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Full-length article

Python-driven sensitivity analysis of geometric parameters: Evaluating the impact of geometric variations on environmental performance of large office in Boston

Zinat Javanmard *, Consuelo Nava

ABITA Lab, Department of Architecture (Theory and Design), Mediterranea University of Reggio Calabria, Italy

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ABSTRACT

This research conducted a quantitative analysis of the impacts of design decisions made in the early stages of the design process, specifically focusing on their environmental effects. Through Sensitivity analysis, this study explores the relationship between design parameters of spatial structures and environmental consequences for each geometric form within a large office space in Boston, employing a multidisciplinary approach that integrates Python with parametric modeling software. Specifically, it aims to determine which variables—such as length, width, and height for a cube, and height, radius, and length for a cylinder—most significantly influence the environmental outcomes. The research primarily employs Rhino and Grasshopper for parametric modeling of a cube and a cylinder, followed by climate analysis using Honeybee and Ladybug tools. Subsequently, the Environmental Impact of energy consumption during the operational phase (B6 stage) is assessed through OpenLCA. The findings indicate that the cylinder configuration offers significantly better energy efficiency and 5.3% lower environmental impact compared to the cube. Sensitivity analysis through Scatter plot, FRE, XGBoost, RF, and SHAP values diagrams highlight that among the cube's parameters (length, width, height), length is a critical factor for its sustainable design, while for the cylinder varieties (height, radius), height holds greater significance. Among the various environmental impacts assessed, fossil fuel depletion emerged as the most crucial category. The investigation conclusively underlines the imperative of optimizing geometric parameters to significantly influence reduce the ecological footprint, thereby advocating for strategic, evidence-based design decisions in the sustainable architecture field.

1. Introduction

Sustainability has become a critical focus in response to escalating climate challenges, with architecture and urban planning playing a key role through interdisciplinary collaboration. Incorporating insights from environmental science, engineering, and social sciences, a holistic approach to urban development and building design is essential [1,2]. The field of sustainability science emphasizes the need for collaborative efforts across various disciplines to address urban complexities effectively [3]. Cities are increasingly recognized as essential actors in global sustainability efforts, requiring a transdisciplinary approach that integrates natural and social sciences, engineering, and humanities to foster sustainable urban solutions [4]. This integrated approach is vital for developing urban environments that are environmentally sound, socially equitable, and economically resilient [5–7].

Recent studies underscore the significant impact that architectural geometry can have on a building's environmental performance. The architectural geometry and urban form, including factors such as building orientation, density, and street patterns, can significantly influence a building's environmental performance and energy consumption [8–10]. The pivotal role of architectural geometry in achieving sustainable and energy-efficient buildings represents a significant research area within the field of environmental design [11]. Building Information Modeling (BIM) is becoming increasingly popular in the construction of eco-friendly environmentally friendly structures, prompting the creation of techniques for grading green buildings that use BIM elements. This makes it easier to assess the environmental implications of different building configurations [12]. Researchers are diligently exploring various facets of geometry to understand its impact on the environment [13]. This involves investigating how different shapes, orientations, and structural features of buildings can enhance energy efficiency and sustainability [9]. These studies aim to integrate architectural form with environmental functionality, thereby reducing a

* Corresponding author.
E-mail addresses: Zinat.Javanmard@unirc.it (Z. Javanmard), Consuelo.Nava@unirc.it (C. Nava).

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building's carbon footprint while improving its livability [14,15]. The literature emphasizes the fundamental role of architectural geometry in shaping the built environment, necessitating further scholarly investigations into specific geometric modifications on building facades and their subsequent environmental impacts. Building upon a comprehensive literature review spanning from 2015 to 2024, this research extensively examines the role of geometry in the built environment and explores the application of machine learning in sustainable design. Following this review, a summary of key findings is presented, illustrating how architectural geometry critically influences environmental performance.

Károlyf and Szép emphasize that the geometry and form of a building directly influence the choice of structure and materials used. Consequently, the conceptual design phase is critical for exploring alternative solutions. They propose a method to generate alternative structural solutions and assess their embodied environmental impact during this phase. This is achieved by combining parametric design with building information modeling (BIM), utilizing tools such as Rhino and Grasshopper for parametric design [16]. Dastoum et al. focus on using geometric patterns and perforated screens on facades to optimize daylight and improve energy efficiency. Their approach aims to balance natural light distribution and reduce solar heat gain, ultimately decreasing dependence on artificial lighting and cooling, thus enhancing building energy performance [17]. Rane et al. in 2023 demonstrate how parametric design and computational modeling allow architects to exploit geometric complexity to enhance building performance. By iteratively modifying design parameters, architects can develop innovative forms that improve energy efficiency, structural integrity, and aesthetic appeal [18]. Guolian Cui emphasizes the profound impact of architectural geometry on building performance. They highlight how strategic design elements, such as building orientation, shading devices, and envelope systems, can significantly influence solar heat gain and indoor temperatures, thereby impacting thermal comfort and energy consumption [19,20].

Along with efforts to find sustainable solutions to address climate change, the integration of different sciences into building design is expanding. One of the most promising areas is the application of machine learning techniques to optimize sustainable building design and enhance energy efficiency.

Utilizing Machine learning allows for precise and scalable analysis, leveraging its capabilities to handle complex simulations and data-intensive models [21,22] [23]. This approach not only extends the current academic discourse but also provides practical insights that can guide future sustainable architectural practices [24,25].

However, Tianzhen Hong et al. (2020) have highlighted that while machine learning has been applied across various stages of the building life cycle, there are still significant challenges that hinder its broad adoption in the industry. These challenges need to be addressed to fully leverage the potential of machine learning in enhancing building design, construction, and maintenance processes [26]. In response, researchers from diverse scientific disciplines are actively exploring innovative ways to apply machine learning techniques to promote sustainable architectural practices. This body of research is increasingly focused on developing and refining algorithms that can efficiently process and interpret complex datasets to make more sustainable and economically feasible architectural decisions. For instance, Javanmard et al. (2024) applied machine learning to sustainable design by optimizing cladding systems for better energy and economic efficiency using Multivariate Polynomial Regression. This approach improved thermal performance and cost-effectiveness, demonstrating how machine learning can significantly contribute to environmentally sustainable and financially viable building practices [27]. In Shah's 2019 study, the utilization of AI and machine learning frameworks for multi-objective optimization is highlighted to derive Pareto-optimal solutions that effectively balance energy consumption, occupant comfort, and environmental impact. This approach underscores the capacity of advanced computational methods to address multiple sustainability goals simultaneously, providing a holistic enhancement to building performance [28]. Gilan and Dilkina (2015) proposed an integrated method that combines machine learning and optimization techniques to aid in the design of high-performance, sustainable buildings. Their approach employs active learning coupled with Gaussian Process models and genetic algorithms, which have proven effective in enhancing building design optimization. This methodology not only produces superior design solutions but also significantly reduces the required simulation time, demonstrating its effectiveness and efficiency in architectural design processes [29]. Suguna et al. (2023) utilized various machine learning algorithms, such as decision trees and gradient boosting, to predict the heating and cooling loads of buildings based on their attributes. This methodological approach significantly advances sustainable construction practices by enabling more precise and efficient energy management in building designs [30]. Anand et al. (2024) enhanced the accuracy and adaptability of energy efficiency predictions for buildings by focusing on improved feature selection, incorporating ensemble learning, and integrating IoT devices. This approach significantly boosts the application of machine learning in sustainable building design and energy management across various locations and building types [31].

Valentina et al. (2022) introduce a machine-learning framework that utilizes IoT sensors and BIM to advance sustainable building maintenance. By employing anomaly prediction models that analyze data from IoT networks, the framework anticipates maintenance requirements and detects potential faults in systems like HVAC. Their research highlights how the integration of these technologies enhances facility management through real-time monitoring and predictive maintenance, ultimately supporting sustainable building operations [32]. Sokratis Papadopoulos et al. (2018) suggest employing machine learning to boost HVAC efficiency, a major global energy consumer. Their study combines machine learning with Genetic Algorithm optimization to efficiently evaluate and optimize numerous building configurations, aiming to achieve optimal energy use. This technique provides a quicker, less resource-intensive alternative to traditional Building Performance Simulation, facilitating more extensive and rapid analysis [33]. Ibrahim Elwy and Aya Hagishima (2024) explore the use of AI in enhancing building performance for sustainability, focusing on machine-learning-based surrogate models (SMs). Their review of seventy-two Scopus studies evaluates these models' effectiveness in architectural design optimization, discussing trends, accuracies, and impacts on building performance [34]. G.R. Araújo et al. (2024) applied machine learning to sustainable design by integrating it with multi-objective optimization to enhance building retrofits. Their approach uses an Energy Performance Certificate database to predict energy needs and identify optimal retrofit solutions, facilitating significant energy reductions and improving return on investments. This method streamlines the retrofit process, making it more accessible and effective for stakeholders [35]. Cong Li and Youming Chen (2024) used machine learning to enhance building designs for lower energy consumption. Their method involved modeling, data generation, and using regression to train models predicting energy requirements. They explored several optimization algorithms, notably XGBoost with Differential Evolution and Gradient Boosting with Particle Swarm Optimization, which substantially reduced energy consumption in various air conditioning settings, highlighting machine learning's efficacy in improving energy efficiency [36].

The application of machine learning methodologies to assist designers in creating sustainable buildings is increasingly being adopted. Researchers across various domains of urban planning and architectural design are actively exploring and examining its multifaceted implications. Table 1 offers a consolidated summary of additional scholarly articles that contribute to this expanding field of research.

Table 1
A review of publications.

Author(s)	Key finding	Methods used
[37]	The study utilizes a transformer-based topic model, deep learning, machine learning, and computer vision to analyze facade design, incorporating physics-informed neural networks and multimodal datasets.	ML/DL techniques including decision trees, random forest, support vector machines, and neural networks..
[38]	Explored AI technologies in the building lifecycle for energy efficiency enhancements, particularly through predictive and adaptive control using ML/DL.	ML/DL techniques including decision trees, random forest, naive Bayes, support vector machines, and various neural networks.
[39]	The study reveals significant discrepancies between 2D and 3D CFD models in predicting greenhouse ventilation, with errors exceeding 50% when using 2D models alone.	Machine learning, 2D and 3D CFD simulations, regression tree models
[40]	Optimizing sustainable building design with metaheuristic algorithms improves energy efficiency and reduces carbon footprint.	Metaheuristic algorithms (PSO, ACO, GA, ECBO) applied to building design optimization
[41]	CNN models outperform LSTM and hybrid CNN–LSTM models in predicting indoor temperatures in smart buildings, with multivariate input configurations enhancing prediction accuracy	Used Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and hybrid CNN–LSTM models, incorporating multivariate input configurations and SHapley Additive exPlanations (SHAP) analysis for model interpretability.
[42]	AI techniques like Deep Learning and Computer Vision are being utilized to improve facade design, but challenges include generalizability and dataset quality.	Transformer-based topic model, Deep Learning, Machine Learning, and Computer Vision applied to various aspects of facade design. Incorporates Physics-Informed Neural Networks and multimodal datasets.
[43]	Machine learning techniques like multivariate polynomial regression, SVR, MLP, and XGBoost accurately predict building loads for nearly zero-energy buildings, with feature selection significantly improving model accuracy.	Multivariate polynomial regression, Support Vector Regression, Multilayer Perceptron, Extreme Gradient Boosting
[44]	This study demonstrates how AI simulation models and digital twins (DT) enhance building design by predicting the impacts on efficiency, comfort, and safety, confirming their vital role in smart building systems.	Structural equation modeling (SEM), CSAQ survey
[45]	This review highlights the advancement and application of machine learning, particularly deep learning from 2018 onwards, in building energy modeling to enhance energy efficiency analyses	Bibliometric analysis, machine learning (supervised, unsupervised, reinforcement), deep learning.
[46]	The study assessed the impact of various building features on electricity consumption and evaluated the performance of several ML methods in predicting electricity usage.	Mutual Information, Decision Tree, Random Forest, Multilayer Perceptron, Gradient Boosting
[47]	Smart Cities have successfully integrated AI to improve urban innovation and sustainability, leading to significant improvements in government, mobility, and environmental strategies.	Comparative analysis of Smart Cities in Spain, using Cohen's wheel for urban data evaluation.

As this research delves into the complex interplay between architectural form and environmental performance, it becomes clear that traditional methods often neglect the subtle impacts of geometric variations on building sustainability and environmental consequences. Recognizing the importance of balancing multiple factors, such as ease of construction, structural safety, cost-effectiveness, landscape integration, and space utilization, this study intentionally narrows its focus to critically assess the impact of specific geometric parameters. This strategic limitation enables a more targeted analysis, ensuring that the primary objective—to reduce environmental impacts through the optimization of spatial structures—is rigorously examined without compromise. Spatial structures are selected for this analysis because of their inherent advantages in efficiency, safety, cost-effectiveness, and aesthetic versatility. These structures provide a robust framework for exploring the relationship between form and energy efficiency. Future studies may systematically address other constraints, such as construction methods and broader usage considerations. The primary aim of this investigation is to push the boundaries of sustainable architectural design by refining and optimizing the geometric parameters of these structures, thereby enhancing their overall performance.

This research conducted a quantitative analysis of the impacts of design decisions made in the early stages of the design process, specifically focusing on their environmental effects. The aim of this research is to emphasize the critical need for integrating diverse knowledge bases within sustainable architectural practices in response to climate change challenges. By employing parametric design, life cycle assessment tools, and machine learning, this study proposes a methodology that integrates machine learning with parametric design. This approach provides designers with a framework to make informed decisions at the early stages of design as a passive solution, thereby enhancing the sustainability and environmental responsiveness of their projects.

The layout of the paper: To effectively navigate through this research, the introduction first presents the topic and reviews relevant research in the field. This is followed by an outline of the research's novelty. The methodology section then details the processes used, including the software utilized and the approach taken to achieve the final results. Subsequently, the results of the modeling and analysis are presented. After a discussion of these results, the conclusion section explains how the findings can be practically applied.

Innovation and Novelty: This manuscript highlights several pioneering elements in the study of building environmental impacts, with a particular focus on the role of geometric variations in architectural design:

Advanced Analytical Methodology: One of the novel applications of this study is the innovative use of Python-driven sensitivity analysis. This technique stands out due to its integration with parametric modeling software, enabling a dynamic examination of how geometric parameters affect building performance. Unlike traditional methods, this advanced analysis provides quantitative evaluations of each geometric parameter's influence, offering precise insights into their contributions to environmental sustainability.

Focus on Operational Phase Impact: This research uniquely focuses on the operational phase (Stage B6) of a building's lifecycle, employing indirect methods to assess the significant environmental impact of different geometries. While many studies explore various lifecycle stages, including construction and demolition, this study's emphasis on the operational phase introduces a critical architectural dimension that is often less emphasized. By concentrating on this phase, the research illuminates the long-term environmental consequences of energy consumption patterns and investigates how having sensitivity knowledge about design modifications can effectively mitigate these effects. This focus is crucial for advancing sustainable architectural practices, as it underscores the potential of design parameters to make a significant, positive impact on a building's environmental performance during its most energy-intensive phase.

Holistic Evaluation of Spatial Structures: This research chooses and analyzes spatial constructions, with a focus on their integrated architectural approach that takes aesthetic, structural, and environmental factors into account. Unlike previous research, which frequently examines these issues in isolation, this study acknowledges that decisions like as ease of construction, safety, cost-effectiveness, and aesthetic flexibility are inextricably tied to the environmental effects of spatial structures. By selecting spatial structures, this study covers these key variables, which are frequently separated in other types of architectural research. This holistic approach provides a complete foundation for creating energy-efficient buildings that not only expand without affecting the environment but also meet broader architectural requirements.

Practical Insights for Architectural Design: This practical advice is important to architects and designers, allowing them to make educated decisions that optimize building designs for the lowest environmental effect throughout the operating phase. This study bridges the gap between theoretical research and practical implementation in sustainable architecture by revealing the direct effects of design decisions, making a significant contribution to the discipline.

Empirical Validation of Theoretical Models: This research utilizes sophisticated simulation tools such as Rhino, Grasshopper, Honeybee, and Ladybug, with environmental impact analysis using OpenLCA, to both theoretically and empirically substantiate the environmental benefits of some geometric shapes compared to others. This validation is essential for enhancing the reliability of sensitivity analysis as a tool in sustainable design.

By introducing these innovative elements, this research significantly advances the field of sustainable architecture, providing both theoretical and practical contributions that could influence future building designs. We believe that the methodologies and findings reported herein will inspire further research and practical applications in architectural design and environmental planning.

2. Methodology

The goal of this research was to investigate when designing a spatial structure, which parameters in each geometry significantly impact its environmental impact. It aims to suggest a method to architects on how to develop geometries and their sizes with minimal environmental impacts. This study centers on a case study of a large office prototype in Boston, where the researcher conducted a comparative analysis of two simple geometric shapes—a cube and a cylinder—to assess their environmental impacts. The focus was particularly on the energy consumed for heating and cooling the operational phase (B6). For this analysis, parametric modeling techniques were employed using Grasshopper, a graphical algorithm editor integrated with Rhino's 3D modeling tools. The assessment also included climate data through Honeybee and Ladybug, Grasshopper's plugins that facilitate environmental analysis. Each geometric shape underwent extensive modeling iterations, including simulations for over 170,000 cube models and 1700 cylinder models, ensuring a comprehensive and robust analysis. Life cycle impacts were evaluated using the OpenLCA framework, which modeled the generation of low-voltage electricity in Boston, calibrated per kilowatt-hour. The spatial dimensions considered ranged from 100 to 2500 square meters in area, and 380 to 47,000 cubic meters in volume. Additionally, a sensitivity analysis was performed using the Python programming language to analyze the data and extract meaningful insights.

Two distinct scenarios were modeled: initially, Rhino software's default settings were used, applying default ceiling material for crusts with angles under 60 degrees and default wall materials for those above 60 degrees. In the second scenario, all crusts were treated as roofing, with materials uniformly designated as default roofing materials. It is important to note that this analysis focused on comparing geometric configurations rather than precisely quantifying energy consumption, hence, the minimal influence of materials on energy usage was considered acceptable for the purpose of maintaining consistency across designs. Given that the cylinder and cube are fundamentally different forms with completely distinct angles, the primary results of Scenario One would not have been suitable for comparative analysis due to the varying amounts of materials used for walls and roofs in each form. Therefore, Scenario Two was applied to both models to ensure uniformity in the material impacts across both forms. Fig. 1 serves as a roadmap, guiding the reader through the logical progression of the methodology, from the initial conceptual framework to the empirical analysis and subsequent discussion of findings. It encapsulates the methodical process employed to address the research questions, showcasing the step-by-step procedure that underpins the investigative journey.

Essential Settings:

(1) Geometry parameters for cubes (length, width, height) and cylinders (radius, length, height)

(2) Boston's weather data file (ASHRAE 2019 standards), energy simulation settings included default material configurations as per Rhino default (scenario one: ceiling/walls differentiated by angles of 60°) and uniform roof material settings (scenario two). Energy simulations explicitly accounted for thermal loads, heating, and cooling requirements. Outputs (thermal load, cooling, heating) were stored in structured datasets for further analysis.

(3) Ecoinvent database v3.6, specifically the dataset 'Market for Electricity, Low Voltage', calibrated per kWh within the NPCC region. Environmental impacts were calculated using the TRACI 2.1 methodology, standardizing impacts into CO_2 equivalents (global warming potential) using normalization factors from the US 2008 inventory. All outputs (impact category values, normalized CO_2 equivalents) were structured for consistency and ease of further sensitivity analysis.

(4) Python (with SHAP, Random Forest, XGBoost, Recursive Feature Elimination libraries). Python scripts processed input data (geometric parameters from Grasshopper) and environmental impact outputs (from OpenLCA). SHAP sensitivity analysis identified and visualized the critical geometric parameters influencing environmental impacts, supported by statistical correlations (Pearson and Spearman). Outputs included feature importance scores and SHAP plots.

Overall, the methodology was structured into four distinct steps, each of which is explained in detail below, along with the specific settings and parameters applied at each stage.

Step (1) Parametric Design: The parametric design was conducted using Grasshopper within the Rhino environment. The primary objective was to explore the relationship between geometric design variations and their parametric definitions with the environmental impacts of Buildings. AS Fig. 2 illustrates for the cube geometry, the parameters defined included Length (X), Width (Y), and Height (Z), with consideration given to maintaining specific metric constraints. The surface area was constrained to a range between a minimum of approximately 100 square meters and a maximum of 2500 square meters, while the volume was controlled between about 376 cubic meters and 47000 cubic meters. For cylindrical geometries, the parameters included Radius,

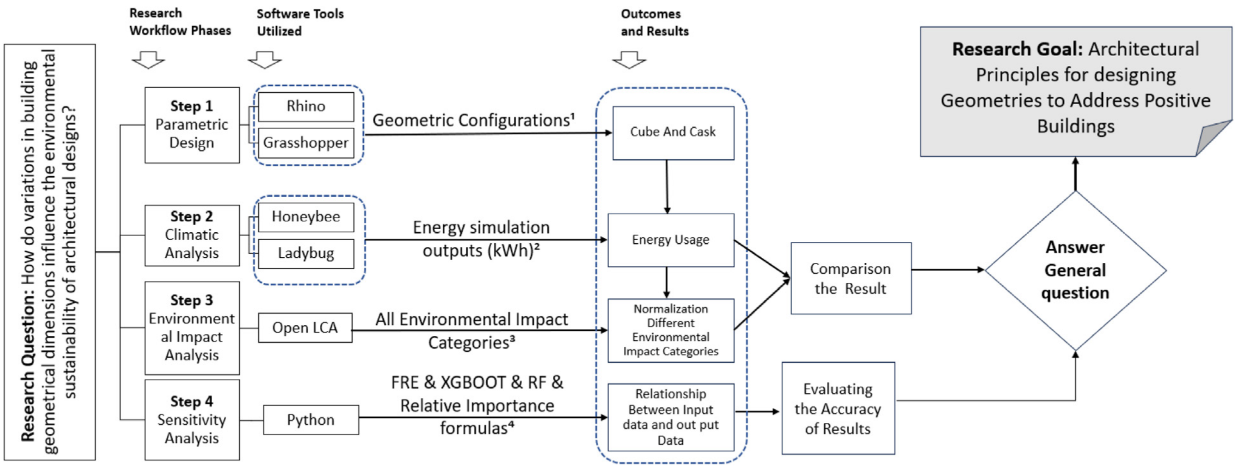

Fig. 1. The road map.

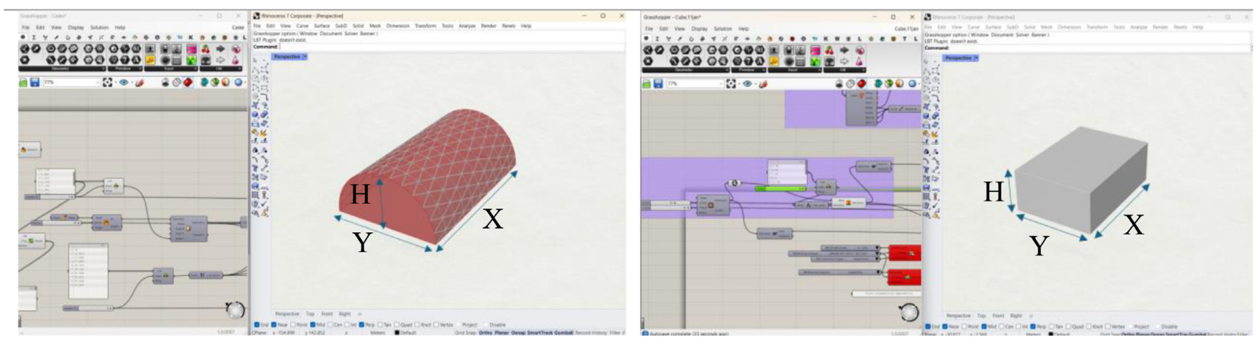

Fig. 2. Design Parameters for Each Geometry (X: Length, Y: width, H: Height).

Height, and Length. The constraints for the surface area and volume were similar to those of the cubes. These parameters and constraints facilitated a comprehensive analysis of the spatial and volumetric efficacies of the designs under study. Consequently, 170,000 cube models and 1700 models for Cylinders were generated.

Step (2) Climatic Analysis: Climatic analysis was conducted using Honeybee and Ladybug, two plugins compatible with Rhino software, to evaluate the thermal and environmental performance of two building geometries configured as a large office in Boston. The analysis settings adhered to ASHRAE 2019 standards to ensure consistency and reliability in the simulation outcomes. The TMYx dataset files were obtained from climate.onebuilding.org, which provides climatic data up to 2024. Tables 2 and 3 summarize the energy analysis results, highlighting the energy consumption profiles for each geometry under standardized conditions. This assessment provides crucial insights into the energy efficiency and potential savings of each configuration, offering a comparative basis for determining the environmental impact of each geometry.

Step (3) Environmental Impact Analysis: This study assumes that the energy required for heating and cooling is supplied through electricity, aligning with Massachusetts' clean energy initiatives aimed at reducing reliance on fossil fuels. Using the OpenLCA framework, the 'Market for Electricity, Low Voltage | Electricity, Low Voltage | Cutoff, U' dataset from the Ecoinvent database was utilized. This dataset represents low-voltage electricity within the Northeast Power Coordinating Council (NPCC) region of the United States, reflecting the energy mix of 2016 based on 2014 data. The analysis models the introduction of 1 kWh of electricity into the low-voltage network, accounting for its transmission via overhead and underground infrastructure. Environmental impacts were evaluated for the functional unit of 1 kWh, encompassing generation, transmission, and distribution stages. The TRACI 2.1 methodology was employed to quantify these impacts comprehensively.

Normalization of Data Based on CO2 kgEquivalent: The normalization process converts specific environmental impacts into a unified metric of global warming potential, expressed in CO2 equivalents. This standardization allows for consistent comparisons across different impact categories. Each category is assigned a normalization factor derived from the US 2008 inventory data, facilitating the calculation of normalized results. These results express the environmental impacts relative to the global warming impact in terms of CO2 equivalents, employing the normalization factor for global warming, set at 24,038.981612583 kg CO2 eq. Table 4 details the environmental impacts and their respective normalization factors for each category.

Table 5 provides normalized environmental impacts relative to CO2 Equivalents. The normalization process highlights Fossil Fuel Depletion as having the most substantial normalized CO2 equivalent impact, indicating significant environmental concerns. Each category's CO2_eq value contextualizes its specific impact in terms of CO2 equivalent emissions, offering a common ground for comparison and underscoring the importance of adopting comprehensive strategies for reducing ecological footprints and protecting both ecosystems and human health.

Step (4) Defining Input and Output Data for Sensitivity Analysis: In this study, the system boundary for the life cycle assessment's B6 stage was defined to specifically include the environmental impacts associated with energy use during the operational phase. The cumulative environmental impact was calculated by multiplying the energy consumption of each geometry by its corresponding environmental impact factors. Conducting a sensitivity analysis required a precise definition of the input data in Python and the corresponding output variables. The primary aim of this research was to elucidate the relationships between variations in these variables and their environmental impacts.

Table 2
Energy analysis of cube.

input: Length (x)	input: Width (y)	input: Height (z)	output: Thermal Load (kWh)	output: Cooling (kWh)	output: Heating (kWh)	output: Cooling (kWh/m^2)	output: Heating (kWh/m^2)	output: Thermal Load (kWh/m^2)	output: Area (m^2)	output: Volume (m^3)
10.45	10	3.76	3.76	9010.65	363.74	8646.91	3.48	82.75	86.23	104.50
10.45	10	5.64	5.64	11 218.36	453.80	10 764.57	4.34	103.01	107.35	104.50
10.45	10	7.52	7.52	13 456.05	545.78	12 910.27	5.22	123.54	128.77	104.50
10.45	10	9.4	9.4	15 705.53	636.25	15 069.28	6.09	144.20	150.29	104.50
10.45	10	11.28	11.28	17 972.86	732.65	17 240.20	7.01	164.98	171.99	104.50
10.45	10	13.16	13.16	20 252.38	831.26	19 421.12	7.95	185.85	193.80	104.50
10.45	10	15.04	15.04	22 535.08	925.16	21 609.92	8.85	206.79	215.65	104.50
10.45	10	16.92	16.92	24 822.20	1018.45	23 803.75	9.75	227.79	237.53	104.50
10.45	10	18.8	18.8	27 114.79	1111.68	26 003.11	10.64	248.83	259.47	104.50
…	…	…	…	…	…	…	…	…	…	…
49.4	49.91	13.16	13.16	182 629.8	6728.83	175 900.9	2.73	71.34	74.07	2465.55
49.4	49.91	15.04	15.04	193 173.6	7242.72	185 930.9	2.94	75.41	78.35	2465.55
49.4	49.91	16.92	16.92	203 649.0	7590.87	196 058.1	3.08	79.52	82.60	2465.55
49.4	49.91	18.8	18.8	214 112.3	7871.44	206 240.8	3.19	83.65	86.84	2465.55

Table 3
Energy analysis of cylinder.

Input: Radius	Input: Length (Y)	Input: Height (Z)	Output: Thermal Load (kWh)	Output: Cooling (kWh)	Output: Heating (kWh)	Output: Cooling (kWh/m^2)	Output: Heating (kWh/m^2)	Output: Thermal Load (kWh/m^2)	Output: Area (m^2)	Output: Volume (m^3)
5	10	1	8264.15	335.97	7928.18	3.36	79.28	8264.15	100.00	392.70
5	10	1.045	8329.70	188.86	8140.84	1.89	81.41	8329.70	100.00	410.37
5	10	1.06	8412.52	191.34	8211.79	1.91	82.12	8412.52	100.00	416.65
5	10	1.033	8417.13	342.31	8074.82	3.42	80.75	8417.13	100.00	405.66
5	10	1.081	8504.69	184.22	8320.48	1.84	83.20	8504.69	100.00	424.51
5	10	1.089	8572.39	203.79	8368.60	2.04	83.69	8572.39	100.00	427.65
5	10	1.16	8839.48	174.59	8664.89	1.75	86.65	8839.48	100.00	455.53
…	…	…	…	…	…	…	…	…	…	…
20	62.497	1.081	192 984.80	733.87	185 650.9	2.93	74.26	71 976.30	2499.88	42 448.73
20	62.497	1.089	193 339.40	7336.67	186 002.7	2.93	74.40	77 339.47	2499.88	42 762.88
20	62.497	1.16	195 020.90	3926.84	191 094.1	1.57	76.44	78 012.11	2499.88	4550.91
20	62.497	1.197	198 929.20	3898.68	195 030.5	1.56	78.02	79 575.51	2499.88	4703.82
20	62.497	1.154	199 803.80	7536.74	192 267.1	3.01	76.91	79 925.37	2499.88	45 315.30
20	62.497	1.2	203 630.50	7642.31	195 988.1	3.06	78.39	81 456.09	2499.88	47 121.63

Table 4
Environmental impacts & normalization factors for each category based on CO_2 eq.

Impact category	Result	Normalization factor
Fossil fuel depletion (MJ surplus)	0.497635447	21,286.92217
Global warming (kg CO_2 eq)	0.233240495	24,038.98161
Ecotoxicity (CTUe)	0.200677104	10,975.08108
Smog (kg O3 eq)	0.005114277	1,447.95751
Acidification (kg SO2 eq)	0.000411533	94.55018
Eutrophication (kg N eq)	0.000133957	20.72579
Respiratory effects (kg PM2.5 eq)	4.94753E−05	29.55903
Ozone depletion (kg CFC-11 eq)	2.91448E−08	0.14578
Non carcinogenic (CTUh)	7.85226E−09	0.00103
Carcinogenic (CTUh)	1.7759E−09	0.00005

Through systematic analysis of these variations, the study seeks to identify significant patterns and insights that could inform strategies to mitigate the adverse environmental effects associated with energy consumption in building operations. Tables 6 and 7 present the input and output data for the Cube and Cylinder geometries during the B6 stage of the building's life cycle.

3. Result and discussion

Table 8 presents the energy analysis results for two different geometric forms, the Cylinder and the Cube, during their operational phase. The result shows that both geometries exhibit higher energy consumption for heating compared to cooling. Specifically, the cylinder shows a maximum thermal load of 203630.45 kWh, while the cube reaches up to 214112.26 kWh. Generally, the energy required for maintaining comfort conditions in the cylinder is considerably lower than in the cube. Fig. 3 presents a visual comparison of the minimum energy usage required to provide comfort conditions for both geometries.

The visual data presented in Fig. 4 elucidate the energy consumption patterns for two geometric configurations, the Cube and the Cylinder, during their operational phases. Both configurations exhibit a predominant energy demand for heating, which accounts for 96% of the total energy usage, overshadowing the cooling demand, which constitutes only 4%. This stark imbalance underscores the critical role of heating in the operational energy profile of building geometries. Furthermore, the comparison of both geometries reveals that the Cube represents a slightly larger share of the overall thermal load, at 52%, compared to 48% for the Cylinder.

To assess the environmental impacts of cube and cylinder geometries on climate, this study normalized the environmental impacts per kilowatt-hour of energy consumption for a comprehensive analysis. Since the primary energy for cooling and heating systems predominantly comes from low-voltage electricity, the environmental impact of 'Electricity – Low Voltage – Cutoff U' was calculated using OpenLCA software. The dataset used provides details on the electricity available at the low voltage level from the Western Electricity Coordinating Council in the US for the year 2014. The environmental impact calculations consider the transmission of 1 kWh of low-voltage electricity via aerial lines and cables. The maximum annual thermal load for each geometry was then multiplied by emissions from one kWh to employ an indirect method for assessing the operational phase's environmental impacts.

The results highlight significant impacts in categories such as fossil fuel depletion (FFD), global warming potential (GWP), and eutrophication (EP), as shown in Fig. 5. Notably, both geometrical forms

Table 5
Normalized environmental impacts relative to CO_2 equivalents.

Environmental category	Normalized CO_2 equivalent impact	Description
Fossil Fuel Depletion	2.409	Marked by the most substantial normalized CO_2 equivalent impact, indicating a significant environmental concern due to the high dependency on non-renewable energy sources.
Global Warming Potential	1	Assessed at 0.233240 kg CO_2 eq, this serves as the baseline for CO_2 equivalence, emphasizing the need for climate change mitigation strategies.
Ecotoxicity	1.885	Reflects the potential harmful effects on ecosystems from toxic pollutants, stressing the importance of cleaner production technologies.
Smog Formation	0.364	Indicates a notable concern for air quality and respiratory health, particularly in urban settings, though lower in normalized impact compared to other categories.
Non-carcinogenic Impacts	0.784	Shows potential health effects from chemical exposure, highlighting the need for ongoing management and monitoring in the energy sector.
Carcinogenic Impacts	3.679	Indicates a significant potential for cancerous health effects from chemical exposures, underscoring the need for stringent controls and public health protection.
Eutrophication	0.666	Reflects nutrient enrichment in water bodies, leading to potential ecological disruptions, and emphasizing the need for nitrogen emission control.
Ozone Depletion	0.021	Shows minimal impact on the stratospheric ozone layer from this energy source, yet monitoring remains crucial due to long-term global effects.
Acidification	0.449	Associated with emissions that can lead to acid rain, impacting ecosystems and requiring sulfur emission controls.
Respiratory Effects	0.173	Relates to health implications from fine particulate matter, highlighting critical environmental concerns in populated or industrial areas.

Table 6
Environmental Impact Analysis of Cube, (Tl: Thermal Load (kWh/m^2), AP: Acidification (kg SO_2 eq), CA: Carcinogenic(CTUh), ET: Ecotoxicity(CTUe), EP: Eutrophication (kg N eq), FFD: Fossil Fuel Depletion (MJ surplus), GWP: Global Warming (kg CO_2) NC: Non-Carcinogenic (CTUh), ODP: Ozone Depletion (kg CFC-11 eq), RE: Respiratory Effects (kg PM2.5 eq), SM: Smog (kg O_3 eq)).

	Input Data			Output Data											
	Length	Width	Height	TL	Area	AP	CA	ET	EP	FFD	GWP	NC	ODP	RE	SM
Max	49.4	49.91	18.8	214 112.3	2465.554	88.11425	0.00038	42 967.43	28.68184	106 549.9	49 939.65	0.001681	0.00624	10.59328	1095.029
Min	10.45	10	3.76	9010.651	104.5	3.70818	1.60E−05	1808.231	1.20704	4484.019	2101.649	7.08E−05	0.000263	0.445805	46.08296

Table 7
Environmental Impact Analysis of Cylinder, (Tl : Thermal Load (kWh/m^2), AP: Acidification (kg SO_2 eq), CA: Carcinogenic(CTUh), ET: Ecotoxicity(CTUe), EP: Eutrophication (kg N eq), FFD: Fossil Fuel Depletion (MJ surplus), GWP: Global Warming (kg CO_2) NC: Non-Carcinogenic (CTUh), ODP: Ozone Depletion (kg CFC-11 eq), RE: Respiratory Effects (kg PM2.5 eq), SM: Smog (kg O_3 eq)).

	Input Data			Output Data											
	Radius	Width	Height	TL		AP	CA	ET	EP	FFD	GWP	NC	ODP	RE	SM
Max	20	62.497	1.2	203 630.5	2499.88	83.80064	0.000362	40 863.97	27.27772	101 333.7	47 494.87	0.001599	0.005935	10.07469	1041.422
Min	5	10	1	8264.148	100	3.400969	1.47E−05	1658.425	1.10704	4112.533	1927.534	6.49E−05	0.000241	0.408872	42.26514

Table 8
Energy analysis.

		Out: Thermal Load (kWh)	Out: Cooling (kWh)	Out: Heating (kWh)
Cylinder	Max	203 630.45	7642.31	195 988.1
	Min	8264.15	335.97	7928.18
Cube	Max	214 112.26	7871.44	206 240.8
	Min	9010.65	363.74	8646.91

exhibit substantial impacts, with particularly high values for fossil fuel depletion and global warming potential. This analysis underscores the importance of considering geometric influences on energy efficiency and environmental sustainability in architectural design, providing a basis for targeted mitigation strategies.

Following the initial environmental impact assessments, a sensitivity analysis was conducted on the cube and cylinder geometries designed as large office spaces. The primary objective of this analysis was to determine how changes in specific architectural design variations, such as length, width, and height, affect the overall environmental impact. This sensitivity analysis sought to establish which alterations in these dimensions could yield significant environmental benefits. By analyzing the response of environmental impact metrics to modifications in each dimension, the study highlights critical areas where architectural design decisions can lead to more sustainable outcomes for building operations. Fig. 6 & 7 present scatter plots for the Cylinder and Cube models, illustrating the environmental impacts related to varying dimensions. For the Cylinder, the plots show a clear positive trend where increases in radius significantly influence environmental outputs like carcinogenic, ozone depletion, and global warming, with tightly clustered data points along steep trend lines, indicating high sensitivity to radius changes. Similarly, the Cube model scatter plot reveals that length is the most impactful dimension, markedly affecting factors such as fossil fuel depletion, respiratory effects, and thermal load. Data points closely adhere to pronounced trend lines, demonstrating strong correlations with environmental impacts as the length increases. This analysis underscores that both the radius in the Cylinder and the length in the Cube are critical dimensions in their respective designs, significantly influencing their environmental performance.

To rigorously assess the environmental impact sensitivities inherent in architectural designs, this study utilized sophisticated statistical methodologies, including Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Recursive Feature Elimination (RFE). The initial

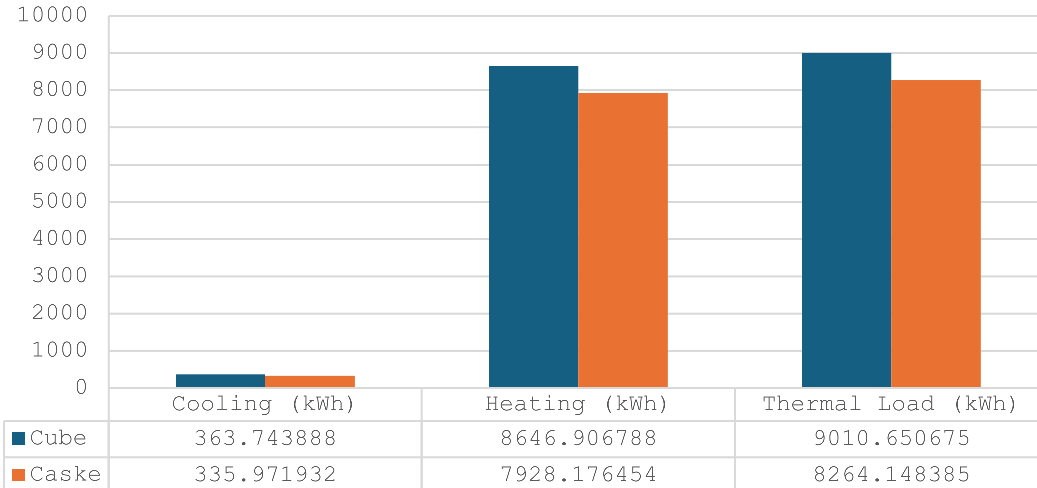

Fig. 3. A Comparison of Cube and Cylinder in terms of Minimum Energy Usage.

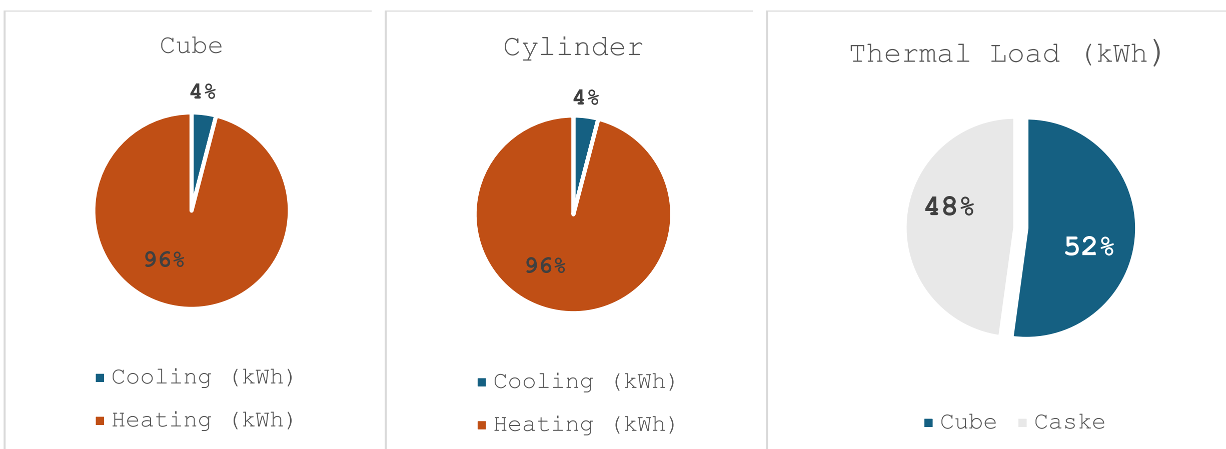

Fig. 4. Thermal Load Distribution for Cube and Cylinder Geometries.

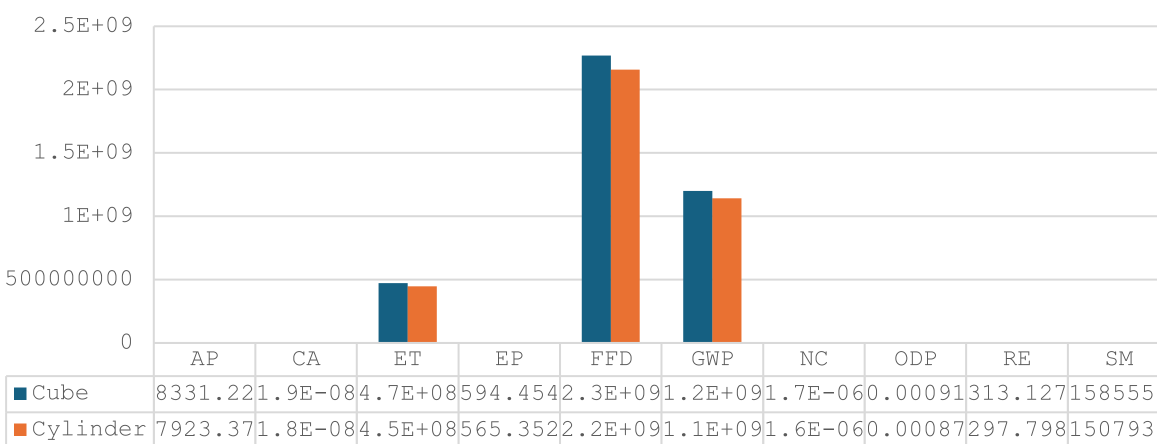

Fig. 5. Environmental Impact Distribution for Cube and Cylinder Geometries Based on CO2 eq.

phase of the analysis focused on the Cylinder model, where the Feature Importance metrics from both Random Forest and XGBoost identified the radius as the paramount parameter influencing environmental outcomes, as illustrated in Fig. 8. Further examination of the Cube model's dimensions—namely Length, Width, and Height—revealed distinct influential factors. The RF analysis underscored Length as the predominant determinant of environmental impact. Conversely, XGBoost and RFE recognized Width as the critical dimension, with RFE particularly emphasizing its significance in the sequential elimination of features. These findings underscore the necessity of integrating multiple analytical techniques to elucidate the complex interplay of different design dimensions on environmental impacts, thereby ensuring a thorough and nuanced understanding.

The SHAP summary plots (Fig. 9), utilizing XGBoost, reveal the differentiated significance of dimensions in the Cylinder and cube models concerning environmental and energy-related outputs. For the

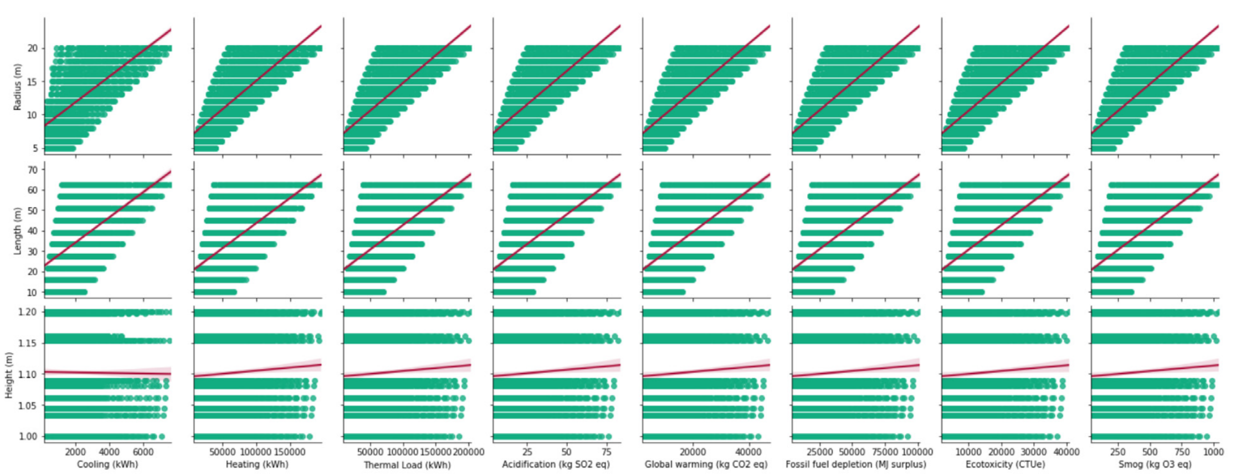

Fig. 6. Scatter plot diagram, Cylinder.

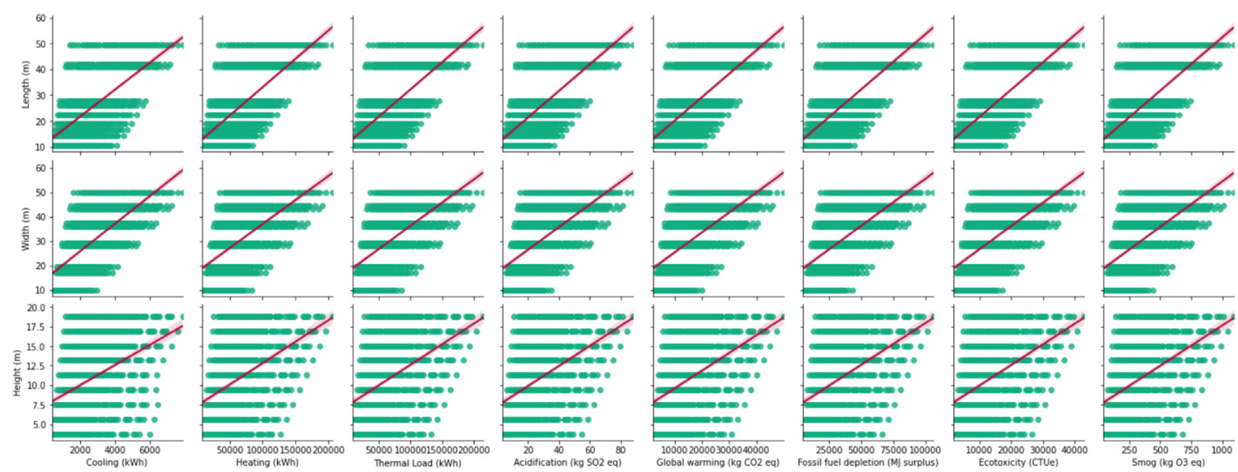

Fig. 7. Scatter plot diagram, Cube.

Cylinder model, ‘Radius (m)’ shows a broad distribution of SHAP values, indicating a substantial and varied influence across cooling, heating, thermal load, acidification, global warming, and fossil fuel depletion. This contrasts with ‘Length (m)’ and ‘Height (m)’, where Length displays a notable but less extensive impact than Radius, and Height shows a narrower, more consistent range of effects, primarily on energy consumption.

Similarly, the cube model analysis highlights ‘Length (m)’ as having a significant impact on heating, thermal load, acidification, global warming, and fossil fuel depletion, with a wide spread of SHAP values indicating its pervasive influence. ‘Width (m)’ primarily impacts cooling systems, an important consideration given Boston’s cold climate, which places heating as a priority. The diverse impacts underscored by these models emphasize the importance of considering specific dimensional attributes in the design phase to address environmental and energy challenges effectively.

Fig. 10 provides a comprehensive overview of the sensitivity analysis, clearly demonstrating how the various outputs are affected by input changes within the models. This figure effectively illustrates the relationship between input dimensions, such as radius, length, and width, and their corresponding impacts on environmental and energy-related outcomes. Visualization aids in understanding which design parameters are most critical and how subtle modifications to these can significantly influence the performance and sustainability of the building designs. This overall view is crucial for prioritizing design changes that maximize environmental and energy efficiency.

The heatmap generated from a Pearson correlation analysis, as illustrated in Fig. 11, provides insightful visual data on the linear relationships between different architectural dimensions and their environmental impacts. For the Cylinder model, the radius shows a strong positive correlation of 0.76 with all listed environmental impacts, indicating that changes in radius significantly affect these factors. In contrast, the length of the cube displays a moderate positive correlation, suggesting that increasing the length tends to exacerbate environmental impacts, while changes in width and height show almost no significant correlation. This analysis underscores that, within these models, the environmental impacts are highly interrelated; they tend to increase or decrease together, driven by common factors. Therefore, optimizing the length in cube designs emerges as a crucial strategy for improving environmental performance, as altering width and height appears to have minimal impact.

The Spearman correlation heatmaps (Fig. 12) provide a robust analysis of the relationships between the physical dimensions of cubic and Cylinder structures and their environmental impacts, capturing both linear and non-linear relationships. For the cube, the length shows a moderate positive correlation (around 0.63), indicating that increases in length tend to escalate environmental impacts. In contrast, width and height have negligible correlations with environmental metrics, suggesting minimal influence on the cube’s environmental footprint. The Cylinder model highlights the radius as having a strong positive monotonic relationship (correlations from 0.68 to 0.78) with all environmental impacts, underscoring its significant influence. Both heatmaps reveal

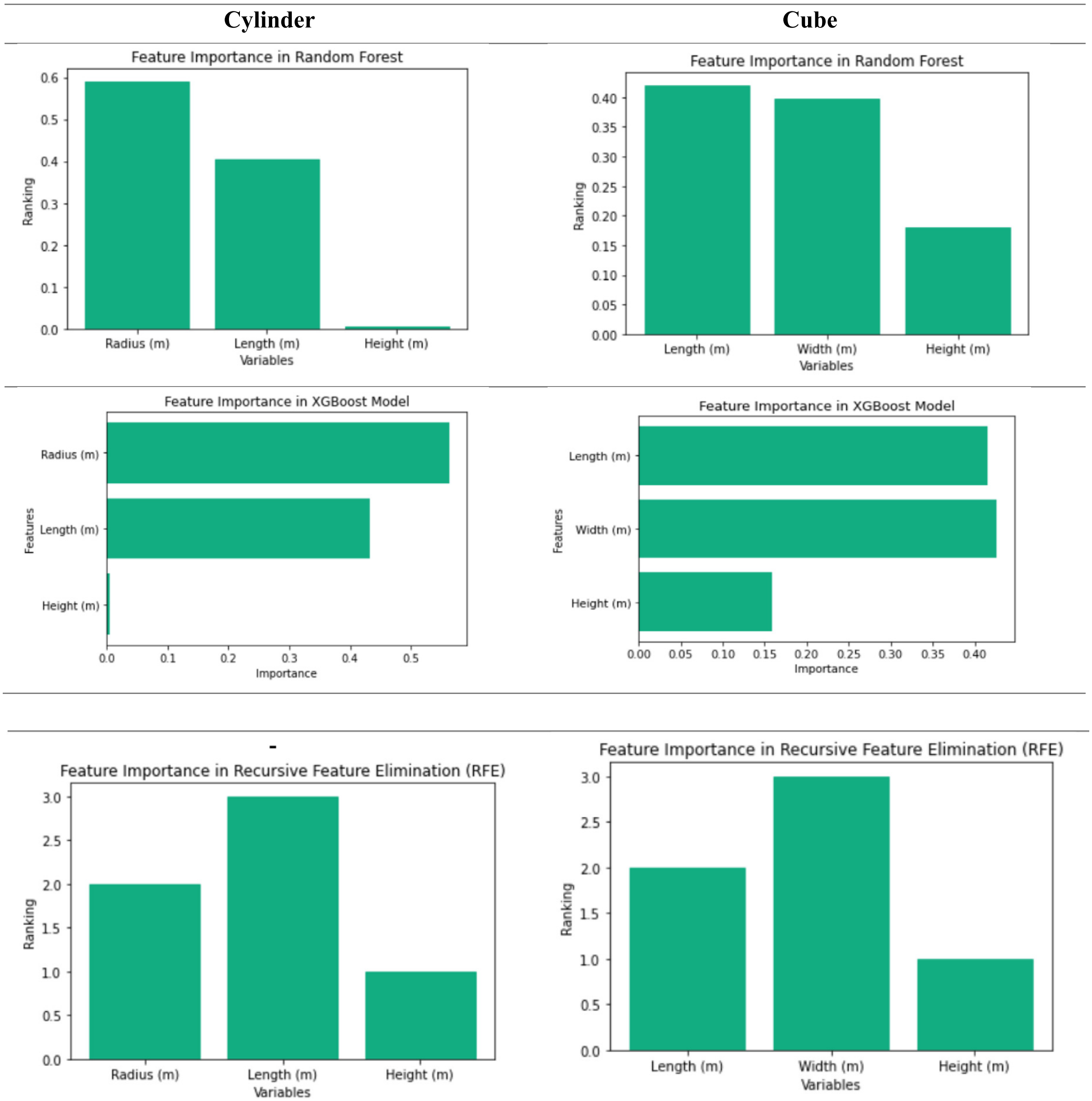

Fig. 8. FRE & XGBoost &RF.

extremely high correlations among environmental factors like cooling, heating, and thermal load, suggesting these impacts typically rise or fall together across both models. These insights emphasize the pivotal role of specific dimensions—particularly length for cubes and radius for Cylinders—in driving environmental consequences, marking them as critical targets for optimization in environmentally conscious design.

Following up on the research goals, this work builds parametric mathematical models for cylindrical and cubic geometries to quantitatively examine the influence of characteristics such as radius, height, length, and width on environmental performance. Conducted under the stable climatic conditions of Boston to ensure consistency, the analysis minimizes extraneous influences by selectively excluding certain variables. The analysis focuses on significant environmental impact categories, providing related formulas to quantify these effects. The key objective of this analysis is to emphasize the multidisciplinary nature of sustainable design and demonstrate how programming languages can empower architects and designers to make data-driven decisions, Therefor By offering predictive formulas for environmental impacts, equips designers with tools to optimize building performance in alignment with sustainability principles, illustrating how strategic design modifications can mitigate negative environmental outcomes (Table 9). Furthermore, these formulas can be applied to similar projects that share the same building function, materials, and climatic conditions, offering a reliable framework for comparative analysis. While the exact numerical outcomes may vary due to contextual factors, the formulas enable the comparison of different design alternatives, helping to identify more sustainable options.

The accuracy of the developed equations was thoroughly assessed. Fig. 13 illustrates the linear regression analysis between predicted and actual values for each environmental impact category, showcasing an impressive R-squared value of more than 0.95 across all categories. This indicates a high degree of accuracy (95%) in the model's predictions

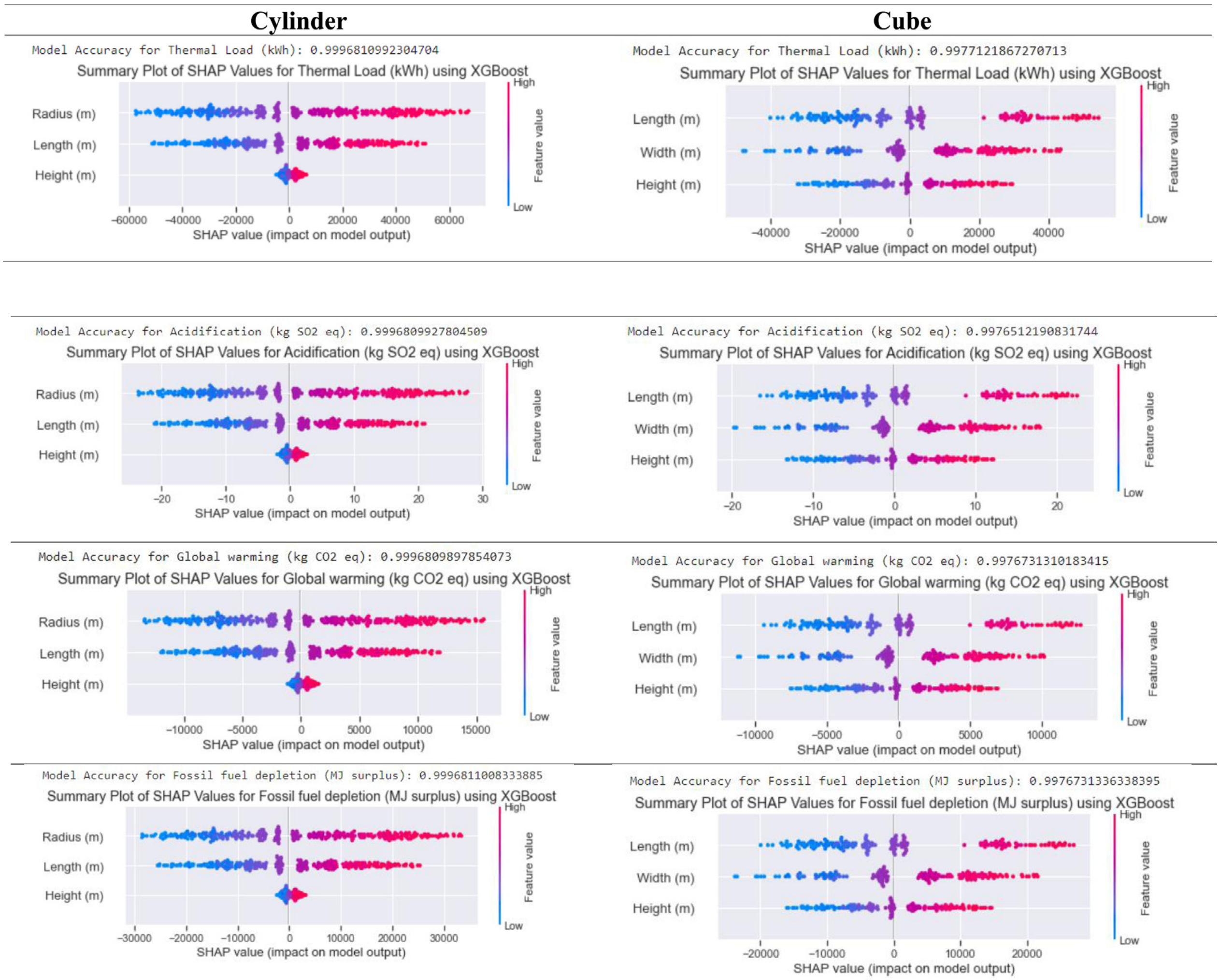

Fig. 9. SHAP values.

Table 9
Parametric relationships: Linking input data to output metrics.

Cube	Eq.1: Thermal Load (kWh) = −75196.95237702856 + (2018.6294733133022 * *Length* (m)) + (1845.97532340824 * *Width* (m)) + (3360.703635383338 * *Height* (m))
Cylinder	Eq.2: Thermal Load (kWh) = −110169.85012833374 + (6981.295571425365 * *Radius* (m)) + (1518.68595693669 * *Length* (m)) + (37322.14705022736 * *Height* (m))
Cube	Eq.3: Global warming (kg CO_2 eq) = −17538.9744247183 + (470.82613837730895 * *Length* (m)) + (430.55619890688297 * *Width* (m)) + (783.8521808126087 * *Height* (m))
Cylinder	Eq.4: Global warming (kg CO_2 eq) = −25696.07042242102 + (1628.3208375779004 * *Radius* (m)) + (354.2190649487787 * *Length* (m)) + (8705.036067923265 * *Height* (m))
Cube	Eq.5: Fossil fuel depletion (MJ surplus) = −37420.66902401942 + (1004.5415806854379 * *Length* (m)) + (918.6227555894478 * *Width* (m)) + (1672.4052564727951 * *Height* (m))
Cylinder	Eq.6: Fossil fuel depletion (MJ surplus) = −54824.42263483919 + (3474.1401437237982 * *Radius* (m)) + (755.7519653308531 * *Length* (m)) + (18572.823336499307 * *Height* (m))
Cube	Eq.7: Ecotoxicity (CTUe) = −15090.306633097296 + (405.09271676210903 * *Length* (m)) + (370.4449819653313 * *Width* (m)) + (674.4162730008053 * *Height* (m))
Cylinder	Eq.8: Ecotoxicity (CTUe) = −22108.566473150182 + (1400.9861775118686 * *Radius* (m)) + (304.7654997397117 * *Length* (m)) + (7489.700385624711 * *Height* (m))

relative to actual observations, as evidenced by the data points closely aligned with the identity line.

4. Conclusion

The significant depletion of resources and the consequent impact of climate change underscore the critical necessity for integrating diverse knowledge bases in sustainable architectural practices. This approach is essential to mitigating adverse environmental impacts throughout buildings' lifecycles and promoting long-term ecological resilience. This research has meticulously analyzed the impact of geometric variations on the environmental performance of office spaces in Boston, demonstrating the powerful utility of integrating Python-driven sensitivity analysis with advanced parametric modeling tools. The study distinctly highlights how geometric parameters such as length, width, height for a cube, and height and radius for a cylinder, directly influence environmental outcomes during the operational phase of building life cycles. Significant findings from this study include the cylinder configuration's superior energy efficiency, which offers a 5.3% reduction in environmental impact compared to the cube. This underlines the critical

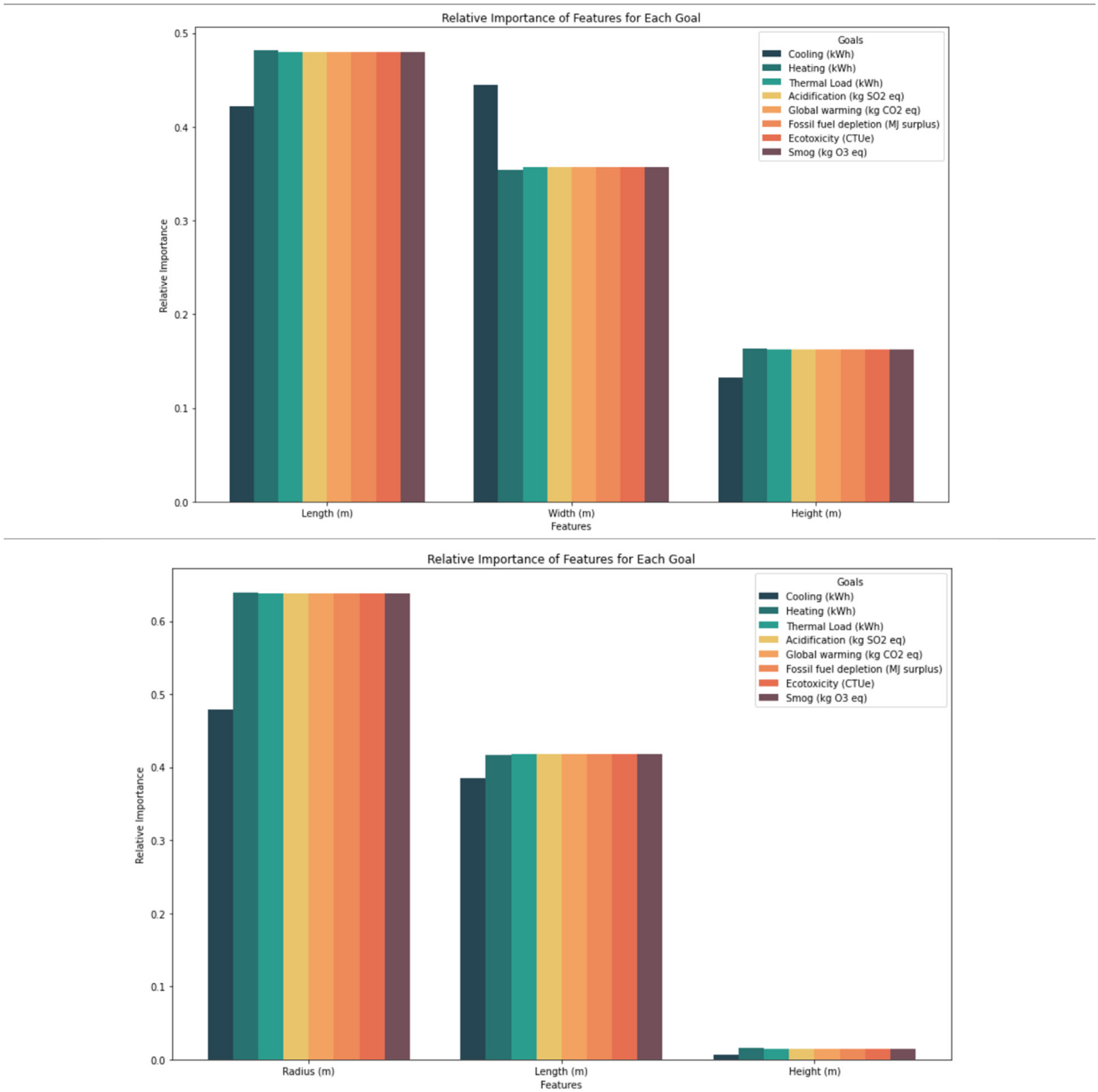

Fig. 10. Relative Importance of features for each goal.

importance of geometric optimization in architectural design, particularly in the context of sustainability. Among the cube's dimensions, length emerged as the most influential factor affecting environmental performance, necessitating careful consideration in design strategies. For the cylinder, height was identified as a significant variable, impacting the structure's environmental footprint more profoundly than the radius. This knowledge is critical for architects and designers looking to improve the sustainability of their projects, as it directs the selection of geometric dimensions that are compatible with energy efficiency and environmental conservation aims.

Overall, the findings advocate for the integration of parametric design and life cycle assessment tools in the architectural planning process, proving that such a multidisciplinary approach not only enhances the precision of design impacts on sustainability but also promotes the adoption of more energy-efficient and environmentally responsive building practices. This research not only contributes to the academic discourse on sustainable architecture but also serves as a practical guide for future architectural endeavors aiming to mitigate environmental impacts through informed geometric design.

In addition to the results presented, this study also provides a reflection on the effectiveness of the applied methodology. The high predictive accuracy of the developed formulas, exceeding 95%, demonstrates the robustness and reliability of the modeling approach. This not only validates the methodological framework within the context of the case study but also suggests its potential applicability to other projects with similar parameters, particularly office buildings in comparable climate zones (e.g., Boston under ASHRAE 2019), using consistent material assumptions. As such, the proposed method offers a practical, data-driven tool for early-stage design decision-making in environmentally conscious architecture. Nevertheless, the study acknowledges certain limitations, including the exclusive focus on operational energy (B6 stage) and uniform material inputs. Future work could expand the methodology to encompass additional life cycle stages or more diverse material configurations, further enhancing its generalizability and impact.

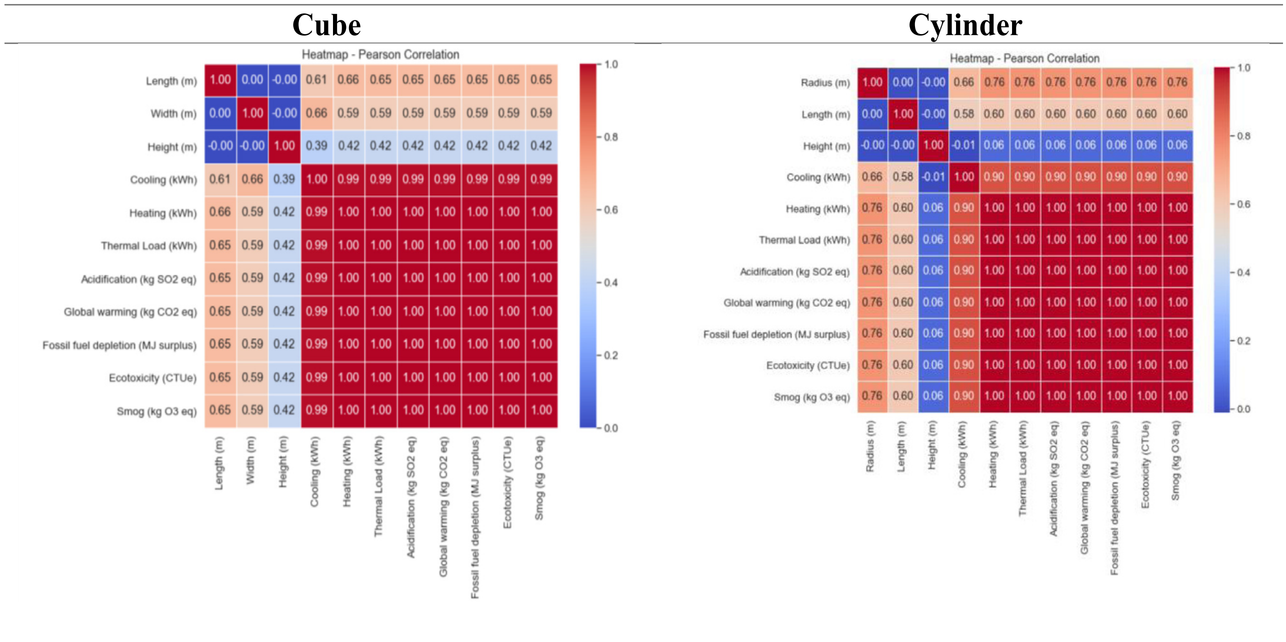

Fig. 11. Heatmap — Pearson correlation.

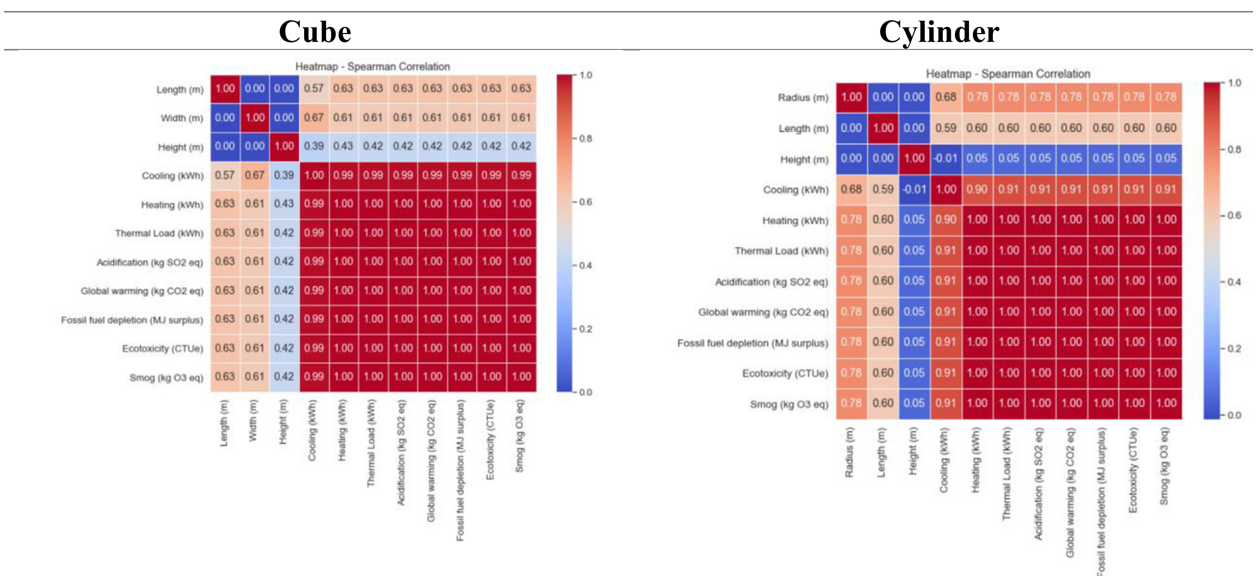

Fig. 12. Heatmap — Spearman correlation.

Future Research Directions: Current methods in architectural research and ongoing efforts to decarbonize buildings may not be sufficient on their own to address present climatic challenges. Utilizing passive strategies can transform buildings into less polluting entities; however, other significant factors throughout the building lifecycle challenge the shift toward truly positive impacts. Future research could focus on integrating these passive solutions, such as geometric features, with active solutions such as smart cladding systems that harness the potential of geometry. This strategy, which incorporates passive and active solutions and applies machine learning science, can enhance the potential to transform buildings into positive resources and can provide practical guidelines for future research efforts.

While this study focused on evaluating the environmental impact of building geometry during the operational phase, it is important to acknowledge the broader implications of form-related decisions. Different geometric configurations may require distinct structural and construction systems, which can significantly influence material use, embodied carbon, and overall environmental performance. Moreover, considerations such as initial construction costs, maintenance requirements, and long-term economic impacts should be incorporated into future analyses to provide a more comprehensive evaluation. Addressing these factors requires an integrated approach that bridges architecture, structural engineering, environmental science, and economics. Future research that combines interdisciplinary expertise to support holistic and sustainable design strategies represents a crucial step toward the realization of positive building structures that not only minimize environmental harm but actively contribute to ecological and social well-being.

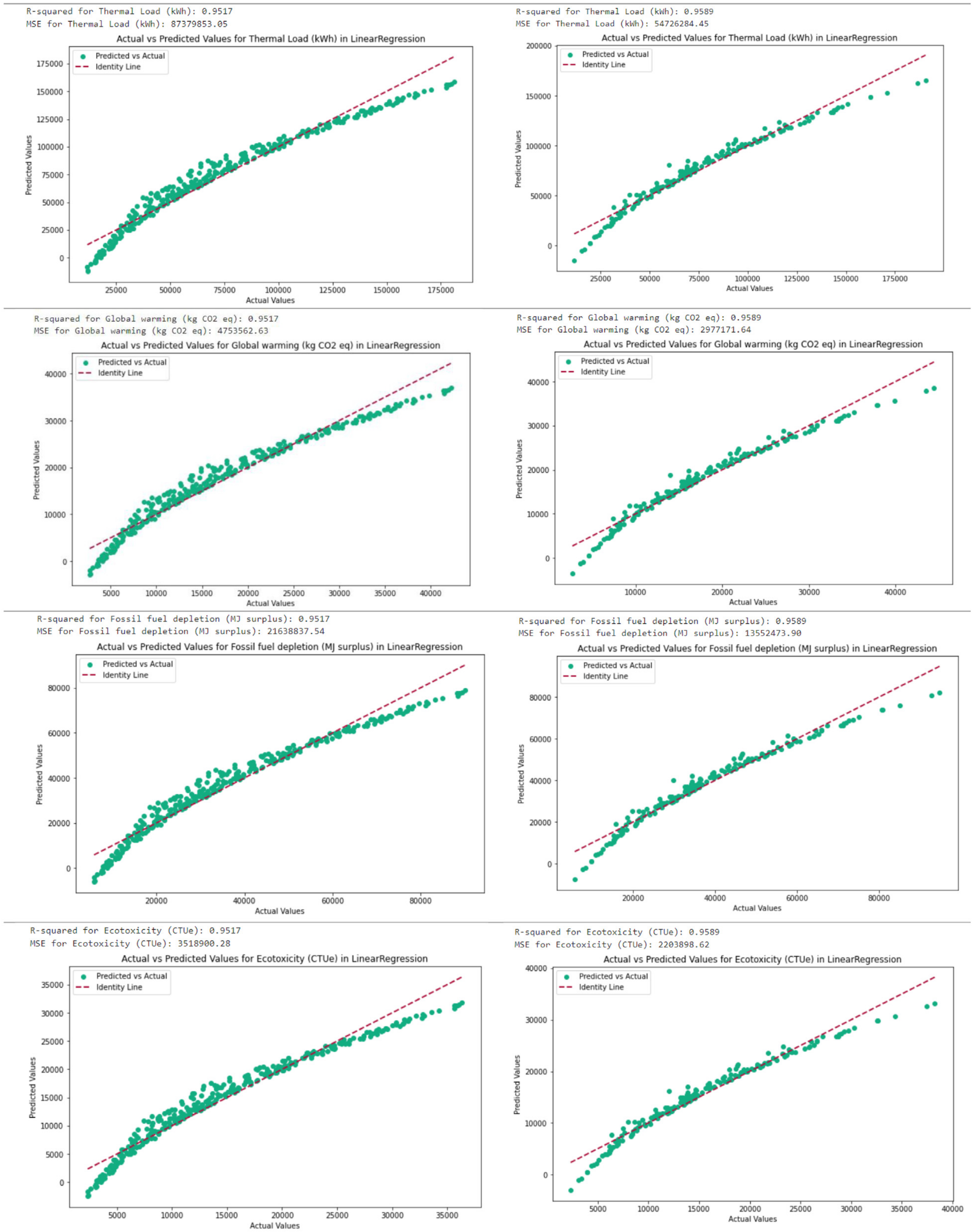

Fig. 13. Actual values vs Predicted values.

CRediT authorship contribution statement

Zinat Javanmard: Writing – original draft, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Consuelo Nava:** Writing – review & editing, Supervision.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author utilized tools such as QuillBot and Grammarly to improve language, comprehension, and grammar checking. After using these tools, the author thoroughly reviewed and edited the content as necessary and takes full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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