module type and an example expression is included below: 100% x $[1-(1-0.02)\times(1-0.03)\times(1-0.02)\times(1-0.02)\times(1-0.005)\times(1-0.015)\times(1-0.01)\times(1-0.03)]=14\%$

2.7 Post-Processing Phase

Finally, a global sensitivity analysis regression-based method was utilized in this study of comparison, where the influence of each design parameter on the expected value and the variance of the output parameters are estimated.

During the post-processing phase, a number of analyses were conducted to compare various techniques, including regression analysis and graphing of the Morris method results, yielding sensitivity and uncertainty measures. Following the Standardized regression coefficient calculation, all SRRCs were established for green building parameters, indicating the sensitivity of each parameter, noting that higher values correlate to increased parameter sensitivity and epistemic uncertainty. Standardized regression coefficient are an effective statistical technique to quantitively determine the most impactful green building parameter, while analyzing the impact on a modelled structure's carbon footprint.

2.8 Validation of the Building Energy Model

During the analysis, sustainable building properties are considered as input variables x_1, x_2, x_m (i.e., heating/cooling energy consumptions, annual carbon emissions, and annual energy usage) as the energy cost or environmental cost function E_F.

$$E_F = f(x_1, x_2, \dots, x_m)$$

Predictions for heating and cooling energy consumption are compared against those delivered from a popular building performance simulation (BPS) software tool, i.e., Green Building Studio, to verify the accuracy of the current sustainable building model. Heating load, cooling load, annual carbon emissions, and annual energy costs are obtained for a tri-plex multi-family building. Each room is defined as one thermal zone.

The building is simulated in Tallahassee, FL and weather files sourced from EnergyPlus are utilized for this simulation. This model assumes that the building is on the ground and facilitating typical residential thermal energy exchange. Interior heat gain sources such as occupant schedule/details, equipment types, lighting, and main building envelope factors are focal points of simulation with a Residential premium efficiency 17 SEER/9.6 HSPF Split HP as the primary HVAC system.

Figure 5 annual energy consumption predictions for annual heating (a) and cooling (b from the current model, compared to Green Building Studio simulations for the year 2021. Both heating and cooling energy loads show a good agreement with Green Building Studio simulations. The total heating and cooling energy consumption delivered by the current model for the entire 2021 year differs less than 7% from Green Building Studio simulations.

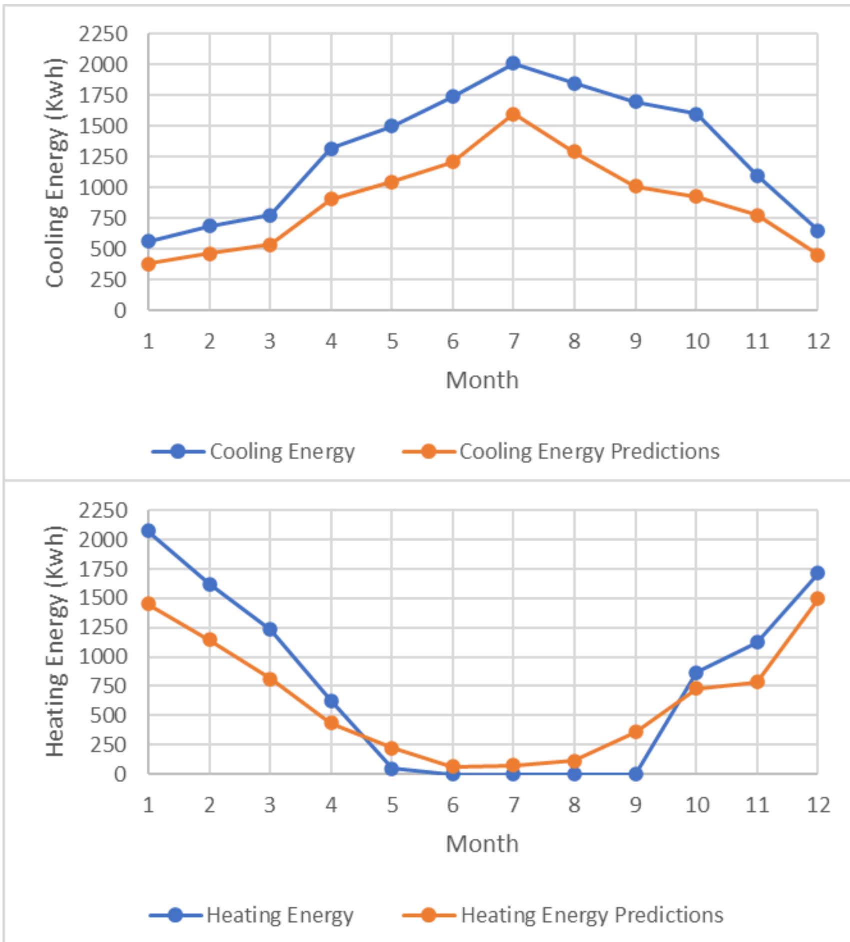

Figure 5 Comparison between monthly heating and cooling energy consumption against GBS simulations (2021).

3. Results

3.1 Sensitivity Analysis Results Using Morris Method

Eighty-four simulations (the number of elementary effects per parameter is set as 8), obtained by sampling all 15 design parameters within their ranges, are conducted for sensitivity analysis using the Morris Method and results are shown in Figure 6. Table 6 displays epistemic uncertainties for robust design options. A value in the x-axis represents the absolute value of elementary effects of a parameter, a reflection of importance. The y-axis value is an indicator that measures the parameter's non-linear effects and its interactions with other parameters. Observations show that most of the design parameters have both linear and non-linear correlated impacts on the environmental objective, while WWR, SHGC, infiltration rate mainly have linear effects. As parameters are ranked based on their values, the top 12 sensitive parameters identified are the same as the regression method.

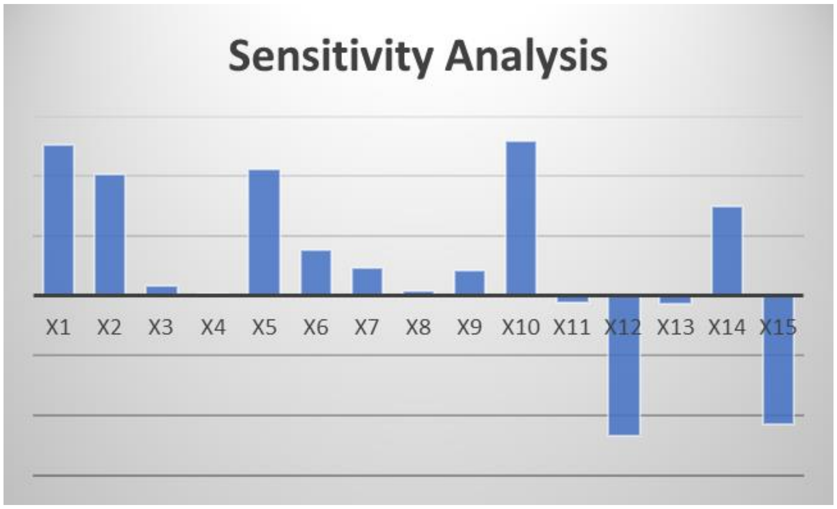

Figure 6 Global sensitivity histogram (annual carbon emissions).

Table 6 Green building parameter epistemic uncertainties.

PARAMETER		**μ**	**σ**
X1	Building Orientation	58.0948	112.5
X2	Lighting Efficiency	0.7303	1.1
X3	Plug Load Efficiency	1.525	0.8302
X4	Infiltration Factor	1.0425	0.8947
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X13	Panel Efficiency	1.8257	18
X14	PV-Payback Limit	8.5391	18.75
X15	PV-Surface Coverage	33.2603	48.75

3.2 Epistemic Uncertainty Analysis-Normality Plots

Uncertainties in design parameters can be described as design variations that occur during the planning process. They are fully determined by the decision-maker and caused by a lack of knowledge or arise due to changes or irregularities in the structure's planning phase. This research compared the normality plots between energy performance and carbon emissions for a new building using different design options. An accounting approach for design uncertainty leads to quality assurance of the model. Research inputs to a photovoltaic decision problem (i.e., thin-film crystalline modules or anticipated multi-crystalline modules) is key during the green building design process. Computation of epistemic uncertainties of response mean and variance is completed by following the equation below:

$$\mu(s) = \alpha_0(s),\ \sigma^2(s) = \sum_{k=1}^{P} \alpha_k^2\,(s)(\varphi_k^2)$$

Figures 7-10 indicate weekly heating loads, cooling loads, carbon emissions, and energy costs according to theoretical quantiles as green building parameters outlined in Figure are utilized throughout the model simulations. Figure 11 displays the frequency of carbon emissions and energy costs per year during the yearly energy cycle of the multi-family home.

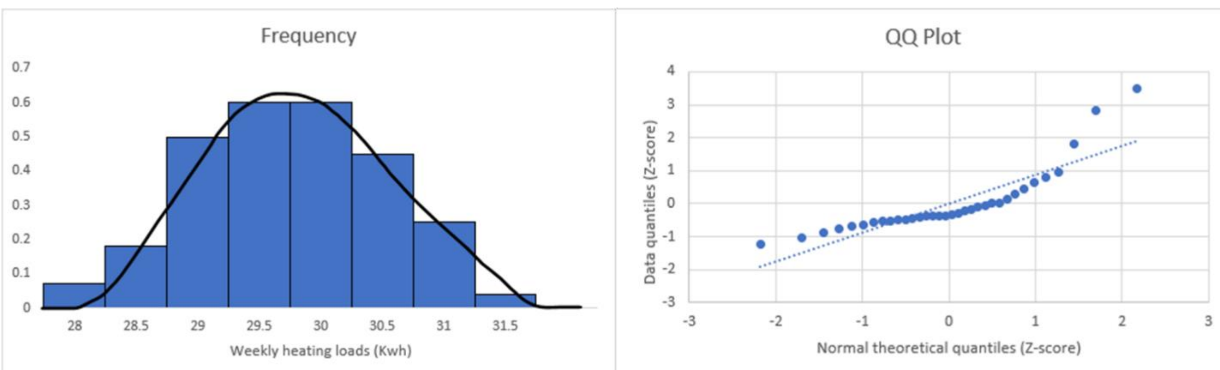

Figure 7 Frequency distribution and normality plot of weekly heating loads when considering epistemic uncertainty in all parameters. The results for weekly heating loads vary between 28 and 31.5 Kwh. The normality plot on the right side displays a normal distribution.

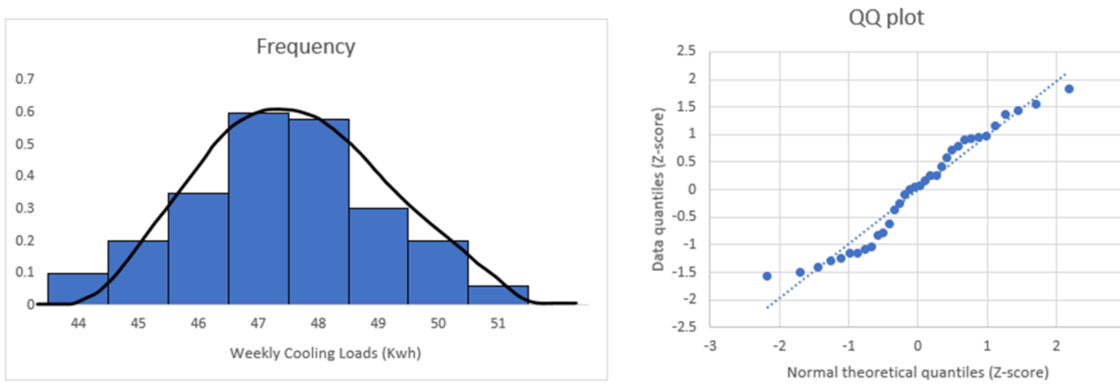

Figure 8 Frequency distribution and normality plot of weekly cooling loads when considering epistemic uncertainty in all parameters. The results for weekly cooling loads vary between 44 and 51 Kwh. The normality plot on the right side displays a normal distribution.

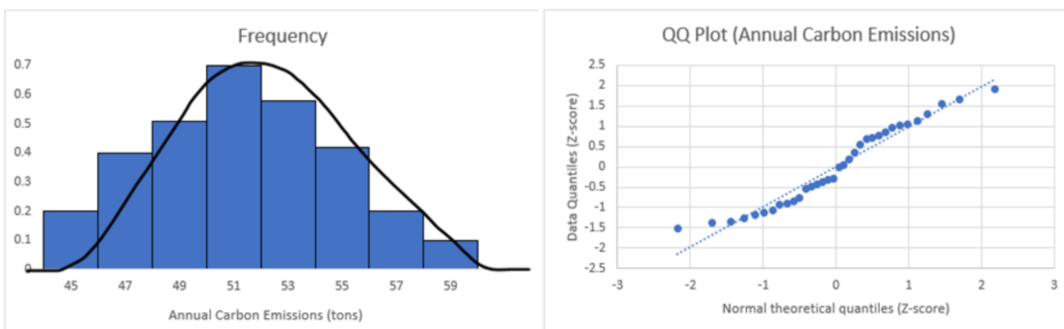

Figure 9 Frequency distribution and normality plot of weekly carbon emissions when considering epistemic uncertainty in all parameters. The results for annual carbon emissions vary between 45 and 59 Kwh. The normality plot on the right side displays a normal distribution.

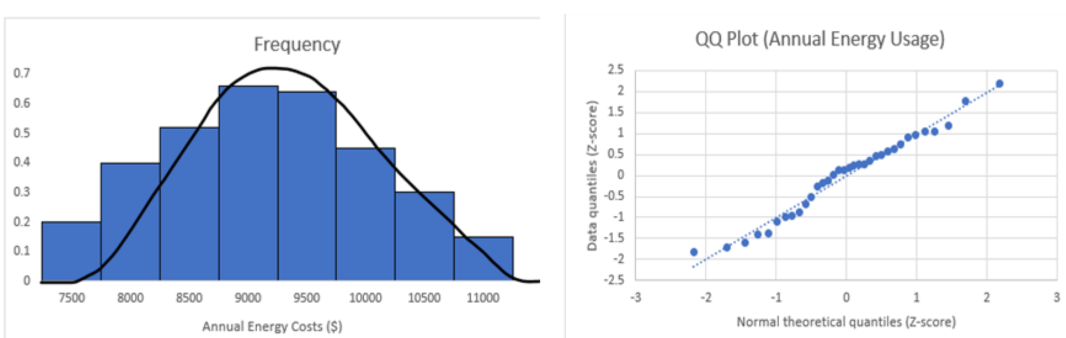

Figure 10 Frequency distribution and normality plot of weekly energy costs when considering epistemic uncertainty in all parameters. The results for annual energy costs vary between $7,500 and $11,000. The normality plot on the right side displays a normal distribution.

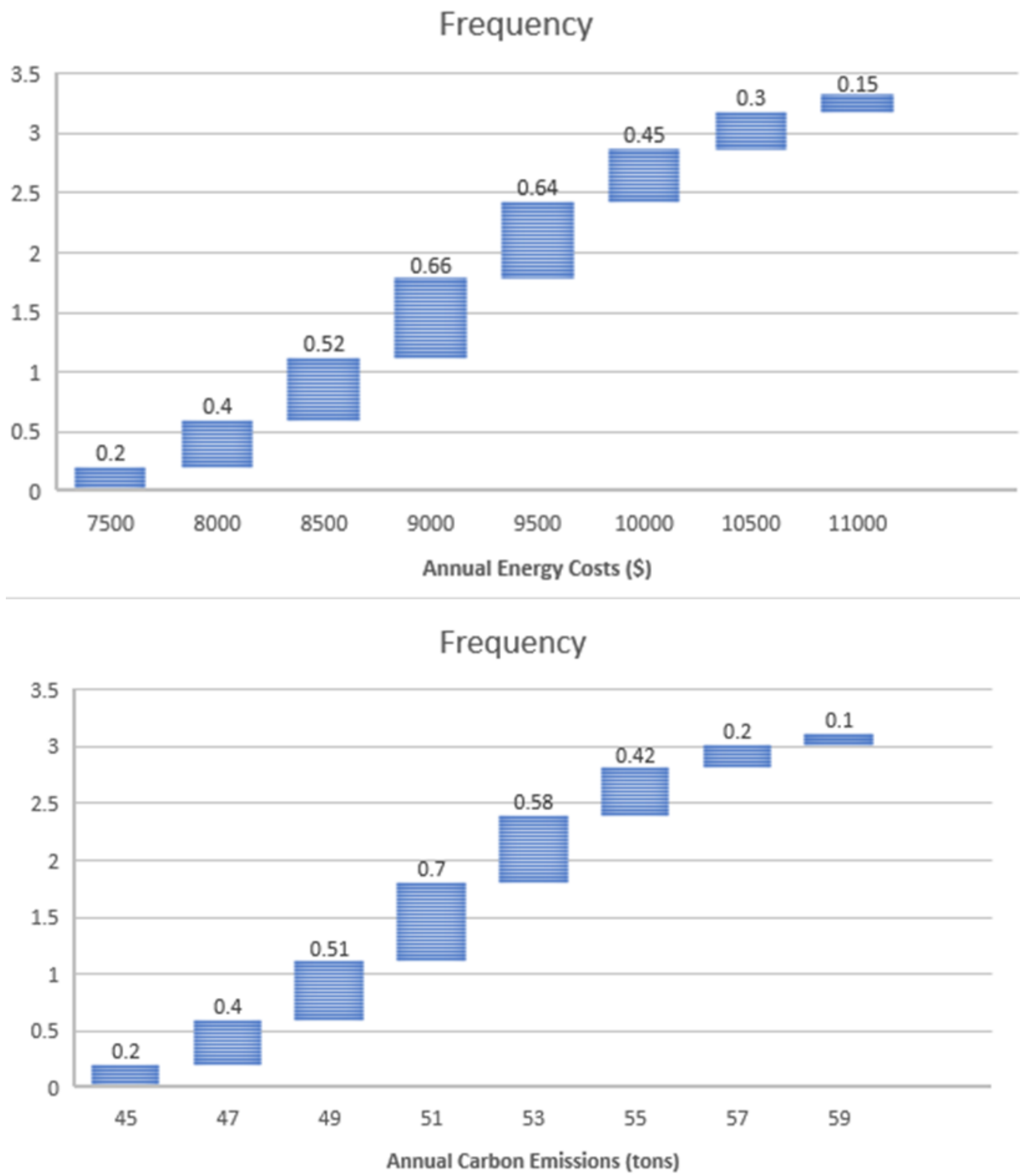

Figure 11 Operational annual energy costs and carbon emissions frequency diagram.

4. Discussion

4.1 Epistemic Uncertainty Representations of a Random Variable

The histogram above represents the cumulative frequency distribution of annual carbon emissions when considering epistemic uncertainty in physical parameters.

Finally, standardized regression coefficients (SRCs) were used to determine which design parameters are most sensitive and therefore explain the most variability in the models. The units of coefficient βj depend on the units of xj, which do not have the same order of magnitude.

Standardized Regression Coefficients are obtained by multiplying each coefficient by the ratio of estimated standard deviations obtained from Monte-Carlo simulation of xj; x_j; y:

$$U_{SRC}(x_i, y) = \frac{\beta_j x s_j}{sj}$$

Observed results showed that PV panel efficiency and lighting efficiency significantly affect annual carbon emissions. Standardization must occur before comparing green building parameters, which in this research differ in scale (i.e., building orientation of 45 degrees and wall construction factor of 0.2). Normalization of linear regression coefficients permitted a more thorough and accurate comparison between parameters with varying scale degrees [38].

By normalizing the regression coefficients using a standard deviation of the sampled parameter values, the effects due to the scale of the parameters are eliminated.

$y_i = a + \sum_j b_j x_{ij} + \varepsilon_i$, where y_i , $i = 1, \ldots, m$, are the output values of the model; $b_j, j = 1, \ldots, n$, are determined coefficients, and ε_i is the residual computational error due to approximation, (m represents the number of inputs in the sample, n represents the number of input variables). The reliability of the SRC results depends on R2 of the linear model. The following form of the regression equation was utilized to predict annual carbon emissions:

$$y(x_1, x_2, \ldots, x_n) = \beta_0 + \sum_{j-1`}^{n} B_j x_j$$

where y is annual carbon emissions, x_j represents the value of design parameter j, and β_j is the corresponding regression coefficient.

4.2 Sensitivity Analysis Results Using Regression Method

In this research, we compared the environmental impact for a new building using different design options, by first focusing on the ranges of chosen design variables. The input variables are taken as continuous distributions, assuming each variable is equally probable. The Latin Hypercube method samples fifteen selected design parameters within their ranges. A total number of 10000 samples are generated by the Monte Carlo simulation for the sensitivity analysis using the regression method. The standardized rank regression coefficient (SRC) is used as a sensitivity measure. Figure 12 displays a sensitivity analysis plot based on parameter impact, which measures the linearity of design parameters. A positive indicator value means an increase of a design parameter increases defined performance objectives. Results in Figure 13 display that the lighting efficiency, SGHC, and wall construction have the most significant influence on the building performance. The parameters of system design and construction quality (i.e., plug load efficiency, infiltration factor, window glazing, WWR, Surface absorptance of roof and external walls, surface coverage, panel efficiency) have higher impacts on environmental impacts compared with the photovoltaic design parameters (i.e., infiltration factor, wall and roof construction factors, and building orientation.) This means that utilizing PV panel systems, increasing lighting efficiency, Low-e hot climate glazing, shading, and acceptable construction quality can contribute significantly to the performance objective of carbon emissions reduction. The sensitivity measures of SHGC (solar heat gain coefficient), infiltration factor, and window shading are larger than building orientation. Wall construction and roof construction factors have more significant impacts when compared with surface absorptance.

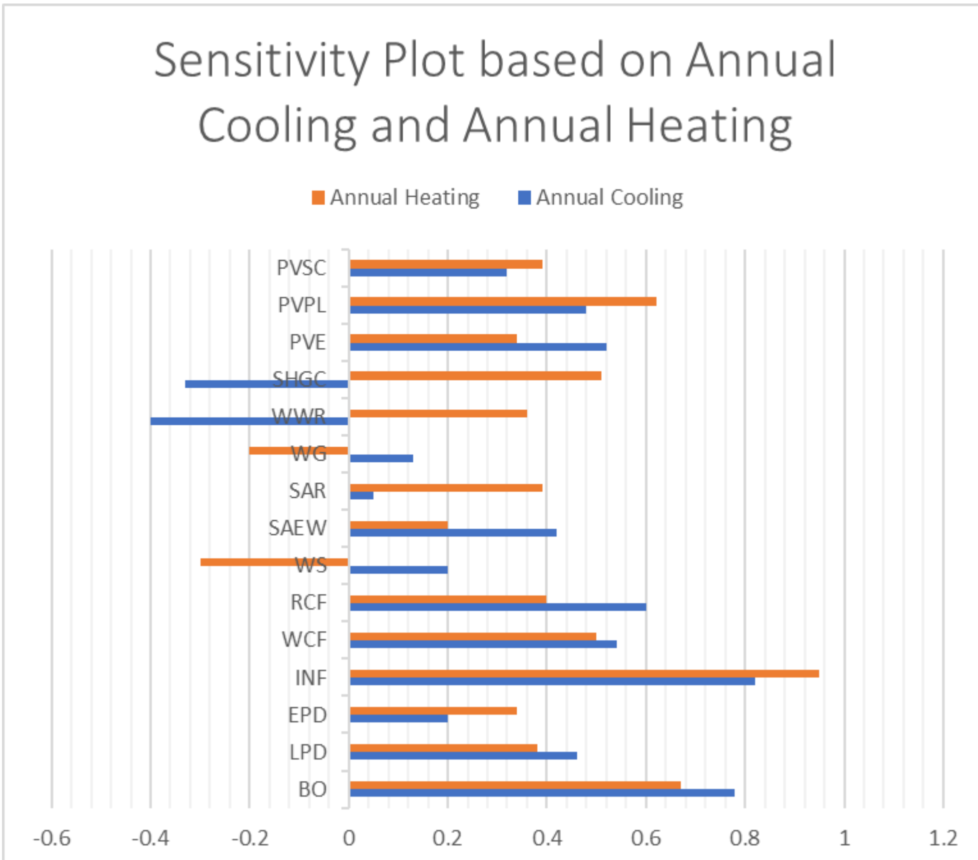

Figure 12 Sensitivity plot and table displaying all parameters based on operational heating and cooling energy usage.

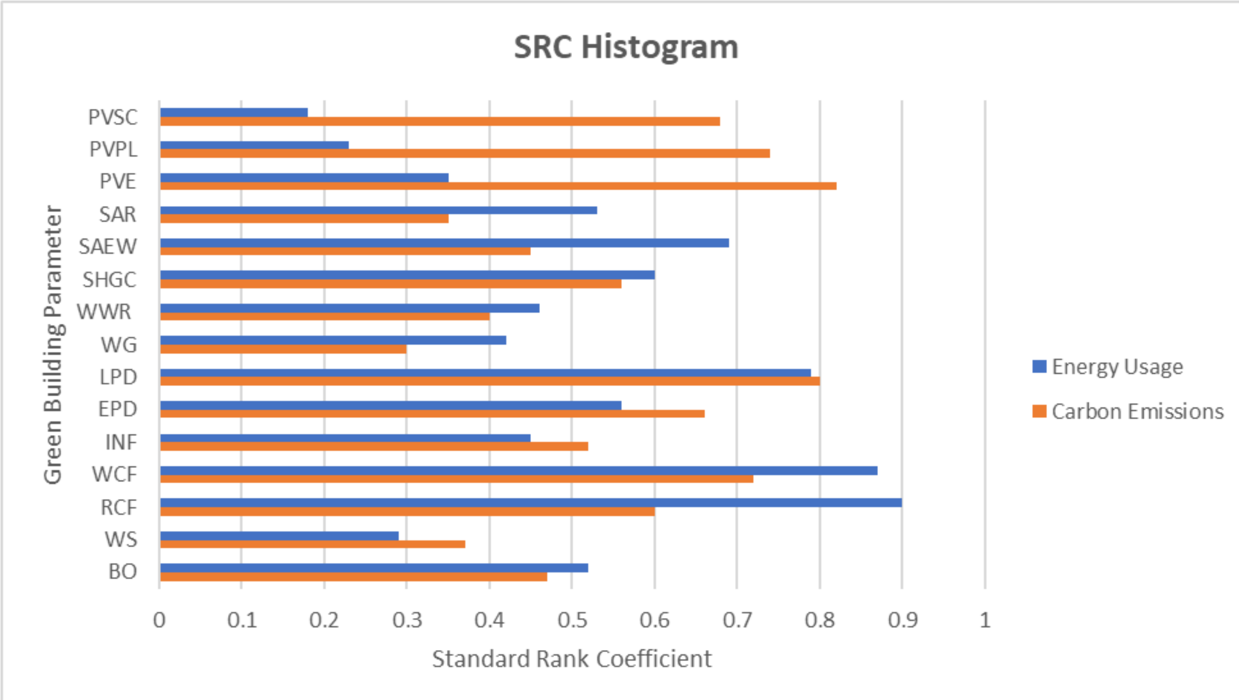

Figure 13 SRC histogram green building design parameters (annual carbon emissions and annual energy usage).

5. Conclusion

An approach combining green building design alternatives in energy performance simulation tools and a multi-stage sensitivity analysis method is proposed for the sustainable design of multi-family homes in Florida to mitigate carbon emissions. Based on the case study results, conclusions can be made as follows. Results show that PV panel efficiency, PV payback limit, lighting efficiency, plug load efficiency, and SGHC are highly influential parameters. Furthermore, the building envelope design and renewable energy system interactions were accounted for. Building orientation and surface coverage affect power generation, while PV panels affect building cooling load and affect optimal building design choice due to the impact on envelope design parameter choices.

This analysis proved epistemic reliability applicability to model-form uncertainty parameters with varying ranges. Although epistemic uncertainty was used, there is still a possibility of modeling error, therefore incorrectly skewing results; however, this method is a vital tool for error reduction when combined with sampling uncertainty. The proposed method for this research displays the ability of epistemic uncertainty and aleatory separation under our modeling methodology. Based on preliminary results from an unsatisfactory optimal design, we decided to reduce the epistemic uncertainty achieved by sampling more design options, proved theoretically and numerically in the results section under model conditions. Uncertainty methods often have increased computational cost; however, this methodology reduces computational overhead, simplifies the research approach, and allows for rapid outputs of building design decisions despite uncertainty propagation. A more in-depth study is necessary to account for interdependencies amongst chosen green building design parameters while also considering an inverse modeling approach for design evolution uncertainty during the building's life cycle.

Sensitivity analysis for green building design optimization can provide insights about the building system as a part of the simulation process and can present opportunities for improved handling and analysis of data so that energy estimates can be improved while quantifying uncertainties. The annual carbon emissions are sensitive to measures affecting building envelope components, renewable energy system options such as solar energy production, characteristics of windows, and building envelope. Further research is needed to determine the sensitivity of weather data in Green Building Studio (GBS) since this significantly impacts energy model data outputs. A hybrid metaheuristic optimization algorithm can also be utilized in future studies to find the optimal solution between occupant comfort, annual carbon emissions, construction costs, and life cycle costs**.**

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Author Contributions

Siera Sylvester - Concept, Methods, Analysis, Results, Conclusion; Jalaycia Hughes - Background Information; Dr. Clayton Clark - Results and Additional Ideas.

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Competing Interests

The authors have declared that no competing interests exist.

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