Universidade Federal do Rio de Janeiro
Faculdade de Arquitetura e Urbanismo
Programa de Pós-Graduação em Arquitetura

TOWARD CLIMATE-RESILIENT RESIDENTIAL BUILDING DESIGN IN LATIN AMERICA: A NOVEL ASSESSMENT APPROACH

Alexandre Santana Cruz

Rio de Janeiro
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Tese de Doutorado apresentada ao Programa de Pós-graduação em Arquitetura, Faculdade de Arquitetura e Urbanismo, da Universidade Federal do Rio de Janeiro, como parte dos requisitos necessários à obtenção do título de Doutor em Ciências em Arquitetura, Linha de pesquisa Arquitetura, Projeto e Sustentabilidade.

Orientador: Leopoldo Eurico Gonçalves Bastos

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Abril - 2025

O trabalho aqui é bem feito
Respeita o ***serviço negro***
Não te dou uma semana pedindo para voltar
(Rainha da favela - LUDMILLA)

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Abstract

The Global South (GS) faces a dual challenge: severe housing shortages and heightened vulnerability to climate change. Over 1 billion people face cooling access risks, while more than 2 billion are expected to rely on inefficient cooling devices, driving up energy consumption and carbon emissions. Addressing this issue requires sustainable and equitable climate-resilient solutions for the built environment, particularly in Latin America, where, despite economic progress, significant housing deficits persist, and informal settlements continue to expand. This thesis contributes to this effort by integrating data science techniques—including surrogate modeling, transfer learning, multi-objective optimization, and multi-criteria decision-making methods—into the field of building performance simulation (BPS). The research is structured around four core chapters. The first two are systematic literature reviews that synthesize the state of the art in: (1) the potential of multi-objective optimization based on surrogate models for sustainable building design, and (2) the use of BPS tools for adaptation and mitigation assessments with future weather files. Expanding upon the findings from these chapters, the subsequent two chapters propose a simulation-based assessment focused on Latin American residential buildings. More specifically, the investigation considers the cities of Rio de Janeiro, Sao Paulo, Santiago, Bogota, and Lima. By employing Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) as surrogate models and integrating future urban weather files that account for both IPCC emissions scenarios and urban heat island (UHI) effects, this investigation efficiently explores design alternatives. Optimization algorithms, such as the Adaptive Geometry Estimation-based Multi-objective Evolutionary Algorithm (AGE-MOEA) and the Non-Dominated Sorting Genetic Algorithm III (NSGA-III), then identify Pareto-optimal solutions that balance thermal comfort, energy demand, carbon emissions, and construction costs. Additionally, multi-criteria decision-making (MCDM) methods facilitate transparent trade-off evaluations. This work bridges architectural research and data science at a macro-level geopolitical scale, demonstrating the feasibility of climate-resilient building design in the Global South. Beyond its methodological contributions, the thesis provides practical guidelines for policymakers, industry professionals, and researchers seeking to develop more sustainable, climate-adapted building policies. Ultimately, it offers a scalable framework for transforming Latin America's residential sector and encourages further exploration of cost-effective, high-performance building solutions for other regions in need.

Keywords: Global South, Latin America, Housing Deficit, Climate Change, Multi-objective Optimization, Machine learning, Building Performance Simulation

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Resumo

O Sul Global enfrenta um duplo desafio: a grave escassez habitacional e a crescente vulnerabilidade às mudanças climáticas. Mais de 1 bilhão de pessoas enfrentam riscos de acesso à refrigeração, enquanto mais de 2 bilhões devem adquirir dispositivos de resfriamento ineficientes, aumentando o consumo de energia e as emissões de carbono. Abordar essa questão exige soluções sustentáveis e equitativas para a resiliência climática no ambiente construído, especialmente na América Latina, onde, apesar do progresso econômico, os déficits habitacionais continuam significativos e os assentamentos informais seguem em expansão. Esta tese contribui para esse esforço ao integrar técnicas de ciência de dados—incluindo modelagem substitutiva, aprendizado por transferência, otimização multiobjetivo e métodos de tomada de decisão multicritério—ao campo da simulação de desempenho de edificações (BPS). A pesquisa é estruturada em quatro capítulos principais. Os dois primeiros são revisões sistemáticas da literatura que sintetizam o estado da arte em: (1) o potencial da otimização multiobjetivo baseada em modelos substitutivos para o design sustentável de edificações e (2) o uso de ferramentas de BPS para avaliações de adaptação e mitigação utilizando arquivos climáticos futuros. Expandindo as descobertas desses capítulos, os dois capítulos subsequentes propõem uma avaliação baseada em simulação, focada em edificações residenciais latino-americanas. Mais especificamente, a investigação considera as cidades do Rio de Janeiro, São Paulo, Santiago, Bogotá e Lima. Ao empregar *Extreme Gradient Boosting* (XGBoost) e *Artificial Neural Networks* (ANN) como modelos substitutivos e integrando arquivos climáticos urbanos futuros que consideram tanto os cenários de emissões do IPCC quanto os efeitos da ilha de calor urbana (UHI), esta investigação explora de forma eficiente alternativas de projeto. Algoritmos de otimização, como o *Adaptive Geometry Estimation-based Multi-objective Evolutionary Algorithm* (AGE-MOEA) e o *Non-Dominated Sorting Genetic Algorithm III* (NSGA-III), identificam soluções de Pareto ótimas que equilibram conforto térmico, demanda energética, emissões de carbono e custos de construção. Além disso, métodos de tomada de decisão multicritério (MCDM) facilitam avaliações transparentes de compensação entre esses critérios. Este trabalho estabelece conexões entre a pesquisa em arquitetura e a ciência de dados em uma escala geopolítica macro, demonstrando a viabilidade do design resiliente ao clima no Sul Global. Além de suas contribuições metodológicas, a tese fornece diretrizes práticas para formuladores de políticas, profissionais do setor e pesquisadores que buscam desenvolver políticas habitacionais mais sustentáveis e adaptadas ao clima. Por fim, ela oferece um modelo escalável para transformar o setor residencial na América Latina e incentiva a exploração de soluções construtivas de alto desempenho e custo-benefício para outras regiões em necessidade.

Palavras-chave: Sul Global, América Latina, Déficit Habitacional, Mudanças Climáticas, Otimização Multiobjetivo, Aprendizado de Máquina, Simulação de Desempenho de Edifícios

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Acronyms

ABH	Average building high
AEC	Architecture, Engineering, and Construction
AFN	Airflow Network
AGE-MOEA	Adaptive Geometry Estimation based Multi-objective Evolutionary Algorithm
AHP	Analytic Hierarchy Process
AHT	Anthropogenic heat from traffic
ANN	Artificial Neural Networks
AR	Assessment Report
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
Aw	Tropical Savanna
AWD	Ambient Warmness Degree
BES	Best Equilibrium Solution
BPS	Building performance simulation
BRL	Brazilian Real
CE	Carbon emissions
Cfa	Humid subtropical climate
CH_4	Methane
CLP	Chilean Peso
CMA-ES	Covariance Matrix Adaptation Evolutionary Strategy
COP	Colombian Peso
CS	Cost
C-TAEA	Constrained multi-objective evolutionary algorithm with an improved two-archive strategy
Cwa	Monsoon-influenced humid subtropical climate
DA	Daylight Autonomy
DBT	Dry-bulb temperature
DH	Degree-hours
DMIM	Delta Moment-Independent Measure
DoE	Design of Experiments
DP	Deep learning
DSY	Design Summer Year
DT	Decision Tree
DY	Daylighting
ED	Energy demand
EG	Energy
ELM	Ensemble Learning Model
EPI	Equivalent Performance Index
EPS	Expanded polystyrene
ES	Equilibrium Solution
FAST	Fourier Amplitude Sensitivity Test
FFD	Fractional Factorial Designs
FSR	Façade-to-site ratio
GBDT	Gradient-boosted decision trees
GC	Green coverage
GCM	Global Climate Model
GHG	Greenhouse Gas
GHR	Global horizontal radiation

GPR	Gaussian Process regression
GS	Global South
HS	Hours of safety
HVAC	Heating, Ventilation and Air Conditioning
ICF	Insulated Concrete Form
IOD	Indoor Overheating Degree
IoT	Internet of things
IPCC	Intergovernmental Panel on Climate Change
IS	IPCC Scenario
KNN	K-Nearest Neighbors
LCA	Life Cycle Assessment
LCCA	Life Cycle Cost Analysis
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LCZ	Local Climate Zone
LHS	Latin Hyperbolic Sampling
LR	Linear Regression
LRA	Low-rise apartment
MAE	Mean Absolute Error
MAPE	Mean absolute percentage error
MARS	Multivariate Adaptive Regression Splines
MCDM	Multi-criteria Decision-making
MODE	Multi-objective Differential Evolution
MOEA/D	Multi-objective Evolutionary Algorithm Based on Decomposition
MOGA	Multi-objective Genetic Algorithm
MOMRFO	Multi-objective Manta Ray Foraging Optimizer
MOPSO	Multi-objective Particle Swarm Optimization
MSE	Mean square error
NO_2	Nitrogen dioxide
NSGA-II/III	Non-dominated Sorting Genetic Algorithm II or III
OSB	Oriented strand board
OT	Operative temperature
PCA	Principal Component Analysis
PCC	Partial Correlation Coefficients
PD	Peak of energy demand
PEN	Peruvian Sol
POE	Post Occupancy Evaluation
PRCC	Partial Rank Correlation Coefficient
PVC	Polyvinyl chloride
QRS	Quasi-random Sampling
R^2	Coefficient of determination
RCM	Regional Climate Model
RCP	Representative Concentration Pathways
RCP	Representative Concentration Pathways
RDA	Redundancy Analysis
RED-FAST	Random Balance Designs - Fourier Amplitude Sensitivity Test
RF	Random Forest
RH	Relative humidity

RMSE	Root Mean Square Error
RS	Random sampling
RT	Recovery time
SA	Sensitivity analysis
SCIP	Structural Concrete Insulated Panels
SCR	Site coverage ratio
SEGA-Q	An improved algorithm based on GA
SHAP	SHapley Additive explanation
SHGC	Solar heat gain coefficient
SINAPI	Brazilian National Survey System for Construction Costs and Indices
SLR	Systematic Literature Review
SPEA2	Strength Pareto Evolutionary Algorithm 2
SRC	Standardized Regression Coefficients
SRES	Special Report on Emissions Scenarios
SRRC	Standardized Rank Regression Coefficient
SSP	Shared Socioeconomic Pathways
SVR	Support Vector Regression
TA	Thermal autonomy
TC	Thermal comfort
TL	Thermal Load
TMY	Typical Meteorological Year
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TRY	Test Reference Year
TY	Typical Year
UA	Uncertainty Analysis
UDI	Useful Daylight Illuminance
UDI	Daylight illuminance
UHI	Urban heat island
UHII	Urban Heat Island Intensity
US	Utopia Solution
U-value	Thermal transmittance
UWG	Urban Weather Generator
WBGT	Wet Bulb Globe Temperature
WWR	Window-to-Wall Ratio
XGBoost	Extreme Gradient Boosting
XMY	eXtreme Meteorological Year
XPS	Extruded polystyrene

Contents

1. Chapter 1: Introduction

1.1 Problem statement

Approximately 1.2 billion people worldwide lack access to affordable and safe housing, with the majority concentrated in Global South (GS) regions, including Africa, Latin America and the Caribbean, the Pacific Islands, Asia, and Oceania (excluding Israel, Japan, Australia, and South Korea) (DADOS; CONNELL, 2012). Simultaneously, reports from the Intergovernmental Panel on Climate Change (IPCC) indicate that GS regions are particularly vulnerable to the impacts of climate change (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). Within this context, over 1 billion people face cooling access risks, while more than 2 billion are projected to acquire inefficient cooling devices (IEA, 2018). The rising purchasing power in GS countries has amplified the demand for HVAC systems, making it a critical concern in the global energy debate. Conditioned spaces in emerging economies are expected to grow by 80%, significantly increasing energy demand in urban areas that offer substantial potential for energy savings (IEA, 2022). Consequently, addressing the global housing deficit requires innovative construction regulations and advanced technologies to create climate-resilient built environments. Climate-resilient building design begins by assessing vulnerability, which may inform the development of adaptation and mitigation strategies to enhance resistance against future weather conditions (ATTIA et al., 2021; HOMAEI; HAMDY, 2021; KESIK; O'BRIEN; OZKAN, 2022; MILLER et al., 2021). However, solutions must ensure thermal comfort, reduce energy demand, and lower carbon emissions at an affordable cost, enabling GS communities to adapt to future weather conditions effectively (CRUZ et al., 2024b).

1.2 Context

The decisions made during the early stages of design have a significant impact on building performance, with the envelope playing a crucial role in controlling indoor and outdoor heat transfer (IKUDAYISI et al., 2023). However, designing sustainable buildings is often challenging due to various considerations, including thermal, energy, environmental, and cost concerns (BAI et al., 2022). With numerous variables affecting building performance, finding an optimal design solution is not straightforward. By combining appropriate design features, the architecture design process can lead to sustainable buildings and foster a climate-resilient built environment (ATTIA et al., 2021; HOMAEI; HAMDY, 2021; KESIK; O'BRIEN; OZKAN, 2022; MILLER et al., 2021).

In this context, simulation studies play a crucial role in extending research findings beyond the limitations of traditional experiments, such as small scale and location constraints. Building performance simulation (BPS) tools are increasingly used in resilience assessments to examine overheating risks from climate change, providing valuable insights for building design (CRAWLEY; LAWRIE, 2019). Instead of relying on traditional historical climate data, researchers recommend modifying weather files to reflect climate change trends. The Intergovernmental Panel on Climate Change (IPCC) has developed various emissions scenarios within its Assessment Reports (AR), projecting future climate conditions based on different greenhouse gas (GHG) emissions levels (COLE; EVINS; EAMES, 2024; MACHARD et al., 2020). By utilizing these scenarios, BPS tools can provide detailed analyses of how buildings may perform under different future climates, aiding in the development of strategies to enhance building resilience (COLE; EVINS; EAMES, 2024; CRAWLEY; LAWRIE, 2019; ESCANDÓN et al., 2023; MACHARD et al., 2020; RODRIGUES; FERNANDES; CARVALHO, 2023).

In many cases, BPS tools are integrated with automation software to streamline detailed analyses using techniques such as parametric, sensitivity, or optimization. Optimization is a process of minimizing (or maximizing) several objective functions by systematically finding the best solution within given constraints. Although optimization is a promising technique, it can be computationally intensive (GONÇALVES et al., 2024; KRELLING et al., 2024). An alternative is optimization based on surrogate models. These models, also known as meta, statistical, or response surface approximation models, are frequently developed using machine learning algorithms (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019). They initially learn the relationship between the input and output variables by reading the previously recorded data, and subsequently, mimic the behavior of the original model to be able to fast predict the outputs according to the newly given inputs with high accuracy (AMASYALI; EL-GOHARY, 2018; SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017). Additionally, transfer learning enables a machine learning model to be effectively retrained on new datasets while retaining core insights learned from the initial data (HOSNA et al., 2022; KO; PARK, 2021b). Essentially, it is a technique where knowledge acquired from one task is leveraged to improve performance on a related task, often by reusing pre-trained models or learned features (LAGUNAS et al., 2023; PAN; YANG, 2010). Finally, these surrogate models can be combined with an optimization algorithm for performing several evaluations.

Building designing often involves conflicting objectives, highlighting the complexity of achieving sustainability in construction. For instance, within climate-resilient building design, improving thermal comfort and energy efficiency may require balancing environmental impacts and construction costs (HAMIN; GURRAN, 2009; XU et al., 2019). A common approach to solve conflicting objectives is the Pareto front in which a range of optimal solutions span the trade-off between objectives (EVINS, 2013; MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). This approach can be beneficial for the decision-makers to choose the optimal solution depending on different preferences (NGUYEN; REITER; RIGO, 2014). Although several decision-making strategies can be employed to select the best solution from the Pareto front, Multi-Criteria Decision-Making (MCDM) techniques are the preferred approach due to its ability to systematically balance multiple metrics, offering a structured, objective, and adaptable method (HWANG; YOON, 1981; YANG; CHEN; HUNG, 2007).

1.3 Research scope

Latin America has experienced notable social and economic growth, fueled by diversification into manufacturing, services, and technology, alongside increased foreign investment and favorable trade agreements (LUBBOCK; VIVARES, 2022; WORLD BANK, 2024). However, a significant housing deficit persists, with millions living in informal settlements like slums or favelas (OECD, 2015). Construction across the region is characterized by the widespread use of concrete and masonry, driven by affordable raw materials and low labor costs that enable labor-intensive, self-built housing (LUBBOCK; VIVARES, 2022; MARÍN-RESTREPO et al., 2023). These housing structures often suffer from poor thermal performance and weak structural integrity (UN, 2022, 2023a). Public policies addressing the housing deficit typically adopt standardized social housing prototypes, but this approach often neglects local climate needs and the rising risk of overheating from climate change (ALVES; DUARTE; GONÇALVES, 2016; ALVES; GONÇALVES; DUARTE, 2021; FILIPPÍN et al., 2017; RODRIGUES et al., 2023; RODRIGUES; PARENTE; FERNANDES, 2024; ROUAULT et al., 2019; SILVERO et al., 2019; WANG et al., 2022; YU et al., 2023). Therefore, the housing deficit (INTER-AMERICAN DEVELOPMENT BANK, 2022; VIGEVANI; RAMANZINI JUNIOR, 2022), common construction methods (UN, 2022, 2023a), shared socioeconomic conditions (MARÍN-RESTREPO et al., 2023; OECD, 2015), and regional agreements (LUBBOCK; VIVARES, 2022; WORLD BANK, 2024) create an ideal environment for collaboration to address climate change in the building sector in Latin America. This offers an opportunity for neighboring countries to exchange technical knowledge and expertise, fostering the development of climate-resilient building policies and reports that transcend national boundaries.

1.4 Objectives

1.4.1 General objective

This document aims to propose a method for developing climate-resilient building design for the Global South through multi-objective optimization based on surrogate models. Specifically, this study focuses on identifying promising resilience strategies for the built environment to simultaneously improve thermal, energy, carbon, and cost performances. The investigation places particular emphasis on the residential building sector in Latin America, with a focus on five major cities: Rio de Janeiro, Sao Paulo, Santiago, Bogota, and Lima.

1.4.2 Specific objectives

Each specific objective corresponds to a chapter in this document, and together they contribute to the main objective of the corresponding thesis, as outlined below:

- To conduct a Systematic Literature Review to identify the state-of-the-art, key challenges, and opportunities in multi-objective optimization based on surrogate modeling for sustainable building design.
- To conduct a Systematic Literature Review to examine the state-of-the-art, key challenges, and opportunities in using building performance simulation tools for climate adaptation and mitigation under future weather projections.
- To develop a simulation-based procedure integrating machine learning with optimization techniques to formulate construction guidelines for climate-resilient building design in the Global South, with a focus on the Latin American residential sector.
- To perform a simulation-based study integrating machine learning, optimization, and multi-criteria decision-making techniques to assess the feasibility of climate-resilient building design in the Global South, particularly in the Latin American residential sector.

1.5 Innovation

The innovation of this thesis can be categorized into conceptual and practical perspectives. From a conceptual perspective, this study introduces a macro-level geopolitical analysis while bridging the gap between architectural research and data science. Its focus on Latin America highlights large-scale challenges, encouraging researchers, policymakers, and industry professionals to develop region-specific solutions for issues common across the continent. Additionally, integrating data science methodologies into architectural traditional workflows enhances automation and optimization, improving overall efficiency. This broader point of view and automated strategy promotes more impactful scientific contributions. From a practical perspective, this study advances innovation by combining multi-objective optimization with machine learning techniques while applying transfer learning to building performance simulation field. Furthermore, it explores adaptation and mitigation strategies using future weather projections and integrates urban heat island effects into climate modeling. This approach enables the development of future urban weather files, supporting climate-resilient building design in the Global South, particularly in the Latin American residential sector.

1.6 Structure of the thesis

Apart from the Introduction and Conclusion, this document consists of four additional chapters, each aligned with a specific objective outlined in the objectives section. These core chapters consist of reports, each presenting a distinct methodology and covering the following topics: 1) Systematic literature review on multi-objective optimization based on surrogate models; 2) Systematic literature review on the use of building performance simulation tools for climate adaptation and mitigation through future weather file predictions; 3) A simulation-based procedure integrating machine learning with optimization techniques for developing construction guidelines to support climate-resilient building design for the Global South - the Latin American residential building sector; 4) A simulation-based investigation that integrates machine learning with optimization and multi-criteria decision-making techniques to illustrate the feasibility of climate-resilient building design in the Global South - the Latin American residential building sector.

The synergy between key research gaps identified in Chapters 2 and 3 informs the contributions presented in the following chapters, specifically Chapters 4 and 5. Moreover, each chapter is presented in journal article format, functioning as a standalone report. This structure allows readers to engage with specific sections of the thesis independently, based on their interests. However, readers are encouraged to explore the entire document for a more comprehensive understanding of the topic. Table 1 shows a summary of chapters that compound the core of the current thesis and their expected title.

Table 1. Articles that compound the core of the thesis.

Chapter	Title	DOI
2	Multi-objective optimization based on surrogate models for sustainable building design: A systematic literature review	https://doi.org/10.1016/j.buildenv.2024.112147
3	What lies ahead? The future performance of Global South residential buildings amid climate change: A systematic literature review	https://doi.org/10.1016/j.jobe.2024.111486
4	How can we promote climate-resilient building design within the Global South context? A simulation-based procedure for the Latin America residential sector	Under review
5	How feasible is climate-resilient building design within the Global South context? Insights from Latin American residential sector	Under review

2. Chapter 2: Multi-objective optimization based on surrogate models for sustainable building design: A Systematic Literature Review

Abstract: Surrogate models can overcome the building performance simulation complexity and replace time-consuming simulation engines within multi-objective optimization studies. Although this approach can leverage the development of sustainable building design, just a few studies integrate these concepts collectively. Therefore, this paper explores simulation studies that combine these techniques through a Systematic Literature Review (SLR). Specifically, this study illustrates the state-of-the-art literature, main challenges, and opportunities regarding multi-objective optimization based on surrogate models. The three significant contributions resulting from this study are: 1) a list of research gaps with issues partially addressed, 2) a framework for future evaluations, and finally, 3) directions for future research in the field. Based on 54 documents analyzed, there are research areas that demand further attention and present opportunities for significant contributions. For instance, there has been limited exploration of data mining and transfer learning techniques, a lack of optimizations considering uncertainty parameters that could enhance the resilience of the projects, and a deficiency in building decarbonization discussions. Furthermore, developing user-friendly tools or web applications could streamline the replication of the optimization approach, thus promoting more sustainable building design. Simultaneously, ethical standards could support a research environment that is transparent, accountable, and trustworthy. Finally, this SLR consolidates previous scientific achievements, acting as a valuable resource to facilitate the adoption of multi-objective optimization based on surrogate models for future researchers, thereby serving as a functional and reference guide and allowing the design of more sustainable buildings.

Keywords: review; optimization; machine learning; building performance simulation; sustainable building design; energy efficiency

2.1 Introduction

Despite the challenges, the Architectural, Engineering, and Construction (AEC) industry has great potential to promote energy savings and carbon emission reduction through building design (EU COMMISSION, 2023; IKUDAYISI et al., 2023). However, sustainable building design is a complex and time-consuming process. Buildings are unique, and no solution fits all. Furthermore, building performance is affected by various factors such as floor layout, envelope properties, energy systems and equipment, occupant behavior, and local climate (BAI et al., 2022). The decisions made in the early design stages significantly impact building performance throughout its entire lifecycle, which could determine the building design's success or failure in terms of user satisfaction and environment impact. Thus, to understand the building performance behavior, engineers, architects, and designers usually rely on different evaluation methods to support the building design.

Building performance is typically evaluated using three main methods: 1) White box models (physics-based models), 2) Black box models (data-driven models), 3) Grey box models (hybrid models) that combine the previous two models (AMASYALI; EL-GOHARY, 2018; MENDES et al., 2024b; SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017). Physical models are developed using the principles and equations governing heat and mass transfer. These models are very complex as they consider all the properties, features, and mechanisms of a building. For this approach, various validated simulation tools are accessible for assessing building performance, such as EnergyPlus, DesignBuilder, eQUEST, and TRNSYS. Yet, simulating multiple design options demands extensive time, labor, and expertise. In addition, simplification methods can induce high prediction gaps that compromise the reliability of the decision taken using simple numerical simulations (WANG; SRINIVASAN, 2017). In contrast, data-driven models lack explicit physical interpretation. They rely on statistical and mathematical methods to implicitly extract patterns from data. These models learn the relationships between input and output variables using historical data and then mimic the behavior of the original system to quickly predict outputs for new inputs with high accuracy (SUN; HAGHIGHAT; FUNG, 2020). Lastly, the grey box model incorporates both knowledge of the physical model and input-output data, leveraging the advantages of both approaches. These grey box models, also known as surrogate, meta, statistical, or response surface approximation models, show potential for delivering building performance evaluations that are grounded in physical knowledge, yet are significantly faster than traditional simulation-based design analyses (AMASYALI; EL-GOHARY, 2018).

Machine learning (ML) techniques, a subset of Artificial Intelligence (AI), offer a promising approach for building performance prediction, autonomously identifying patterns in data to forecast future outcomes, particularly through black and grey box modeling. (WESTERMANN; EVINS, 2019). Predicting building performance often involves supervised regression, leveraging labeled data to forecast continuous numerical values (AMASYALI; EL-GOHARY, 2018; SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017). Any ML model dealing with supervised regression can be applied to building performance prediction (GAO et al., 2021). Linear Regression (LR), Random Forest (RF), Support Vector Regression (SVR), K-Nearest Neighbors (KNN), Decision Tree (DT), and Artificial Neural Network (ANN) are among the most popular ML algorithms, valued for their simplicity, versatility, performance, flexibility for non-linearity, robustness, noise tolerance, interpretability, and historical significance (AMASYALI; EL-GOHARY, 2018; SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017).

2.1.1 Main concepts

2.1.1.1 Surrogate modeling applied to building performance

Increasing data accessibility and recent progress in ML techniques are driving advancements in building performance evaluation. In the building domain, three primary categories of data exist: sensor data collected from building management systems and Internet of Things (IoT); stock data derived from annual energy demand and floor area for numerous buildings; and simulation data generated by simulation tools (WESTERMANN; EVINS, 2019). The first two categories comprise historical observations of existing buildings, valuable for optimizing operations, developing retrofit strategies, and benchmarking energy performance (AMASYALI; EL-GOHARY, 2018). Consequently, building performance simulations that adhere to physical laws continue to be indispensable for the design of new buildings (SUN; HAGHIGHAT; FUNG, 2020).

The idea of surrogate modeling is to emulate an expensive high-fidelity model using an ML technique. The surrogate is trained on a small set of simulation input (variables) and output (labels) data. Once it is validated to approximate the detailed simulation model, it can be used to almost instantly predict outcomes of the high-fidelity simulation given an appropriate set of building design information (GAO et al., 2021). Furthermore, the surrogate model can be combined with an optimization algorithm for performing several evaluations (WESTERMANN; EVINS, 2019). Instead of coupling building performance simulation tools with automation platforms, the surrogate model can replace the simulation engine to streamline design optimization. In this new approach, the simulation tool primarily generates a database that will be used by an ML algorithm to develop the surrogate model. Then, this surrogate model is integrated with a multi-objective optimization algorithm to find the optimal design solution. Figure 1 illustrates the main steps of this new approach that combines multi-objective optimization and ML techniques.

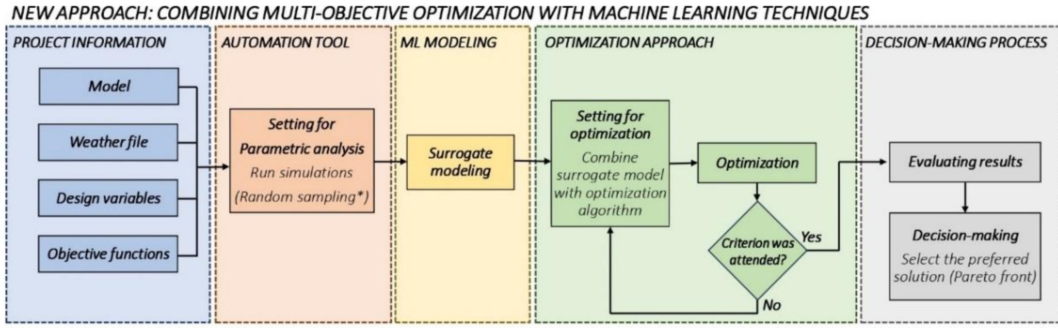


Figure 1. Multi-objective optimization based on surrogate models.

Surrogate modeling significantly enhances building performance assessment by reducing the need to repeatedly run complex simulations, thereby lowering computational costs. It eliminates the necessity of invoking simulation software at each optimization step (or context) by efficiently capturing the relationships between design variables from a dataset. As a result, these grey box models can effectively approximate the behavior of detailed simulations, simplifying and accelerating the building performance assessment process. However, surrogate models also have limitations. Their accuracy is contingent upon the quality of the underlying simulation data and the model's ability to capture complex interactions. Errors can arise if the model oversimplifies critical dynamics or if the synthetic data used for training do not adequately represent real-world conditions (SUN; HAGHIGHAT; FUNG, 2020). Consequently, while surrogate modeling is powerful, its reliability depends on careful validation and calibration against actual performance data (WESTERMANN; EVINS, 2019).

2.1.1.2 Multi-objective optimization of building design

Optimization is a process of minimizing (or maximizing) several objective functions by systematically finding the best solution within given constraints. The following mathematical Equation describes a given generic optimization problem:

$$\min_{x \in C} f(x_1, x_2, \dots, x_n) \;\; where\; C(c_1, c_2, \dots, c_n) \geq 0 \; and \; x_i \epsilon \; v_i$$

Where $f(x_1)$ is one of the several objective functions (also called cost or fitness functions) that should be minimized (or maximized) based on several constraints *(C)*. Additionally, each design variable (x_i) is restricted to particular values (v_i), either discrete or defined by boundary constraints (EVINS, 2013). One widely adopted method of optimization is referred to as parametric analysis, wherein input values of each variable are varied while others are held constant. However, this method ignores nonlinear variable interactions, often leading to local improvements and discontinuities (MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). To address these limitations and to derive an optimal (or near-optimal) solution, several optimization algorithms have been developed in recent years such as evolutionary algorithms, derivative-free search methods, and hybrid algorithms (NGUYEN; REITER; RIGO, 2014).

Building performance assessments often involve multiple conflicting objectives, reflecting the complexity of designing buildings that are sustainable, cost-effective, and efficient. For instance, improving thermal comfort and energy efficiency may require balancing environmental impact with construction costs (PAN et al., 2023). Exhaustively exploring all combinations is only feasible with few design variables, but building design often involves exponentially growing combinations. Optimization algorithms are efficient in extensive search spaces because they can strategically navigate complex problem landscapes (MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). Techniques like evolutionary algorithms efficiently search for optimal solutions, focusing on promising areas and using heuristic strategies to reduce evaluations while managing constraints (NGUYEN; REITER; RIGO, 2014). Additionally, performing uncertainty and sensitivity analysis beforehand helps identify variables with minimal impact, thereby reducing the search space and streamlining the optimization process (RIVALIN et al., 2018; WEI, 2013). This approach enables faster solution discovery, making it superior for complex building design challenges (WESTERMANN; EVINS, 2019).

In this context, two common approaches for resolving conflicting objectives are the Weighted Sum method and the Pareto front (EVINS, 2013; MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). In the first approach, the various goals are normalized, combined through their associated weighting factors, and summed up to provide a single objective that will be traditionally optimized. Unfortunately, this approach does not provide information about the interference of different sub-objectives (MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). In the second approach, a range of optimal solutions (called the Pareto front) span the trade-off between each objective. This approach can be beneficial for the decision-makers to choose the optimal solution depending on different preferences or through multi-criteria decision methods (MCDM) (NGUYEN; REITER; RIGO, 2014). In Figure 2, optimization targets the minimization of two objectives, with red circles indicating non-dominated solutions (the Pareto front) and blue dots representing feasible but inferior solutions.

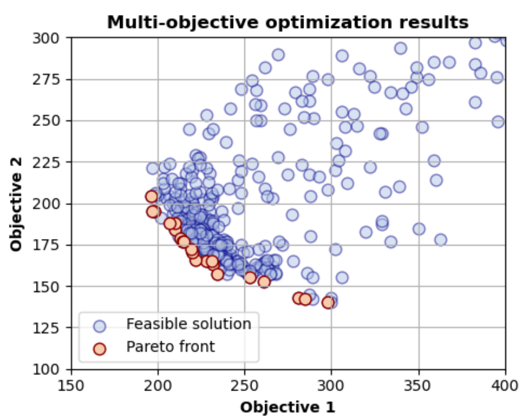


Figure 2. Pareto front approach.

2.1.2 Scope and main contribution

Despite the ability of integrated building performance simulation tools and automation platforms (e.g., modeFRONTIER, GenOpt, JEPlus+EA, and MATLAB) to efficiently identify optimal solutions without exhaustive testing, the process remains time-consuming (NGUYEN; REITER; RIGO, 2014). Conversely, grey box modeling for building performance assessment has garnered significant interest in the research domain. This approach reduces computational resources and improves processing speed while maintaining high accuracy (GAO et al., 2021; WESTERMANN; EVINS, 2019). In addition, surrogate models can overcome the complexity of building performance simulation tools and replace time-consuming simulation engines within multi-objective optimization studies, enhancing sustainable building design. Yet, there are just a few studies that integrate these concepts collectively.

Therefore, this paper aims to explore simulation studies that combine these techniques through a Systematic Literature Review (SLR). Specifically, this study illustrates the state-of-the-art literature, understand the main challenges, and identify opportunities regarding multi-objective optimization based on surrogate models. Furthermore, there are three significant contributions resulting from this study: 1) a list of research gaps with issues partially addressed, 2) a framework for future evaluations, and finally, 3) directions for future research in the field. This SLR consolidates and compiles previous scientific achievements, acting as a valuable resource to facilitate the adoption of multi-objective optimization based on surrogate models for future researchers, thereby serving as a functional and reference guide and allowing the design of more sustainable buildings.

Finally, to provide a clear structure, the remaining sections of this paper are organized as follows: Section 2.2 outlines the research method conducted, explaining all steps followed to perform the SLR. Section 2.3 illustrates the findings (quantitative and qualitative results) discovered during the SLR regarding three main topics: "surrogate modeling", "sensitivity and uncertainty analysis", and "multi-objective optimization methods". Section 2.4 discusses the key synergies that emerged from the SLR providing a framework and insights into future research directions in the field. Finally, Section 2.5 presents the last thought regarding this study with conclusions.

2.2 Research method

The SLR approach identifies gaps in the state-of-the-art literature. It focuses on moving forward scientific research, facing the vast number of studies conducted yearly and, in many cases, with conflicting results (WATSON; WEBSTER, 2020). The SLR is defined by three main principles: a) explicit method, b) replicability, and c) synthesizing reviewed evidence (DENYER; TRANFIELD, 2009). It lays a strong knowledge base with its transparent structure, aiding theory development, addressing oversaturated research areas, and identifying research gaps (BUDGEN; BRERETON, 2006). The key advantage of SLR is diminished bias in selecting literature. However, its drawbacks include increased time and effort compared to traditional reviews, and source limitations based on specific criteria like keywords and search strings (HALLINGER, 2013; HART, 1998). Finally, SLR is increasingly used in academic environments due to its procedural applicability and analytical objectivity (SAUNDERS; LEWIS; THORNHILL, 2019).

Following previous studies (BRINER; DENYER, 2012; KHAN et al., 2003; KITCHENHAM; CHARTERS, 2007), the SLR is organized into four main stages: 1) formulating research questions; 2) locating scientific studies; 3) selecting and evaluating relevant articles; and 4) synthesizing and reporting results. Even though the procedure appears completely sequential, many stages involve interactions. Figure 3 depicts the SLR procedure. This framework helps illustrate and summarize all objectives, approaches, and strategies to support each stage.

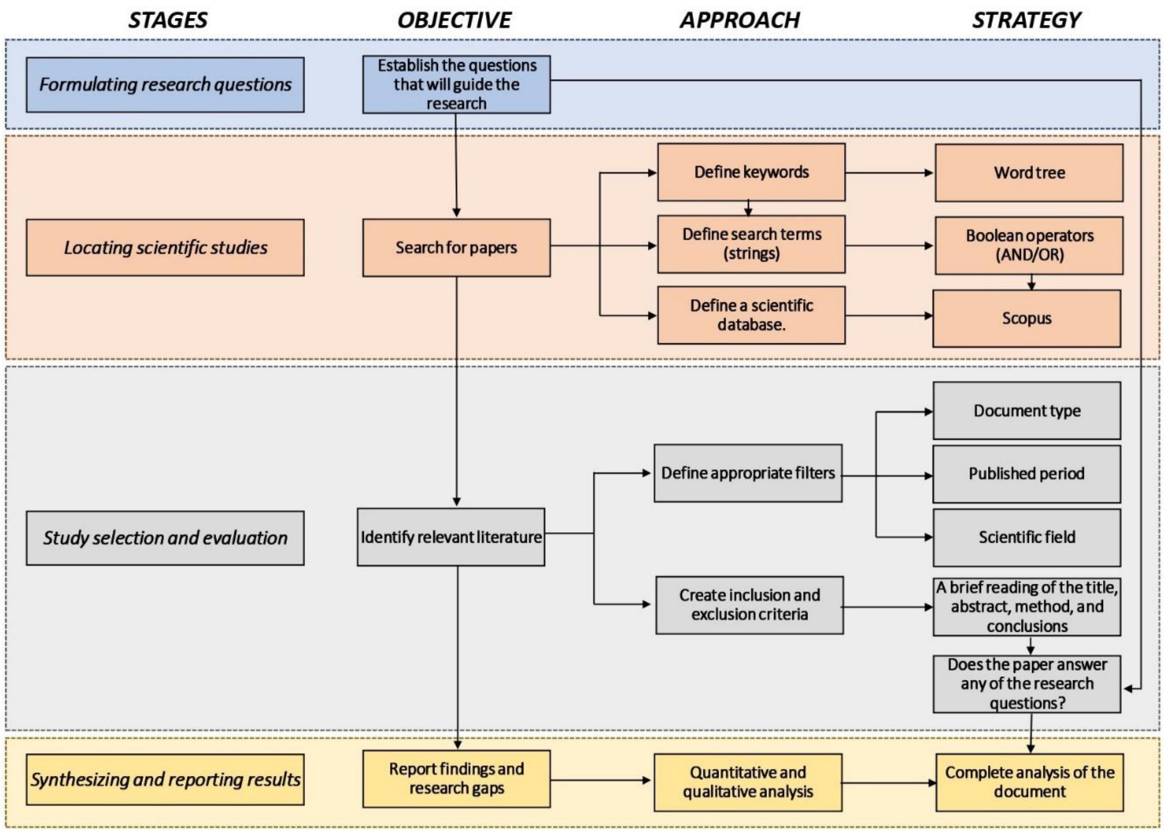


Figure 3. SLR framework.

2.2.1 Formulating research questions

First, to explore multi-objective optimization studies based on surrogate models, it is necessary to understand how the involved areas relate to each other (BRINER; DENYER, 2012; KHAN et al., 2003; KITCHENHAM; CHARTERS, 2007). Within this context, the following research questions are assumed in this study:

- How can integrating multi-objective optimization approaches with ML techniques enhance sustainable building design?
- What are the main challenges and opportunities regarding multi-objective optimization approaches based on surrogate models?

2.2.2 Locating scientific studies

In the second stage, the process of locating studies begins with formulating keywords based on a words tree concept (HART, 1998). An efficient translation of research questions into search terms and strings helps find the maximum number of relevant articles to the research (HALLINGER, 2013). Alternative terms must be considered as a range of words that describe the same topic (KITCHENHAM; CHARTERS, 2007). Table 2.1 shows the search string for this SLR.

Table 2. Search string.

String of search terms.
("Multi-objective optimization" OR Simulation OR "Building performance") AND ("Machine learning" OR "Meta-model" OR "Surrogate model") AND (Building OR Residential OR Commercial)

In this stage, individual or pairwise searching for main topics was not conducted. This was due to extensive prior research in each area and the primary objective of identifying synergy between research topics. In addition, the search for papers is conducted through the databases of Scopus, Web of Science, and Engineering Village.

2.2.3 Study selection and evaluation

The third stage focuses on selecting relevant articles from the list of documents found in the previous step (BRINER; DENYER, 2012; KHAN et al., 2003; KITCHENHAM; CHARTERS, 2007). Therefore, this step centers on applying appropriate filters to restrict some papers based on inclusion/exclusion criteria (DENYER; TRANFIELD, 2009; HALLINGER, 2013; SIDDAWAY; WOOD; HEDGES, 2019). Only journal articles from the AEC Industry published between 2014 and 2023 are selected for evaluation in this study. Following guidelines from previous studies, peer-reviewed journal articles are chosen because they are considered the most valuable and reliable sources for literature reviews (SAUNDERS; LEWIS; THORNHILL, 2019; WATSON; WEBSTER, 2020). The referred research period is selected because ML techniques have evolved exponentially in the last decade due to their potential to solve complex problems in several research areas. As the research focuses on building performance simulation, only articles related to the AEC industry are considered. Finally, only pieces that could answer any research questions established in section 2.1 through the defined metrics (initially, title, abstract, and afterward, method and conclusion) are selected for full-text reading (SIDDAWAY; WOOD; HEDGES, 2019).

2.2.4 Synthesizing and reporting results

In the last stage, the results are synthesized and reported (BRINER; DENYER, 2012; KHAN et al., 2003; KITCHENHAM; CHARTERS, 2007). The SLR generates a comprehensive overview of the studies from the final list of selected documents. The overview organizes the content around key topics, grouping information from the selected studies to facilitate a clearer visualization of the research field. Lastly, it indicates research gaps, main challenges and opportunities across various approaches and contexts (SAUNDERS; LEWIS; THORNHILL, 2019).

2.3 Findings of the SLR

2.3.1 SLR overview

Figure 4 shows the SLR overview in terms of: (a) study selection, (b) published articles per year, (c) country, (d) climate, (e) building function, (f) building typology, (g) performance evaluated, (h) main topic, (i) simulation tool, (j) code availability, (l) dataset availability, and (m) concerns related to ethics or transparency.

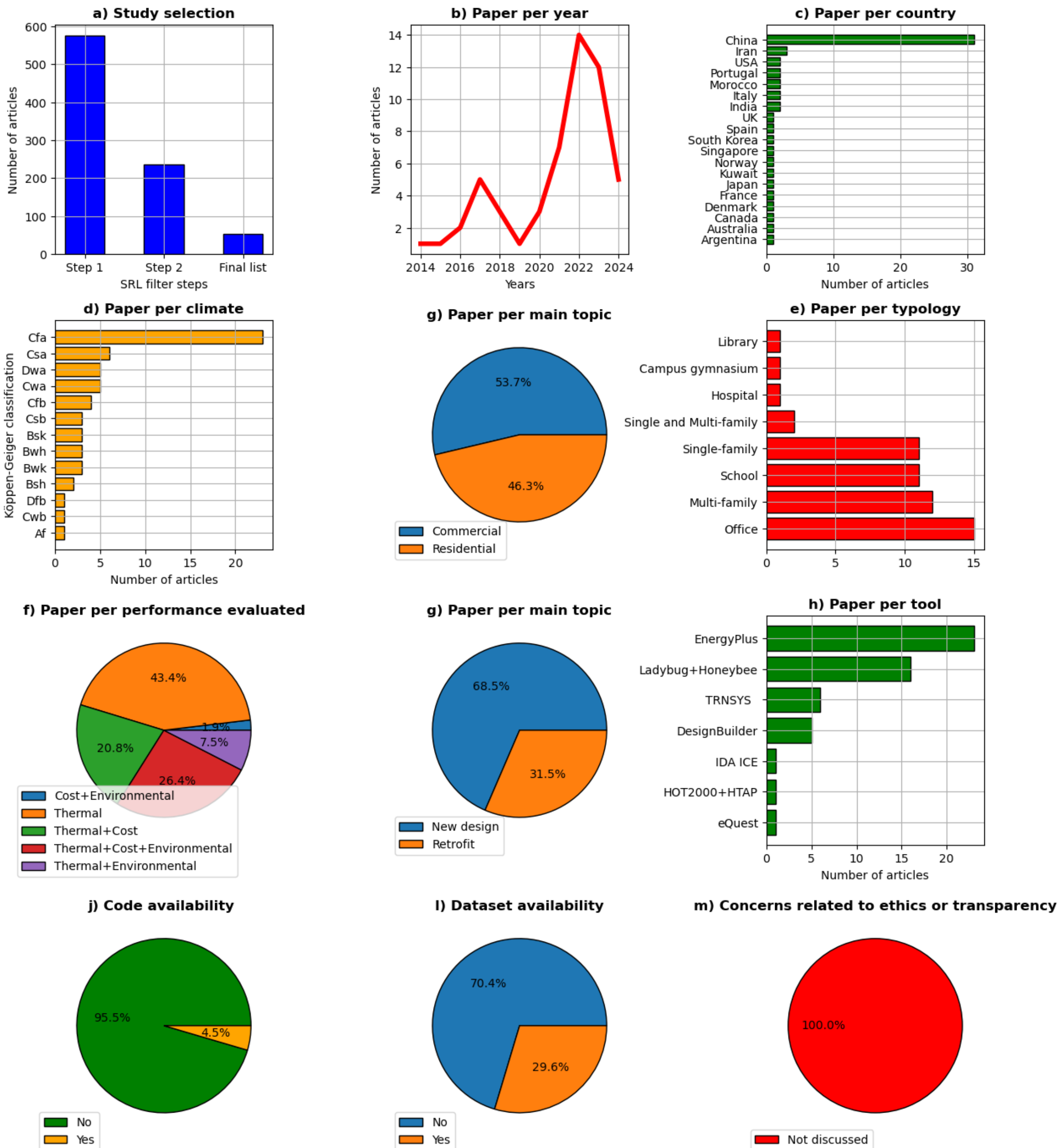


Figure 4. SLR overview.

Figure 4(a) shows the number of articles found in the scientific database (Scopus), after applying selection filters (See section 2.3), and finally, the final sum of selected articles (a total of 54 documents). Figure 4(b) shows that multi-objective optimization based on ML techniques is a growing research tendency, boosting the number of articles published since 2021. This trend likely stems from the growing adoption of ML techniques in building design research, mirroring developments in other AEC domains. Although most studies come as a collaboration among academic institutions from different countries, Figure 4(c) presents the number of articles per country regarding the corresponding author's origin. Complementing this information, Figure 4(d) reveals the climate analyzed (based on the Köppen Geiger classification) of the cities where the case study is located. In both figures, a concentration of studies refers to a specific country and climate. Most studies are from China, and the humid subtropical climate (Cfa) is the most evaluated weather context. China ranks among the top paper producers in AI and ML reviews, underscoring the impact of its innovation ecosystem and AI investments (SAVAGE, 2020). Yet, it is interesting to note that although China has a continental dimension and a high number of studies, this is not reflected in the climate diversity evaluated within the studies. Figure 4(e) and Figure 4(f) present the typologies considered. Half of the studies focus on commercial buildings such as offices and schools, while the other half focus on residential buildings. Furthermore, Figure 4(g) displays that half of the studies focused only on thermal performance (studies on assessing discomfort hours, energy consumption, and daylighting illuminance), leaving cost and environmental impacts aside. Note that the objective functions are explored in detail in section 3.4.1. Although multi-objective optimization based on a surrogate model is an approach to apply during any design phase, Figure 4(h) illustrates that a few studies used this method for retrofit expeditions. One plausible explanation is that retrofit studies frequently prioritize the use of observation-derived data. Figure 4(i) indicates that EnergyPlus is the most used tool in the studies based on simulation data. This result aligns with prior reviews, possibly due to Energy Plus being a widely validated and free software that meets global reference standards (MENDES et al., 2024b). The availability of databases and codes is crucial for knowledge sharing, enabling easier replication of studies, and facilitating the validation or critique of research results. Furthermore, the opacity and complexity of algorithms used in these ML models can make them difficult to interpret, posing significant transparency issues. This is particularly problematic in fields where understanding the decision-making process is crucial. Therefore, addressing the explainability of these models is essential to support ethical considerations. Figure 4(j) and Figure 4(f) reveal that most studies do not publicly share their codes and datasets. Consequently, it is unsurprising that concerns about ethics or transparency are not addressed or emphasized in any document (See Figure 4(m)). Lastly, Table 3 presents the final list of studies selected during the SLR.

Table 3. Summary of studies.

Index	Name	Year	Journal	Reference
1	Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application	2014	Energy and Buildings	(ASADI et al., 2014)
2	Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design	2015	Energy and Buildings	(YU et al., 2015)
3	Systematic approach for the life cycle multi-objective optimization of buildings combining objective reduction and surrogate modeling	2016	Energy and Buildings	(CARRERAS et al., 2016)
4	Multi-objective optimization of building envelope design for life cycle environmental performance	2016	Energy and Buildings	(AZARI et al., 2016)
5	Decision-making based on network visualization applied to building life cycle optimization	2017	Sustainable Cities and Society	(GILLES et al., 2017)
6	CASA, cost-optimal analysis by multi-objective optimization and artificial neural networks: A new framework for the robust assessment of cost-optimal energy retrofit, feasible for any building	2017	Energy and Buildings	(ASCIONE et al., 2017)
7	An approach for building design optimization using design of experiments	2017	Building Simulation	(DHARIWAL; BANERJEE, 2017)
8	A multi-stage optimization of passively designed high-rise residential buildings in multiple building operation scenarios	2017	Applied Energy	(CHEN; YANG, 2017)
9	Multi-Objective Optimization for Energy Performance Improvement of Residential Buildings: A Comparative Study	2017	Energies	(LI et al., 2017)

10	On the performance of meta-models in building design optimization	2018	Applied Energy	(PRADA; GASPARELLA; BAGGIO, 2018)
11	Passive design optimization of newly-built residential buildings in Shanghai for improving indoor thermal comfort while reducing building energy demand	2018	Energy and Buildings	(GOU et al., 2018)
12	Integrated energy performance optimization of a passively designed high-rise residential building in different climatic zones of China	2018	Applied Energy	(CHEN; YANG, 2018)
13	Robust optimal design of zero/low energy buildings considering uncertainties and the impacts of objective functions	2019	Applied Energy	(LI; WANG; TANG, 2019)
14	Many-objective optimization design of a public building for energy, daylighting and cost performance improvement	2020	Applied Sciences (Switzerland)	(SUN; LIU; HAN, 2020)
15	A three-stage optimization methodology for envelope design of passive house considering energy demand, thermal comfort and cost	2020	Energy	(WANG; LU; FENG, 2020)
16	An efficient metamodel-based method to carry out multi-objective building performance optimizations	2020	Energy and Buildings	(BRE; ROMAN; FACHINOTTI, 2020)
17	A metamodel-based multi-objective optimization method to balance thermal comfort and energy efficiency in a campus gymnasium	2021	Energy and Buildings	(YUE et al., 2021)
18	A novel optimization method for conventional primary and secondary school classrooms in southern China considering energy demand, thermal comfort and daylighting	2021	Sustainability (Switzerland)	(XU et al., 2021a)
19	Multi-objective building design optimization considering the effects of long-term climate change	2021	Journal of Building Engineering	(ZOU et al., 2021a)
20	A two-stage multi-objective optimization method for envelope and energy generation systems of primary and secondary school teaching buildings in China	2021	Building and Environment	(XU et al., 2021b)
21	Multi-objective optimization of the multi-story residential building with passive design strategy in South Korea	2021	Building and Environment	(JUNG; HEO; LEE, 2021)
22	Multi-objective optimization of energy efficiency and thermal comfort in an existing office building using NSGA-II with fitness approximation: A case study	2021	Journal of Building Engineering	(GHADERIAN; VEYSI, 2021)
23	Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms	2021	Energy and Buildings	(CHEGARI et al., 2021)
24	Data-driven performance analysis of a residential building applying artificial neural network (ANN) and multi-objective genetic algorithm (GA)	2022	Building and Environment	(SARYAZDI et al., 2022)
25	Intelligent optimization framework of near zero energy consumption building performance based on a hybrid machine learning algorithm	2022	Renewable and Sustainable Energy Reviews	(WU et al., 2022)
26	Multi-objective optimization of building energy consumption and thermal comfort based on integrated BIM framework with machine learning-NSGA II	2022	Energy and Buildings	(HOSAMO et al., 2022)
27	Multi-Objective Optimization of Ultra-Low Energy Consumption Buildings in Severely Cold Regions Considering Life Cycle Performance	2022	Sustainability (Switzerland)	(ZHANG et al., 2022b)
28	Data-driven prediction and optimization of residential building performance in Singapore considering the impact of climate change	2022	Building and Environment	(YAN; JI; YAN, 2022a)
29	Machine Learning-Based Method for Detached Energy-Saving Residential Form Generation	2022	Buildings	(GUO et al., 2022)

30	Multi-Objective Optimization of Building Environmental Performance: An Integrated Parametric Design Method Based on Machine Learning Approaches	2022	Energies	(LU et al., 2022)
31	An integrated framework for multi-objective optimization of building performance: Carbon emissions, thermal comfort, and global cost	2022	Journal of Cleaner Production	(CHEN; TSAY; NI, 2022)
32	A three-stage optimization method for the classroom envelope in primary and secondary schools in China	2022	Journal of Building Engineering	(XU et al., 2022)
33	Artificial Neural Network for Predicting Building Energy Performance: A Surrogate Energy Retrofits Decision Support Framework	2022	Buildings	(ZHANG et al., 2022a)
34	An optimal surrogate-model-based approach to support comfortable and nearly zero energy buildings design	2022	Energy	(CHEGARI et al., 2022)
35	Multi-objective optimization of setpoint temperature of thermostats in residential buildings	2022	Energy and Buildings	(BAGHERI-ESFEH; DEHGHAN, 2022)
36	PCA-ANN integrated NSGA-III framework for dormitory building design optimization: Energy efficiency, daylight, and thermal comfort	2022	Applied Energy	(RAZMI; RAHBAR; BEMANIAN, 2022)
37	Multi-objective optimization of building design for life cycle cost and CO_2 emissions: A case study of a low-energy residential building in a severe cold climate	2022	Building Simulation	(XUE; WANG; CHEN, 2022)
38	Surrogate optimization of energy retrofits in domestic building stocks using household carbon valuations	2023	Journal of Building Performance Simulation	(HEY et al., 2023)
39	Multi-objective optimization of shading devices using ensemble machine learning and orthogonal design of experiments	2023	Energy and Buildings	(ALSHARIF et al., 2023)
40	BIM-supported automatic energy performance analysis for green building design using explainable machine learning and multi-objective optimization	2023	Applied Energy	(SHEN; PAN, 2023)
41	Framework on low-carbon retrofit of rural residential buildings in arid areas of northwest China: A case study of Turpan residential buildings	2023	Building Simulation	(SONG et al., 2023)
42	Multi-objective optimization of thermochromic glazing properties to enhance building energy performance	2023	Solar Energy	(ARAÚJO et al., 2023)
43	Comparing the performance of four shading strategies based on a multi-objective genetic algorithm: A case study in a university library	2023	Journal of Building Engineering	(WEN et al., 2023)
44	A multi-objective optimization strategy for building carbon emission from the whole life cycle perspective	2023	Energy	(CHEN; TSAY; ZHANG, 2023)
45	Research on a surrogate model updating-based efficient multi-objective optimization framework for supertall buildings	2023	Journal of Building Engineering	(WANG et al., 2023)
46	A multi-objective optimization framework for building performance under climate change	2023	Journal of Building Engineering	(LI et al., 2023a)
47	Building information modelling-enabled multi-objective optimization for energy consumption parametric analysis in green buildings design using hybrid machine learning algorithms	2023	Energy and Buildings	(LIU et al., 2023)
48	Optimal design of building integrated energy systems by combining two-phase optimization and a data-driven model	2023	Energy and Buildings	(QU et al., 2023)
49	Multi-objective optimization designs of phase change material-enhanced building using the integration of the Stacking model and NSGA-III algorithm	2023	Journal of Energy Storage	(YANG et al., 2023)

50	Controllable cross-building multi-objective optimization for NZEBs: A framework Utilizing parametric generation and intelligent algorithms	2024	Applied Energy	(LIU et al., 2024)
51	Energy retrofitting of hospital buildings considering climate change: Na approach integrating automated machine learning with NSGA-III for multi-objective optimization	2024	Energy and Buildings	(SHI; CHEN, 2024)
52	Multi-performance collaborative optimization of existing residential building retrofitting in extremely arid and hot climate zone: A case study in Turpan, China	2024	Journal of Building Engineering	(SHI et al., 2024)
53	Prediction and Optimization Analysis of the Performance of an Office Building in an Extremely Hot and Cold Region	2024	Sustainability (Switzerland)	(LIU; WANG; HUANG, 2024)
54	Informing building retrofits at low computational costs: a multi-objective optimization using machine learning surrogates of building performance simulation models	2024	Journal of Building Performance Simulation	(MARKARIAN et al., 2024)

2.3.2 Surrogate modeling

There are eight main sequential steps to create a surrogate model using simulation data: 1) Problem definition, 2) Data collection, 3) Data preprocessing 4) Algorithm selection, 5) Model training, 6) Model validation, 7) Model refinement, 8) Model application.

Firstly, it is essential to define the building design problem clearly, which involves identifying the inputs (design variables or features) and outputs (objective functions). Then, in the second step, an initial high-fidelity baseline model is simulated using a data-collection sampling strategy. The defined design variables are varied to run multiple simulations. The results are then stored in a dataset, representing the combination of input sequences and outputs. Subsequently, in the third step, the database is preprocessed (which may include normalization, strategies for missing information, data refining etc.). Then, the dataset will be divided into training data (cases with known results used to train the model) and test data (cases used to compare the model's predictions with actual outcomes). This can be done in simple split (e.g., 80% training and 20% testing) or through the less biased cross-validation (k-fold). In the fourth step, an appropriate ML algorithm is selected based on the problem's characteristics and the available data. Then, the selected ML algorithm is applied to the training dataset to create the surrogate model, which learns the relationship between the inputs and outputs. Afterward, in the sixth step, the model is validated by measuring its accuracy using the test dataset. Evaluation metrics will quantify the deviation between the ML predictions and the simulation outcomes for the same set of inputs. This step evaluates if the surrogate model can accurately predict outputs for unseen input combinations. Several metrics can be used to evaluate a model's performance, including mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2). The seventh step is the model refinement. If the surrogate model's performance is unsatisfactory, the model is refined by adjusting the training process, exploring different hyperparameters settings, or incorporating additional data. Finally, in the last step, once the surrogate model is validated and refined, it can be used for various applications, such as optimization or real-time predictions, providing fast and computationally efficient approximations to the original model (AMASYALI; EL-GOHARY, 2018; SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017).

Each objective function typically requires its own surrogate model for outcome prediction. However, when objectives like cost and environmental impact have linear relationships between inputs and outputs, this task is unnecessary. For instance, if the exact quantities of materials, along with cost and environmental impact indicators, are known, there is no need to create a predictive model. In such cases, direct calculations can be implemented, reducing computational overhead and simplifying the process.

Figure 5 provides a concise quantitative exploration of surrogate modeling, covering various aspects including: (a) environments, (b) sampling strategies, (c) comparison of ML algorithms, (d) adoption of ML algorithms, (e) hyperparameter optimization adoption, (f) hyperparameter optimization methods, (g) K-Fold Cross-Validation method adoption, (h) interpretable models' adoption, and (i) Average models' accuracy.

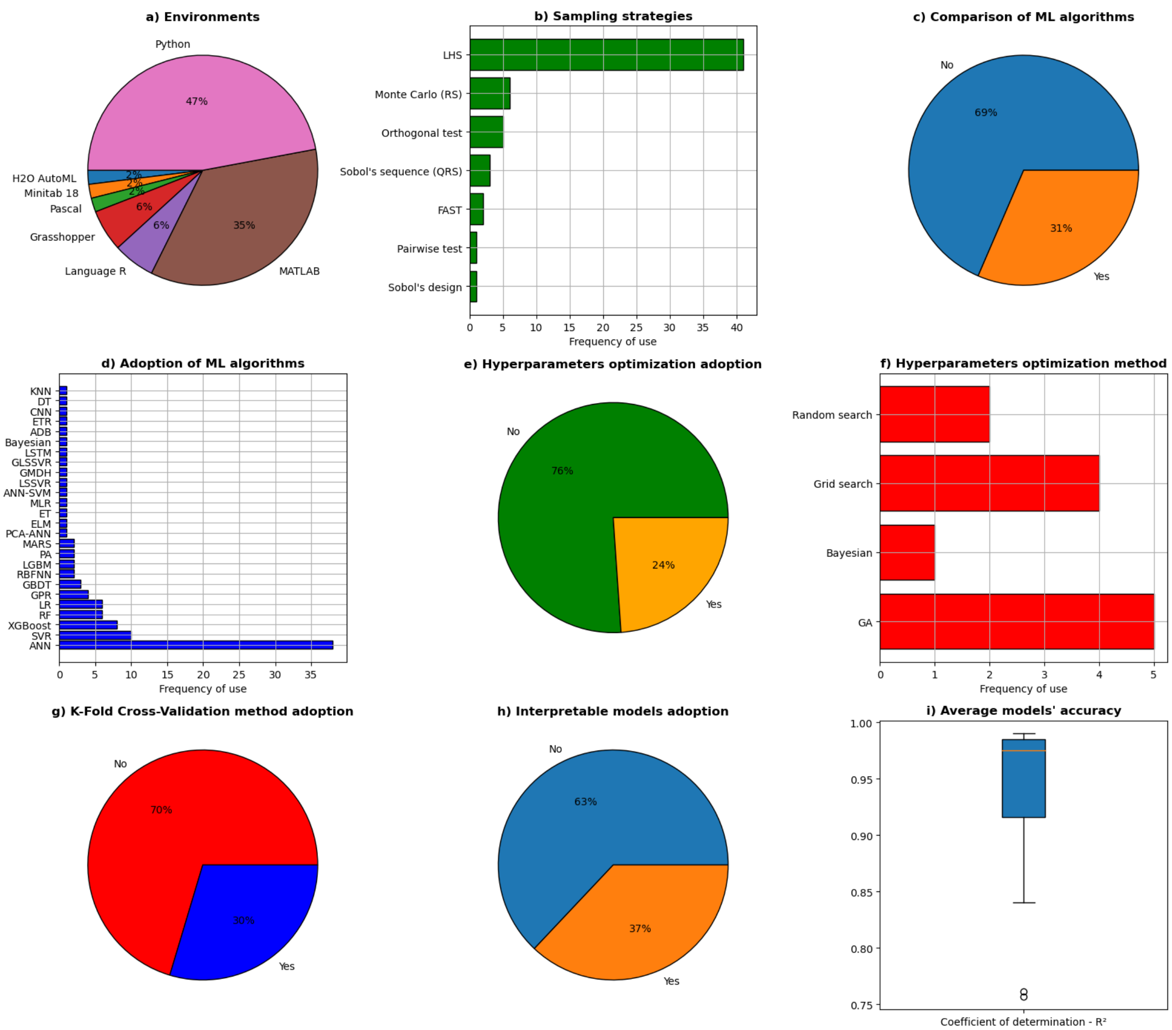


Figure 5. SLR overview - surrogate model.

Figure 5(a) indicates that Python and MATLAB are the leading platforms used for surrogate modeling, while Figure 2.5(b) demonstrates that the Latin Hypercube Sampling (LHS) method is the most commonly employed sampling approach. Based on **Figure 5**(c) and **Figure 5**(d), only 31% of the studies compared different algorithms for surrogate modeling, in which the ANN is the most popular used ML algorithm, followed by the SVR. **Figure 5**(e) and **Figure 5**(f) depict the adoption of hyperparameter optimization and the corresponding methods, respectively. Surprisingly, the refinement of models is of minor concern in the analyzed studies, with the vast majority (approximately 76%) neglecting hyperparameter optimization of the ML models to enhance accuracy. Among those who implemented optimization, the genetic algorithm (GA) and Grid search are the most employed approaches for hyperparameter optimization. **Figure 5**(g) and **Figure 5**(h) reveal that only 30% of the studies employed the K-Fold Cross-Validation method and indicates that 37% of the studies favored interpretable models, respectively. Finally, **Figure 5**(i) highlights that the models, on average, achieved high accuracy, as reflected by the coefficient of determination.

2.3.2.1 Environments

Various environments offer the opportunity for surrogate modeling, such as Python, MATLAB, Language R, Minitab, and Grasshopper. MATLAB includes the Global Optimization Toolbox specifically for surrogate modeling on optimization problems, and similarly, Python offers the SMT toolbox. Other Python tools provide only specific steps, such as PyDOE for different sampling methods; EPPY for quickly changing EnergyPlus input files for simulations; and Scikit-learn, Tensorflow, and PyTorch for different ML algorithms and model validation schemes. In addition, Crow and Octopus plug-ins offer ANN modeling and multi-objective optimizations within Grasshopper, respectively (SUN; LIU; HAN, 2020).

2.3.2.2 Sampling strategies

All sampling strategies (also known as statistical method or design of experiments - DoE) aim to select points in the design space to maximize information gain per simulation run while minimizing sampling time (SUN; HAGHIGHAT; FUNG, 2020). Standard methods include pseudo-random sampling (RS) like Monte Carlo sampling, quasi-random sampling (QRS) like Sobol's sequences, and stratified pseudo-random sampling like LHS or orthogonal array sampling (WESTERMANN; EVINS, 2019). Yet, it is not apparent which one performs best as these techniques depend on the number of design variables and sample size.

Numerous studies have assessed the effectiveness of different sampling techniques and sample sizes. Prada et al. (PRADA; GASPARELLA; BAGGIO, 2018) found no general trend among the RS, LHS, and Sobol's methods. In contrast, Chen; Tsay; Ni, (2022); Chen; Tsay; Zhang, (2023), who explored techniques like the Fourier Amplitude Sensitivity Test (FAST), LHS, and Sobol's, identified Sobol's method as the superior performer. Regarding sample sizes, Xu et al. (2021b, 2021a) concluded that over 1,000 samples were ideal using the Monte Carlo method, with 2,000 samples yielding the best results. Bre; Roman; Fachinotti (2020) introduced an Augmented LHS (generating samples of increasing sizes), noting that to achieve accurate Pareto front results, 800-1600 training samples were requested. Similarly, Saryazdi et al. (2022) identified 3,500 samples as optimal for an accurate surrogate model but emphasized the need for over 9,900 samples for precise non-dominated optimal solutions (Pareto front). Finally, Wang et al. (2023) proposed a method to identify the optimal proportional distribution of training, validation, and test datasets for optimization problems. They suggested that the appropriate proportion of initial sample points for the surrogate model should be determined based on the acquisition time of a single sample and the total number of sample points in the design space.

2.3.2.3 Machine learning algorithms

The input and output data format must suit the ML algorithm approach of choice. For example, most systems require the inputs to be numerical instead of categorical. Categorical variables must be transformed into numerical values using encoding strategies, including methods like One-Hot Encoding, James-Stein Encoder, Label Encoder, and Target Encoder. Some model types require the inputs to be normalized to the same range, especially when categories have vastly different magnitude scales, ensuring equal variable weighting during model training. The ML algorithm type selection is mainly driven by reaching the highest surrogate accuracy possible (HASTIE; FRIEDMAN; TIBSHIRANI, 2001). Yet sometimes a trade-off between optimum accuracy and an interpretable model structure is favored and preferred (AMASYALI; EL-GOHARY, 2018; SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017). Ethical concerns arise from the lack of transparency in ML models, as interpretable models (such as LR, DT and RF) offer clear, understandable reasoning for predictions, promoting trust and facilitating decision-making.

ML algorithms can be categorized into parametric and non-parametric models. Parametric models make assumptions about the functional relationship between inputs and outputs, whereas non-parametric modeling aims to discover the underlying functional relationship between them. Capturing and encoding this behavior manually within a parametric model (such as Linear Regression) can be challenging and time-consuming (WESTERMANN; EVINS, 2019). Non-parametric models streamline this process, making them better suited for quickly modeling the relationship between design parameters and performance indicators. Different types of non-parametric methods exist, including RF, SVR, Multivariate Adaptive Regression Splines (MARS), Gaussian Process regression (GPR), and ANN (HASTIE; FRIEDMAN; TIBSHIRANI, 2001). RF, an ensemble method, combines decision trees for predictions (HO, 1998). It diversifies trees by randomly selecting feature subsets and data samples. SVR, a regression algorithm, employs support vector machines to model input-output relationships, aiming to find a hyperplane around the training data with maximal error margin (SMOLA; SCHÖLKOPF, 2004). MARS fits piecewise linear regression models in input space regions, selecting informative basis functions through a forward-backward algorithm (FRIEDMAN, 1991). GPR uses a probabilistic approach, assuming a Gaussian distribution for the target variable and making predictions based on the conditional distribution given observed data (RASMUSSEN, 2004). ANNs, inspired by biological neural networks, consist of interconnected neurons organized in layers, applying activation functions to inputs and passing results to subsequent layers (HASTIE; FRIEDMAN; TIBSHIRANI, 2001).

Although each ML algorithm has advantages and disadvantages regarding specific modeling requirements, many authors suggest using multiple models to find the most suitable one. For instance, Chen; Yang, (2017) compared LR, MARS, and SVR. The results indicated that SVR could fit a surrogate model with the best prediction performance. In contrast, Guo et al. (2022) found that the ANN model has the highest accuracy compared to SVR. Razmi; Rahbar; Bemanian (2022) developed two distinct ANN models (ANN and PCA-ANN). Principal Component Analysis (PCA) is an unsupervised, non-parametric statistical technique primarily used for dimensionality reduction in ML. PCA is a statistical procedure that allows the information in large data tables to summarize, employing smaller sets for easy analysis. When comparing the two structures for ANN, the PCA-ANN model was chosen due to its high accuracy (RAZMI; RAHBAR; BEMANIAN, 2022). Chen; Tsay; Zhang, (2023) developed a new ML model, Ensemble Learning Model (ELM), which integrates RF, Gradient-boosted decision trees, and ANN. The results showed that the ELM prediction accuracy was improved, but the time consumption for the task was considerably increased (CHEN; TSAY; ZHANG, 2023). Yang et al. (2023) and Shi; Chen (2024) applied the stacked modeling approach, integrating multiple ML techniques to produce an optimal model with computational advantages and improved predictive performance over individual models. Finally, Table 4 enumerates the ML algorithms compared for surrogate modeling and highlights the ML algorithm deemed superior in terms of performance for each study.

Table 4. Comparison of ML algorithms.

Index	Comparison	Best performance	Reference
1	ANN and SVR.	ANN	(GUO et al., 2022)
2	ANN, SVR, RF and RBFNN.	ANN	(YUE et al., 2021)
3	ANN and PCA-ANN.	PCA-ANN	(RAZMI; RAHBAR; BEMANIAN, 2022)
4	LR, ANN, SVR, GPR, RF, XGBoost, ANN-SVM, LSSVR, GMDH and GLSSVR.	GLSSVR	(HOSAMO et al., 2022)

5	SVR, GBDT and ANN.	GBDT	(WANG; LU; FENG, 2020)
6	GPR and ANN.	GPR	(GILLES et al., 2017; WANG; LU; FENG, 2020)
7	LGBM and XGBoost.	LGBM	(SHEN; PAN, 2023)
8	PA, GPR, RBFNN, MARS and SVR.	MARS	(PRADA; GASPARELLA; BAGGIO, 2018)
9	ANN, RF, GBDT and SVR.	RF	(WU et al., 2022)
10	MLR, MARS and SVR.	SVR	(CHEN; YANG, 2017)
11	LSTM, ANN, XGBoost and Bayesian network.	XGB	(YAN; JI; YAN, 2022a)
12	ABR, ETR and XGBoost	ETR	(LI et al., 2023a)
13	LR, RR, SVM, RF, ERF, GBDT, ABR, and XGBoost	The stacked model	(YANG et al., 2023)
14	ETR, DRF, GBM, and ANN	The stacked model	(SHI; CHEN, 2024)
15	ANN, XGBoost, RF, KNN, and DT	ANN	(SHI et al., 2024)
16	ANN, SVM, and CNN	CNN	(LIU; WANG; HUANG, 2024)
17	LR, XGBoost, and ANN	ANN	(MARKARIAN et al., 2024)

2.3.2.4 Hyperparameters settings

Non-parametric models require hyperparameter tuning, as these settings significantly impact the accuracy, efficiency, and generalization ability of the surrogate model. Hyperparameters, which are not learned from data, must be defined by the user either manually through trial and error or using automation methods. Finding the optimal configuration involves balancing variance and bias to prevent overfitting. An overfitted model 'memorizes' the training dataset relationships and fails to generalize effectively to unseen data. Hyperparameter optimization involves systematically searching through different combinations to find the optimal configuration (CLAESEN; DE MOOR, 2015). The analyzed articles employ various methods, including Grid search, Random search, Bayesian optimization, and Evolutionary algorithms (See Table 5). The choice of method is influenced by factors like search space size, available computational resources, and problem-specific characteristics.

Table 5. Hyperparameter optimization methods.

Method	Description	Advantages	Limitations	Reference
Grid Search	Systematic exploration of predefined hyperparameter values.	Simple, exhaustive search.	Computationally expensive for large spaces; not suitable for continuous parameters.	(CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; HEY et al., 2023; XU et al., 2021a)
Random Search	Random sampling of hyperparameter combinations.	Random sampling of hyperparameter combinations.	Less systematic; may miss optimal configurations.	(CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023)
Bayesian optimization	Uses probabilistic models to guide the search.	Efficient for expensive evaluations, adapts to the function's behavior.	Requires defining a surrogate model; computationally demanding.	(SHEN; PAN, 2023)
Evolutionary algorithms	Population-based optimization inspired by natural selection.	Well-suited for discrete spaces; global optimization.	Computationally demanding; may struggle in high-dimensional spaces.	(LIU et al., 2023; SONG et al., 2023; SUN; LIU; HAN, 2020; XU et al.,

			2022; ZHANG et al., 2022a)

Chen; Tsay; Ni, (2022); Chen; Tsay; Zhang (2023) compared Grid and Random search for hyperparameter optimization. Grid search took six times longer than Random search, but the prediction results were almost identical (CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023). Xu et al. (2022) presented an improved algorithm based on a GA for hyperparameters optimization. GA has global convergence but poor local search ability, slow convergence speed, and is prone to premature convergence. The GA improvement strategy is based on elitists, integrates local operators, and proposes a GA hybrid algorithm (SEGA-Q) to enhance elitists. The author took the simplified three-point quadratic interpolation method as the local search algorithm and inserted it into the calculation process of GA to improve the algorithm searchability. The results showed that the SEGA-Q algorithm has more accuracy, stability, and convergence speed, advantages in surrogate modeling, and hyperparameter optimization, but its calculation time increases significantly (XU et al., 2022).

2.3.2.5 Research gaps regarding surrogate modeling

Table 6 presents the research gaps pointed out by the selected articles regarding surrogate modeling, providing a list with some partially addressed issues.

Table 6. Research gaps pointed out and partially addressed related to surrogate modeling.

Index	Challenges, opportunities, demands and suggestions.	Pointed out by	Partially addressed by
1	There is a need to improve the dataset with different building models to achieve better generalization ability	(CHEN; TSAY; ZHANG, 2023; GOU et al., 2018; LI et al., 2017; LIU; WANG; HUANG, 2024; SARYAZDI et al., 2022; SHEN; PAN, 2023; SHI et al., 2024; YU et al., 2015; YUE et al., 2021)	(ASCIONE et al., 2017; HEY et al., 2023; YAN; JI; YAN, 2022a)
2	Although it is feasible to apply trained predictive models to multiple building types using transfer learning technique, their expandability is still limited.	(LIU; WANG; HUANG, 2024; YAN; JI; YAN, 2022a)	
3	Further research should apply rich data mining techniques to AEC industry practice.	(YAN; JI; YAN, 2022a)	
4	The ideal sample size of the dataset still raises questions regarding ML model accuracy.	(BRE; ROMAN; FACHINOTTI, 2020; CHEGARI et al., 2022; SARYAZDI et al., 2022)	(BRE; ROMAN; FACHINOTTI, 2020; SARYAZDI et al., 2022; WANG et al., 2023; XU et al., 2021b, 2021a)
5	New and different ML algorithms should be introduced and explored.	(BRE; ROMAN; FACHINOTTI, 2020; GILLES et al., 2017; GOU et al., 2018; JUNG; HEO; LEE, 2021; LI et al., 2023a; PRADA; GASPARELLA; BAGGIO, 2018; XU et al., 2022; ZOU et al., 2021a)	(CHEN; TSAY; ZHANG, 2023; HOSAMO et al., 2022; RAZMI; RAHBAR; BEMANIAN, 2022; SHEN; PAN, 2023)

6	The ML model's hyperparameters should be optimized to improve their accuracy.	(XU et al., 2021b)	(ASCIONE et al., 2017; GUO et al., 2022; HOSAMO et al., 2022; XU et al., 2021b, 2022; YAN; JI; YAN, 2022a; YU et al., 2015; ZOU et al., 2021a)

The efficiency of the surrogate model should leverage the scope of the studies. Therefore, several papers pointed out the need for the development of ML models more generalized, serving a greater variety of architectural models. In this context, Yan; Ji; Yan, (2022a) utilized a transfer learning technique to boost computational efficiency throughout their study. The transfer learning technique allows the effective retraining of the ML model with a new dataset of a distinct architectural model, while the ML model preserves the fundamental knowledge derived from the data of the prior building. Transfer learning is an ML approach where the knowledge obtained from training on one task is employed to enhance learning and performance on a separate (yet, related task), often by reusing pre-existing models or learned representations. Unfortunately, there are limitations to this technique for multiple building types. For example, the predictive performance of transfer learning may deteriorate when the design parameters of various building types differ significantly or when the building performance goals change (YAN; JI; YAN, 2022a). At the same time, future research should prioritize developing large datasets for various architectural models and applying data mining techniques. The primary goal of data mining is to extract valuable information from datasets and organize it for further use. Techniques like clustering, classification, regression, and association rule learning are used to uncover hidden patterns, supporting strategic decision-making and providing a competitive advantage. Although many articles discuss various sample sizes and propose methods for determining the optimal sample size, such as continuously updated or adaptive sampling techniques, the ideal sample size depends on the complexity of the relationship between inputs and outputs. In other words, it is influenced by the ML algorithm's ability to capture the interactions between design variables (inputs) and objective functions (output predictions). Therefore, each modeling context has its own dynamics and an optimal sample size specific to that scenario. Developing large datasets can improve the ML model's accuracy but, at the same time, increase the computational cost. Additionally, using new and different algorithms combined with hyperparameters optimization is essential, even though the concentration of many studies based on just a few types of ML algorithms is due to the high performance of these models.

2.3.3 Sensitivity and uncertainty analyses

Sensitivity analysis (SA) is a method used to assess the significance of input variables (features) in relation to an output (WEI, 2013). This technique enables the exploration of design variables' influence and facilitates dimensionality reduction by identifying irrelevant or redundant input variables (PANG et al., 2020). The dimensionality reduction can improve the surrogate model's accuracy and simplify problem complexity by reducing the search space for optimization, streamlining the process, and consequently, reducing computational costs. For these reasons, it serves as a preliminary step during surrogate modeling or before optimization (WESTERMANN; EVINS, 2019). However, the importance of design variables may vary within different objective functions. For example, the best constructive guidelines for a naturally ventilated building can be different for a facility that operates only with an HVAC system.

Parallel to this, Uncertainty Analysis (UA) is used to identify the probability of a change in outputs induced by some uncertainty inputs. This probabilistic perspective is crucial as it enables a comprehensive analysis of the building's performance under conditions of uncertainty (RIVALIN et al., 2018). For instance, occupancy behavior simplification is the most common uncertainty input in building performance analysis, promoting significant divergences between simulated values and that one obtained from the post-occupation phase (EISENHOWER et al., 2012).

Figure 6 provides an overview of the SA and UA conducted in the selected articles of the SLR. It outlines (a) the adoption, and (b) goals of SA, as well as (c) the adherence to UA.

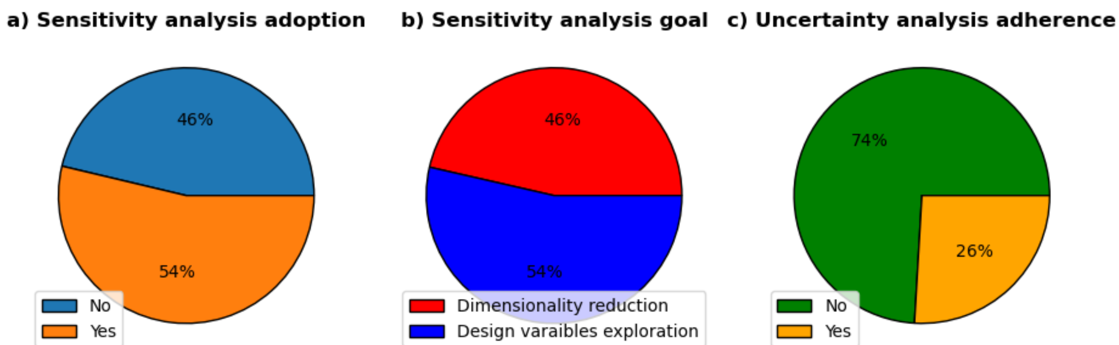


Figure 6. SLR overview - sensitivity and uncertainty analysis.

Surprisingly, Figure 6(a) shows that nearly half of the studies (approximately 46%) do not perform a sensitivity analysis. Furthermore, among the studies that conducted an SA, half focused on exploring the influence of each design variable, while the other half focused solely on dimensionality reduction, as shown in Figure 6(b). Figure 6(c) points out information regarding the studies that consider uncertainty parameters. It is essential to mention that some studies do not specify UA thermology in their papers; however, since they consider uncertainty parameters, these studies were counted as UA performers. Nonetheless, only a few studies addressed UA (around 26%).

2.3.3.1 Sensitivity analysis

There are two SA approaches: local and global methods. Local methods perturb the input of a specific design variable, calculating its partial derivatives to gauge sensitivity. While quick, these methods may yield variable sensitivity due to nonlinear relationships among design combinations, limiting their ability to draw general conclusions. In contrast, global methods assess design variable influence across the entire design space, though at a higher computational cost. Two main global SA approaches exist: one interprets the model and its design variables (e.g., Linear Regression), while the other statistically analyzes a large set of simulation samples, examining the impact of single (first order) or combined (total order) design variable effects on output variance. Regression methods, favored for global SA due to their simplicity and minimal sample requirements, offer various sensitivity indices like Standardized Regression Coefficients (SRC), Partial Correlation Coefficients (PCC), standardized rank regression coefficient (SRRC), and partial rank correlation coefficient (PRCC) (PANG et al., 2020; WEI, 2013). **Table 7** displays the SA methods found in the articles selected.

Table 7. Sensitivity analysis methods found in the SLR.

Index	Method	Advantages	Limitations	References
1	Regression	Simple and widely understood for linear relationships.	Assumes a linear relationship; not suitable for non-linear models.	(ASCIONE et al., 2017; CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; CHEN; YANG, 2018; GOU et al., 2018; LI; WANG; TANG, 2019; LI et al., 2023a; SONG et al., 2023; WANG; LU; FENG, 2020; XU et

				al., 2021b, 2021a, 2022; XUE; WANG; CHEN, 2022; YAN; JI; YAN, 2022a; YANG et al., 2023; ZHANG et al., 2022b)
2	Garson	Designed for ANN to break down variable importance.	Limited to ANN; might miss complex interactions	(CHEGARI et al., 2021; SARYAZDI et al., 2022)
3	Delta Moment Independent Measure (DMIM)	Captures non-linear and interaction effects without model assumptions.	Computationally intensive; requires many model evaluations.	(LIU; WANG; HUANG, 2024; SONG et al., 2023)
4	Random Balance Designs + Fourier Amplitude Sensitivity Test (RBD–FAST)	Efficient for high-dimensional problems; identifies main effects and interactions.	Assumes trigonometric polynomial model response.	(LIU; WANG; HUANG, 2024; SONG et al., 2023)
5	SHapley Additive explanation (SHAP)	Fair allocation of contributions for each feature; model-agnostic.	Computationally intensive; might be complex for non-experts.	(MARKARIAN et al., 2024; SHEN; PAN, 2023; SHI et al., 2024)
6	Sobol’s	Decomposes variance into contributions; captures interactions.	Computationally expensive; many model evaluations needed.	(CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; JUNG; HEO; LEE, 2021)
7	Fourier Amplitude Sensitivity Test (FAST)	Efficient for high-dimensional problems; determines main effects and interactions.	Assumes trigonometric polynomial model response.	(CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; CHEN; YANG, 2018)
8	Fractional Factorial Designs - FFD	Efficient for exploring high-dimensional spaces; requires fewer runs.	Might miss higher-order interactions; assumes linearity and additivity.	(DHARIWAL; BANERJEE, 2017)
9	Random Forest (RF)	Robust feature importance, handles non-linearity, interpretable, efficient with high-dimensional data.	Computationally expensive, biased toward dominant features, limited extrapolation.	(LIU et al., 2023)
10	XGBoost	High accuracy, captures non-linearity, includes regularization.	Computationally heavy, less interpretable, risks overfitting, needs feature engineering.	(LIU et al., 2024)

Combining methods is a common approach to enhance the efficacy of SA. Given the complexity and nonlinearity of design variable interaction, Song et al. (2023) integrated the DMIM and RED–FAST methods with the Regression method. Although the former two methods yielded consistent outcomes, they lacked sufficient precision for practical application (SONG et al., 2023). Wang; Lu; Feng (2020) acknowledged a key limitation in the Regression method - the lack of clear assessment criteria for quantifying absolute importance. Consequently, the authors combined the Regression method with Redundancy Analysis (RDA) to reduce dimensionality (WANG; LU; FENG, 2020).

Moreover, the sensitivity of design variables can vary depending on the objective function under consideration. Therefore, it is crucial to employ strategies that accurately identify the global influence of these variables within the design context. Gou et al., (2018) maintained the less influential variables as constant, based on specific criteria related to the corresponding SRRC. If a variable has a positive impact on comfort but a negative impact on energy demand, its value is set to the maximum. Conversely, if a variable has a negative impact on comfort but a positive impact on energy demand, its value is set to the minimum. For variables with the same impact direction on both objectives, the value is modified to prioritize the objective with a higher SRRC ranking (GOU et al., 2018). Chen; Tsay; Ni, (2022); Chen; Tsay; Zhang, (2023) utilized methods such as Regression, Sobol's, and FAST for dimensionality reduction. They employed nine sensitivity indices: first and total order (FAST and Sobol), SRC, SRRC, PCC, PRCC, Spearman correlation coefficient, Pearson correlation coefficient, and Kolmogorov-Smirnov. These indices determined the average contribution rate of each design variable across all objective functions. Parameters with an aggregate average contribution rate under 5% were excluded from the final analysis (CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023). Finally, Liu et al. (2023) and Liu et al. (2024) performed a sensitivity analysis using ML algorithms. Interpretable models, such as XGBoost and RF, can provide feature importance measures, allowing insight into how input variables influence predictions. This makes them suitable for understanding the impact of each feature on ML model outcomes (LIU et al., 2024, 2023).

2.3.3.2 Uncertainty analysis

UA evaluates the impact of uncertainty inputs on output variations, offering a probabilistic viewpoint on building performance. This comprehensive assessment ensures quality when estimating a building's performance under uncertainty, thus quantifying the robustness of the design (RIVALIN et al., 2018). Additionally, it supports the early design stages where numerous parameters remain uncertain (EISENHOWER et al., 2012). Table 8 presents uncertainty parameters identified in the selected articles of the SLR, categorized into weather, materials' properties, occupant behavior, public policies, and comfort settings.

Table 8. Uncertainty parameters found in the SLR.

Index	Category	Uncertainty parameter	Impact	References
1	Weather	Climate change	Different constructive guidelines	(GILLES et al., 2017; LI; WANG; TANG, 2019; LI et al., 2023a; SHI; CHEN, 2024; YAN; JI; YAN, 2022a; ZOU et al., 2021a)
2	Materials' properties	Thermal bridges	Increased energy consumption and comfort issues	(CHEGARI et al., 2021; LI; WANG; TANG, 2019)
3	Occupant behavior	Occupancy density	Deviation in results for energy demand and thermal comfort.	(ASCIONE et al., 2017; HOSAMO et al., 2022; JUNG; HEO; LEE, 2021; LI; WANG; TANG, 2019)
4		Lighting load		(ASCIONE et al., 2017; CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; LI; WANG; TANG, 2019)
5		Equipment load		(ASCIONE et al., 2017; CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; HOSAMO et al., 2022; LI; WANG; TANG, 2019)
6	Public polices	Public environmental campaign	Preference for more environmentally friendly design options	(HEY et al., 2023)
7		Energy price	Encourage energy saving	(GILLES et al., 2017; JUNG; HEO; LEE, 2021; QU et al., 2023)
8		Sales polices for energy	Encourage purchasing robust renewable systems	(XU et al., 2021b)

9	Equipment efficiency	Deviation in results for energy demand and environmental impacts	(CHEN; TSAY; ZHANG, 2023; HOSAMO et al., 2022; JUNG; HEO; LEE, 2021; SHEN; PAN, 2023)

2.3.3.3 Research gaps regarding sensitivity and uncertainty analysis

Table 9 presents the research gaps pointed out by the selected articles regarding SA and UA, providing a list with some partially addressed issues.

Table 9. Research gaps pointed out and partially addressed related to sensitivity and uncertainty analysis.

Index	Challenges, opportunities, demands and suggestions.	Pointed out by	Partially addressed by
1	Detailed studies focusing on the sensitivity analysis should be carried out.	(DHARIWAL; BANERJEE, 2017)	(ASCIONE et al., 2017; CHEGARI et al., 2021; CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; CHEN; YANG, 2018; DHARIWAL; BANERJEE, 2017; GOU et al., 2018; JUNG; HEO; LEE, 2021; LI; WANG; TANG, 2019; SARYAZDI et al., 2022; SHEN; PAN, 2023; SONG et al., 2023; WANG; LU; FENG, 2020; XU et al., 2021b, 2021a, 2022; XUE; WANG; CHEN, 2022; YAN; JI; YAN, 2022a; ZHANG et al., 2022b)
2	There is a demand for robust studies to overcome the uncertainties associated with some parameters.	(CHEN; YANG, 2017; GILLES et al., 2017; GOU et al., 2018; HOSAMO et al., 2022; LI; WANG; TANG, 2019; SARYAZDI et al., 2022; XUE; WANG; CHEN, 2022; YAN; JI; YAN, 2022a; YUE et al., 2021; ZHANG et al., 2022a; ZOU et al., 2021a)	(ASCIONE et al., 2017; CHEGARI et al., 2021; CHEN; TSAY; NI, 2022; GILLES et al., 2017; HEY et al., 2023; HOSAMO et al., 2022; JUNG; HEO; LEE, 2021; LI; WANG; TANG, 2019; SHEN; PAN, 2023; XU et al., 2021b; YAN; JI; YAN, 2022a; ZOU et al., 2021a)

The potential of SA and UA in building performance is widely recognized. However, some reviewed articles indicate the need to implement these approaches to enhance multi-objective optimization studies. While ML techniques are gaining popularity, it is crucial to integrate them alongside traditional practices in the building performance field. Ultimately, achieving a robust analysis depends on adopting SA and UA techniques to amplify the contributions of studies in terms of complexity and efficiency. One potential solution is to use interpretable ML models that provide feature importance measures, offering insights into how input variables impact predictions.

2.3.4 Multi-objective optimization methods

Multi-objective optimization based on surrogate models is a powerful approach that enhances building design by considering multiple conflicting objectives at a lower computational cost. However, challenges exist in constructing accurate surrogate models (See section 3.2.1), and defining appropriate objective functions, suitable design variables, efficient optimization algorithms, and a decision-making process to identify a preferred solution from the set of optimal solutions (Pareto). Addressing these challenges and integrating the optimization process within the broader building design context is crucial for achieving sustainable building design.

Figure 7 presents an overview of multi-objective optimization methods based on the articles selected in the SLR. It illustrates various aspects, including (a) frequency of objective functions' use, (b) combinations of objective functions, (c) categories of design variables, (d) comparisons of multi-objective optimization algorithms, (e) adoption of multi-objective optimization algorithms, and (f) decision-making processes.

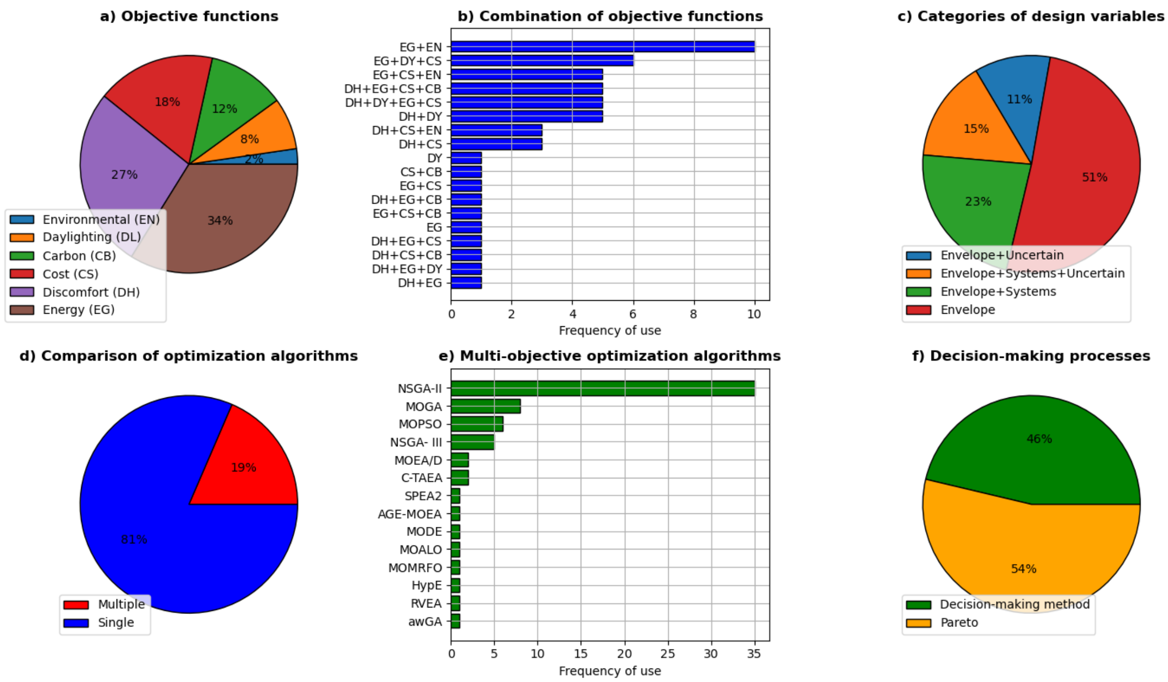


Figure 7. SLR overview - multi-objective optimization methods.

Based on Figure 7(a), the energy consumption, discomfort hours and construction costs are the most popular objective functions within the articles. Surprisingly, carbon emissions, daylighting illuminance and environmental impacts are less representative in the studies. When considering the possible combinations of these objective functions (See Figure 7(b)), once again the discomfort hours combined with energy consumption stand out. Figure 7(c) indicates that regarding the categories of design variables, around 51% of the studies consider only the building envelope properties and leave aside the systems settings or uncertainty parameters (as mentioned in Section 3.3.2). Figure 7(d) and Figure 7(e) illustrate studies comparing different multi-objective optimization algorithms and adopting multi-objective optimization algorithms. The outline shows that only a few studies compared the performance of different algorithms (around 19%), whereas the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is the most used algorithm, being adopted in more than half of the studies. Finally, Figure 7(f) shows the decision-making processes considered in the analyzed studies. More than half of the studies only explored Pareto front settings, while 46% adopted a decision-making process to select the best optimal solution.

2.3.4.1 Objective functions

The objective functions represent the performance criteria or goals that need to be optimized simultaneously. The selection of objective functions should align with the project's sustainability goals, stakeholder priorities, and local regulations and standards (EVINS, 2013; MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). Energy consumption is usually related to energy demand from the HVAC system; discomfort hours are evaluated based on thermal comfort norms, such as ASHRAE 55, ISO 7730, and EN 15251, which specify acceptable temperature ranges and conditions for building occupants. Finally, the construction cost usually is quantified by the global price, Net Present Value (NPV) of the investment or Life Cycle Cost (LCC).

For studies that explore daylighting illuminance, the objective function is usually related to useful daylight illuminance (UDI) or daylight autonomy (DA) (GAO et al., 2021; SUN; LIU; HAN, 2020; YAN; JI; YAN, 2022a). UDI is the annual percentage of hours when the daylight illuminance of space (in occupied hours) is within the useful range of 100–3000 lux, offering a daylighting level where space is neither too dark nor too bright and glaring (XU et al., 2022; ZOU et al., 2021a). On the other hand, DA is a metric that assesses the annual availability of daylight within a space. It measures the percentage of occupied hours in a year when a specified target illuminance level is met solely by daylight, without the need for artificial lighting (LU et al., 2022; RAZMI; RAHBAR; BEMANIAN, 2022; XU et al., 2021b).

Even though carbon emission might be part of environmental impacts measured by global warming potential indicator, studies that addressed carbon emission and environmental impacts were segregated by the metrics related to the objective function. Carbon emissions are expressed in $kgCO_2eq$, which refers to greenhouse gases (GHG). Some studies consider carbon emissions from the building's energy consumption only. The energy demand normally expressed in kWh is converted through a factor that transforms this unit into $kgCO_2eq$ (CHEN; TSAY; NI, 2022; SARYAZDI et al., 2022; SHEN; PAN, 2023; YANG et al., 2023; ZHANG et al., 2022a). Still, there are studies considering carbon emission from other phases, such as material production, transportation, construction and demolition stage, usually obtained through a Life Cycle Analysis (LCA) (CHEN; TSAY; ZHANG, 2023; GILLES et al., 2017; HEY et al., 2023; LI et al., 2017; LIU et al., 2023; SONG et al., 2023; WU et al., 2022; XUE; WANG; CHEN, 2022; ZHANG et al., 2022b)

Environmental impacts encompass various potentials such as eutrophication, acidification, ecotoxicity, land occupation, carcinogenic effects, global warming, ionizing radiation, ozone layer depletion, respiratory impacts, fossil fuel consumption, mineral extraction, and more. These potential impacts are related to different categories of damage, including human health, ecosystem quality, and resource depletion (BAI et al., 2022). The consideration of more than one indicator varies according to the project context. However, considering several indicators demands a weighting process for converting the individual indicators into an aggregated metric or a prior analysis to identify prioritized objectives. Carreras et al. (2016) affirmed that aggregated environmental impacts might change the problem's structure, with the potential risk of losing optimal solutions (CARRERAS et al., 2016). Jung; Heo; Lee (2021) specifically focused on the global warming potential, while the potentials for acidification, ozone depletion, photochemical ozone creation, and eutrophication were post-treated during the Pareto front analysis. The results revealed significant improvements compared to the reference building, with reductions of 39% in global warming potential, 49% in acidification potential, and 50% in photochemical ozone creation potential. However, there were slight increases of 4% in ozone depletion potential and 18% in eutrophication potential (JUNG; HEO; LEE, 2021).

2.3.4.2 Design variables' categories

The selection of design variables and objective functions is critical, as changing them at a later stage may require additional simulations. The number of design variables should be limited to the course of dimensionality. The simulation sample size needed to perform a multi-objective optimization based on a surrogate model grows exponentially with the number of design variables (WESTERMANN; EVINS, 2019). In addition, design variables might be chosen based on the design assignment or sensitivity analysis as the essential parameters should be considered (see Section 3.3).

The design variables refer to the parameters or attributes that can be adjusted that influence the performance of the building across multiple objectives. These variables are typically associated with different aspects of the building's design, including architectural, mechanical, and electrical features. For instance, the building envelope forms a barrier to heat, light, and air; thus, it must be carefully designed to achieve high performance. The specific choice and range of design variables will depend on the optimization objectives and the constraints imposed by the project, such as budget, local regulations, and architectural restrictions (NGUYEN; REITER; RIGO, 2014; PAN et al., 2023). Figure 8 shows the design variables (excluding uncertainty parameters) used for different objective functions and their respective frequency from the selected articles.

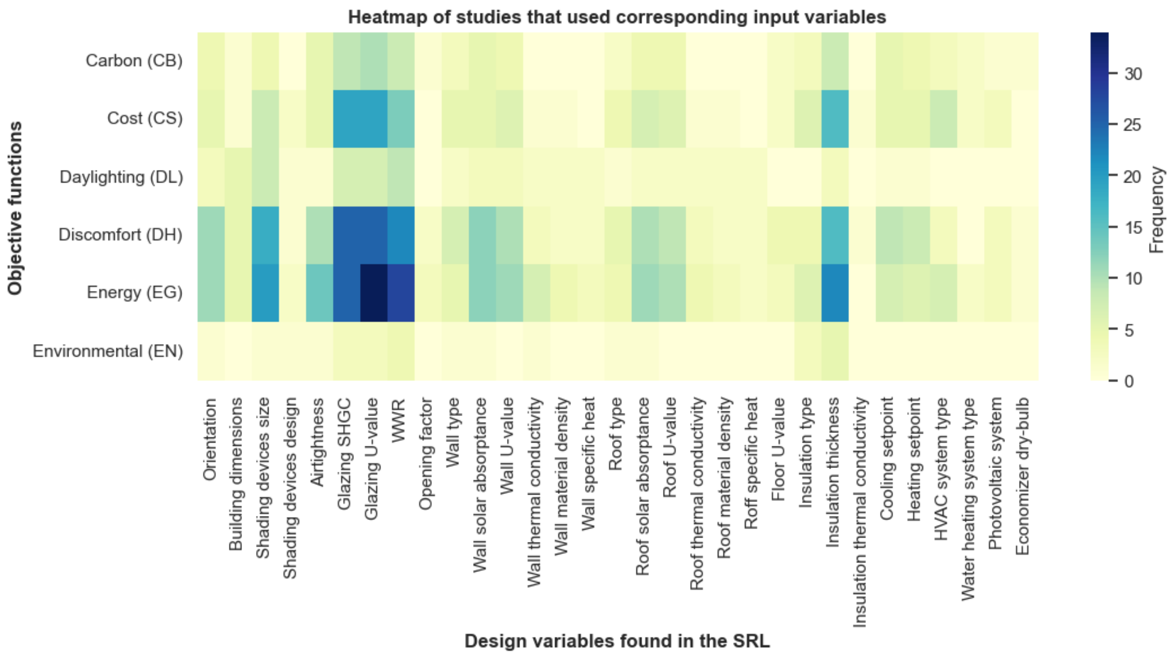


Figure 8. Heatmap of design variables.

The heatmap reveals design variables such as orientation, shading devices, window properties (WWR, SHGC, U-value), and insulation thickness as the main factors for objective functions related to energy consumption, discomfort hours, and construction cost. Yet, some researchers highlighted the optimization of cooling and heating setpoints to achieve energy savings (BAGHERI-ESFEH; DEHGHAN, 2022; CHEN; YANG, 2018; XU et al., 2022). Furthermore, ventilation strategies like cross ventilation (CHEN; YANG, 2017, 2018) and mixed operation modes (XUE; WANG; CHEN, 2022) were identified as promising approaches to harness the potential of natural ventilation.

2.3.4.3 Optimization algorithms

There are many algorithms to optimize building designs. They can be classified as evolutionary, derivative-free search methods, and hybrid algorithms (NGUYEN; REITER; RIGO, 2014; PAN et al., 2023). Evolutionary algorithms are a common meta-heuristic optimization algorithm, i.e., they do not guarantee to arrive at the true optimum but offer an efficient method with a high probability of finding the optimum or getting close to it. They implement Darwin’s principle of "survival of the fittest" through a population-based approach, where underperforming solutions are discarded in each generation. Operators like mutation (random changes) and crossover (swapping elements) generate new solutions. Three examples of evolutionary algorithms are NSGA-II, Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES), and Multi-objective Particle Swarm Optimization (MOPSO). Direct search methods are prominent in derivative-free optimization, employing heuristic rules to explore solution spaces without needing continuous objective function derivatives. For example, the Hooke and Jeeves pattern search method is characterized by a series of exploratory moves that traces the objective function behavior at a pattern of points. Furthermore, another popular approach is to use more than one optimization algorithm, i.e., a hybrid procedure. The typical operation is to use a global search algorithm to find a near-optimal solution and then use the result as a starting point for a local optimizer. (EVINS, 2013; MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). Finally, it is worth mentioning that the optimization algorithm selection depends mainly on the problem to be solved.

As previously discussed, several studies have undertaken comparisons of various multi-objective optimization algorithms' performance. **Table 10** lists the metrics employed in the selected articles to assess the performance of the optimization algorithms.

Table 10. Algorithm performance evaluation metrics.

Index	Metric	Description	References
1	Calculation time	Execution speed.	(CHEGARI et al., 2021; LI et al., 2017; XU et al., 2022)
2	Pareto's dimensions	Number of Pareto solutions.	(XU et al., 2021b, 2022)
3	Diversity	Distribution on the Pareto front.	(CHEGARI et al., 2021; LI et al., 2017)
4	Convergence	Degree of approximation between the obtained solution set and the true Pareto front	(LI et al., 2017; SHI et al., 2024)
5	Hypervolume	Quantifies the size of the space in the objective function that is dominated by a set of solutions.	(CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; RAZMI; RAHBAR; BEMANIAN, 2022; XU et al., 2022)
6	Optimal solutions	Overlapping Pareto fronts.	(ALSHARIF et al., 2023; BAGHERI-ESFEH; DEHGHAN, 2022; SHEN; PAN, 2023)

Among various metrics, hypervolume is widely preferred. It offers a dual advantage by simultaneously measuring the diversity and convergence of Pareto solutions. Chegari et al. (2021) and Xu et al. (2022) favored MOPSO due to its slightly faster computation time when comparing optimization algorithms. On the other hand, Xu et al. (2021b) observed superior performance from NSGA-II regarding the number of Pareto solutions, while RAZMI; RAHBAR; BEMANIAN (2022) noted NSGA-III surpassed NSGA-II in terms of hypervolume at more iterations. Although several researchers have highlighted the potential of algorithms such as Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D), Adaptive Geometry Estimation based Multi-objective Evolutionary Algorithm (AGE-MOEA), Constrained multi-objective evolutionary algorithm with an improved two-archive strategy (C-TAEA), Multi-objective Differential Evolution (MODE), Multi-objective Manta Ray Foraging Optimizer (MOMRFO), Adaptive Weighted Genetic Algorithm (awGA), and Reference Vector Evolutionary Algorithm (RVEA), these algorithms remain underutilized in the building performance domain (ALSHARIF et al., 2023; CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; SHEN; PAN, 2023; SHI et al., 2024). Finally, Li et al. (2017) emphasized caution in drawing conclusions as algorithm performance varies based on the evaluation metric. In addition, adjusting parameters equally (even with default values) for optimization algorithms is challenging due to the varying importance of parameter settings and their impact on performance (LI et al., 2017).

2.3.4.4 Decision-making processes

Analyzing optimization results with multiple objective functions is challenging. As the number of objective functions increases, the complexity of Pareto front visualizations—whether in 2D, 3D, or 4D (with one dimension per objective function)—makes it difficult to identify preferred solutions based solely on visual data. Therefore, evaluating solutions and selecting the best solution from the Pareto front involves decision-making strategies or an MCDM method (HWANG; YOON, 1981; YANG; CHEN; HUNG, 2007). There are four commonly used approaches to select the best solution from the Pareto front: 1) subjective selection, 2) weighted sum, 3) constraint, and 4) MCDM methods. Yet, most studies only explore the optimal configurations suggested by the Pareto front. Based on selected articles, Table 11 illustrates the different strategies used to explore the design options on the Pareto front, while Table 12 lists the decision-making processes to select the best design solution.

Table 11. Strategies for exploring Pareto front.

Index	Strategy	Description	Reference
1	Single objective solutions	Compare the optimal solution setup for each objective function.	(ARAÚJO et al., 2023; AZARI et al., 2016; CHEN; YANG, 2018; LI; WANG; TANG, 2019; XU et al., 2021a, 2022; ZHANG et al., 2022b)
2	Boxplots and Parallel coordinates	Identify the optimal range of values for each design variable.	(LI et al., 2017; RAZMI; RAHBAR; BEMANIAN, 2022; SONG et al., 2023; SUN; LIU; HAN, 2020; WANG; LU; FENG, 2020; YAN; JI; YAN, 2022a; ZHANG et al., 2022b; ZOU et al., 2021a)
3	Equidistant intervals	Slip the Pareto front into equidistant intervals and select points. For instance, first, middle, and last point.	(BAGHERI-ESFEH; DEHGHAN, 2022; HOSAMO et al., 2022; XUE; WANG; CHEN, 2022)

Table 12. Decision-making processes.

Index	Method	Description	Reference
1	Subjective selection	Based on the priorities, preferences, and expertise of stakeholders involved in the building design.	None
2	Weighted sum	Based on converting the problem into a single objective by assigning weights to each objective.	(CHEN; YANG, 2017, 2018; GILLES et al., 2017)
3	Constraint	Based on the Pareto front solutions that satisfy the defined constraints. The acceptable thresholds or limits for each objective are set by decision-makers.	(ASCIONE et al., 2017; WANG; LU; FENG, 2020)
4	MDCM	Based on the relative closeness of alternatives to the ideal solution (the highest achievement of objectives).	(CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; GHADERIAN; VEYSI, 2021; HOSAMO et al., 2022; JUNG; HEO; LEE, 2021; LIU et al., 2024, 2023; LIU; WANG; HUANG, 2024; QU et al., 2023; SARYAZDI et al., 2022; SHEN; PAN, 2023; SHI et al., 2024; SHI; CHEN, 2024; SONG et al., 2023; WU et al., 2022; YANG et al., 2023; YUE et al., 2021; ZHANG et al., 2022a, 2022b)

As indicated, subjective selection relies on human judgment and qualitative assessments to choose a preferred solution from the Pareto front, while the weighted sum method converts the building design into a single-objective problem (CHEN; YANG, 2017, 2018; GILLES et al., 2017). In the constraint method, decision-makers define acceptable thresholds or limits for each objective. This approach allows decision-makers to emphasize particular objectives while ensuring the solutions meet specific performance requirements or criteria. For instance, Ascione et al. (ASCIONE et al., 2017) explored retrofit strategies to improve thermal comfort, reduce energy consumption and construction costs of an office building located in Naples (Italy). Four recommended retrofit packages were found based on the different investment budgets and a discomfort hours threshold of 20%. Finally, the best solution was selected based on the overall cost of the retrofit measures (ASCIONE et al., 2017). Wang; Lu; Feng (2020) employed a similar constraint approach for a residential building in Tianjin, China, to reduce discomfort hours and energy demand. They selected the optimal solution based on the shortest payback period (WANG; LU; FENG, 2020).

Despite existing several approaches to the MCDM methods (HWANG; YOON, 1981; YANG; CHEN; HUNG, 2007), only two methods are found in the selected articles: the Utopia Solution (US) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Both are based on the relative closeness of alternatives to the ideal solution. Yet, the US method aims to find the best alternative that perfectly satisfies all criteria. In contrast, the TOPSIS method seeks the alternative closest to the ideal solution and farthest from the worst solution, considering both positive and negative ideal solutions. The TOPSIS method allows criteria weighting, whereas the US method assumes equal importance for all criteria (SHIH; SHYUR; LEE, 2007).

Chen; Tsay; Ni, (2022); Chen; Tsay; Zhang, (2023) proposed a new formula for selecting the best scheme in the Pareto front. In the US method, due to the different variation ranges of each objective, some targets with significant changes will affect the selection of the final scheme. Consequently, the authors incorporated two refined standard deviation/normalization formulas into the scheme selection process to mitigate the effects of varying objective ranges. Two schemes of optimal solutions were outlined. The equilibrium solution (ES) corresponds to the minimum distance capable of reducing the variation range's impact across different objectives. On the other hand, the best equilibrium solution (BES) represents the maximum distance that can enhance the optimization value under ES conditions. As such, the BES method can simultaneously account for each objective's optimization effect and balance (CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023). Chen; Tsay; Ni, (2022) observed that when employing the US method, the results reported a 36.7% reduction in carbon emissions, a 55.5% decrease in discomfort hours, and a 1.9% increase in costs. This result displayed that the US method did not consider the complexity of building performance. In the physical sense, the US method only considers the shortest distance to the ideal point, leading to different target variation amplitudes, ultimately affecting the final scheme selection. When considering the ES scheme, carbon emissions, discomfort hours, and construction costs were reduced by 23.4%, 24.5%, and 16.7%, respectively (CHEN; TSAY; NI, 2022). The BES scheme reduced carbon emissions, discomfort hours, and construction costs by 34.7%, 26.6%, and 13.9%, respectively. Similarly, Chen; Tsay; Zhang, (2023) found that when considering the BES scheme, carbon emissions, discomfort hours, and global cost were reduced by 53.25%, 42.95%, and 22.33%, respectively (CHEN; TSAY; ZHANG, 2023).

2.3.4.5 Research gaps regarding multi-objective optimization methods

Table 12 presents the research gaps pointed out by the selected articles regarding multi-objective optimization methods, providing a list with some partially addressed issues.

Table 13. Research gaps pointed out and partially addressed related to multi-objective optimization methods.

Index	Challenges, opportunities, demands and suggestions.	Pointed out by	Partially addressed by
1	There is a need for a MCDM method to select a suitable solution from the Pareto front.	(ASADI et al., 2014)	(ALSHARIF et al., 2023; ASCIONE et al., 2017; CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; CHEN; YANG, 2017, 2018; GHADERIAN; VEYSI, 2021; GILLES et al., 2017; HOSAMO et al., 2022; JUNG; HEO; LEE, 2021; SARYAZDI et al., 2022; SHEN; PAN, 2023; SONG et al., 2023; WANG; LU; FENG, 2020; WU et al., 2022; YUE et al., 2021; ZHANG et al., 2022a, 2022b)
2	Multi-objective optimization based on surrogate models should be expanded for existing buildings.	(GHADERIAN; VEYSI, 2021)	(ASADI et al., 2014; ASCIONE et al., 2017; GHADERIAN; VEYSI, 2021; HEY et al., 2023; LI; WANG; TANG, 2019; LIU et al., 2024, 2023; LIU; WANG; HUANG, 2024; PRADA; GASPARELLA; BAGGIO, 2018; SHI et al., 2024; SHI; CHEN, 2024; SONG et al., 2023; WU et al., 2022; XUE; WANG; CHEN, 2022; YUE et al., 2021; ZHANG et al., 2022a, 2022b)
3	Multi-objective optimization based on surrogate models should be applied under diverse climate contexts.	(HEY et al., 2023; MARKARIAN et al., 2024; QU et al., 2023; SARYAZDI et al., 2022; WU et al., 2022)	
4	Future research needs to investigate different building parameters.	(CHEN; TSAY; NI, 2022; GUO et al., 2022; HOSAMO et al., 2022; LI et al., 2023a; WANG; LU; FENG, 2020; XU et al., 2021b, 2021a, 2022; YU et al., 2015; YUE et al., 2021; ZHANG et al., 2022b)	
5	Future research should prioritize the exploration of conflicting objective functions by carefully selecting different objectives.	(ALSHARIF et al., 2023; GILLES et al., 2017; LI et al., 2023a; QU et al., 2023; SARYAZDI et al., 2022; SHI et al., 2024; SONG et al., 2023; WANG et al., 2023; WEN et al., 2023; YUE et al., 2021)	
6	The building design might be influencing by individualized factors such as architectural aesthetics, interest needs, and social impact.	(GUO et al., 2022; XUE; WANG; CHEN, 2022; ZHANG et al., 2022b)	
7	Studies need to focus on the assessment of practical issues and boundary conditions of the investigated buildings.	(ALSHARIF et al., 2023; CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; QU et al., 2023; RAZMI; RAHBAR; BEMANIAN, 2022; WANG et al., 2023)	(ASCIONE et al., 2017; WANG; LU; FENG, 2020)
8	Further studies are needed for evaluating the ML models' accuracy in the vicinity of the optimum solution and its effect on optimization performance	(GHADERIAN; VEYSI, 2021)	(LI; WANG; TANG, 2019; WANG et al., 2023)
9	There is a demand for architect-friendly tools that can work as a	(ALSHARIF et al., 2023; AZARI et al., 2016; CHEN; YANG, 2018;	

	plugin within architectural modeling tools to optimize the building design.	MARKARIAN et al., 2024; SHEN; PAN, 2023; SHI; CHEN, 2024)	
10	Surrogate models can be created for reference buildings and made accessible on a web page for public use and rapid optimization assessments, supporting both educational and professional needs	(ALSHARIF et al., 2023; CHEGARI et al., 2022; DHARIWAL; BANERJEE, 2017; HEY et al., 2023; LIU et al., 2024, 2023; SHI; CHEN, 2024; YUE et al., 2021)	
11	New and different multi-objective optimization algorithms need to be introduced and explored.	(RAZMI; RAHBAR; BEMANIAN, 2022; SHEN; PAN, 2023; SUN; LIU; HAN, 2020; YUE et al., 2021)	(ALSHARIF et al., 2023; CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; GUO et al., 2022; LI et al., 2017; SHEN; PAN, 2023; WU et al., 2022)
12	Further research should plan to investigate optimization on an urban level.	(ALSHARIF et al., 2023; ARAÚJO et al., 2023; XU et al., 2022)	

Many optimal solutions can be seen as both an advantage and a disadvantage, as it might be difficult to choose an optimal solution among several options. Therefore, adopting an MCDM method is essential in multi-objective optimization studies. Although simulation data are initially intended for the design of buildings not yet built, with calibration strategies, these data can serve for retrofit studies. Furthermore, the popularization of multi-objective optimization based on surrogate models in different climates is crucial for advancing the development of sustainable buildings globally. New parameters that affect building performance must be included, while new conflicting objective functions should be prioritized. Some criteria, such as interest needs and social impact, need to be taken into account in these studies; this means that practical issues and realistic boundary conditions need to be addressed for contributions to be sustainable. Within this discussion, the development of plugins to be used in architectural modeling tools or web pages that allow the entry of some data about the building and, from these data, provide guidelines for design optimization are some of the ways and alternatives to disseminate this approach during the design process.

2.4 Future perspectives and needs

2.4.1 Framework for future evaluations

The systematic guide is composed of an agenda developed from the content of reviewed articles in the SLR. It provides a suggested framework for future evaluations, specifically for researchers interested in conducting studies centered on multi-objective optimization based surrogate models. **Figure 9** presents the framework that encompasses six main steps, with each step elaborated on in detail below.

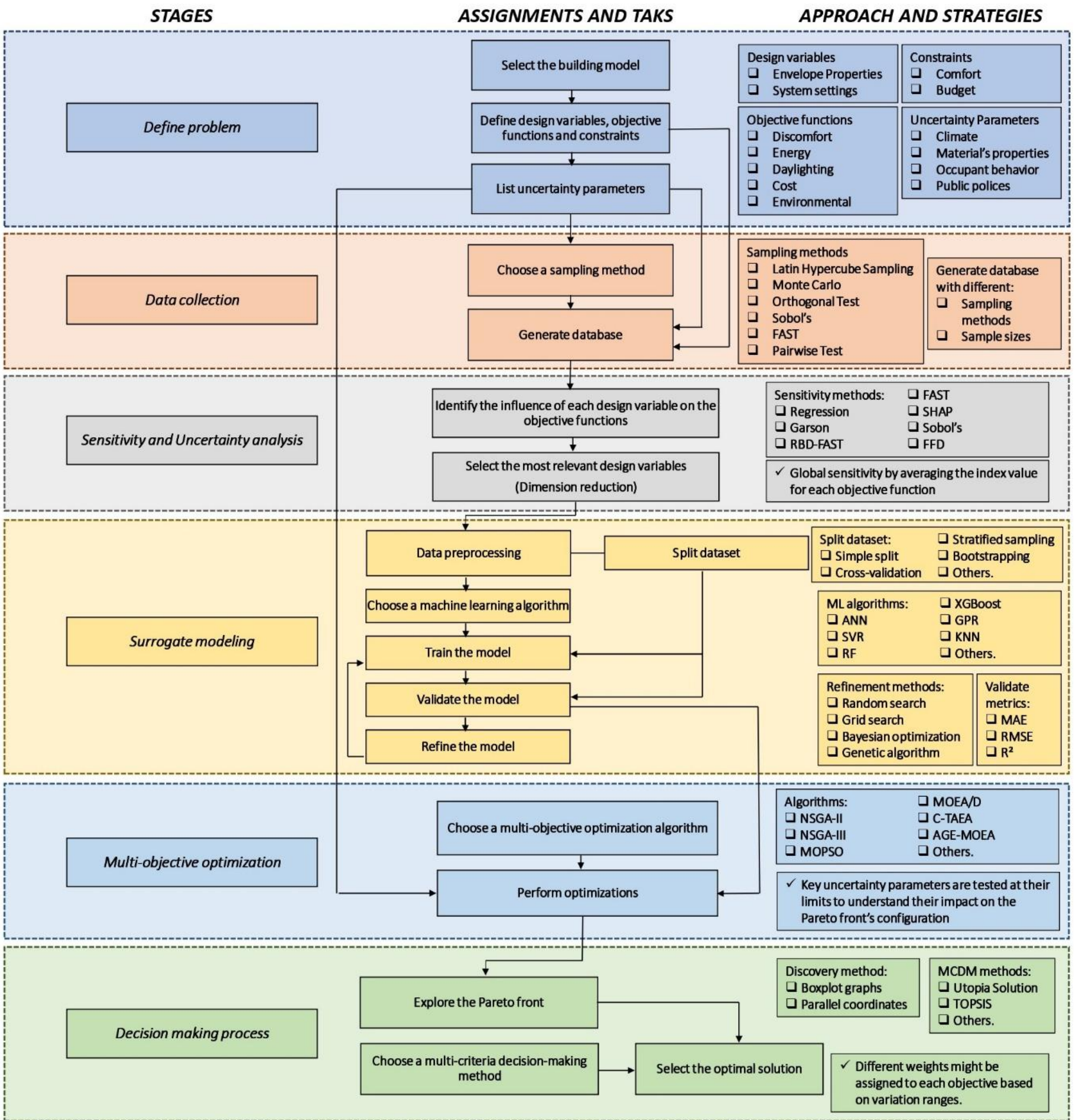


Figure 9. Framework for future evaluations.

The first step is to define the problem. This involves specifying the building model, design variables, objective functions, constraints, and a list of uncertainty parameters related to the project context. Subsequently, a sampling method needs to be selected to create the dataset, thereby establishing the database. It is suggested to use different methods and sample sizes to observe the impact during surrogate modeling and optimization. The third stage involves conducting a sensitivity analysis using the database developed in the previous step. The objective is to assess the influence of each design variable (feature) on the objective functions, particularly the impact of uncertainty parameters. Less influential variables should be discarded and kept at a constant value. This analysis helps reduce dimensions by selecting the most critical variables to narrow down the search space for optimization while saves computational resources. Note that the influence of each design variable (feature) may vary depending on the objective function (and if multiple objective functions conflict with each other). In this case, we advise researchers to calculate the average global sensitivity level of the design variable for all objective functions.

Subsequently, the surrogate modeling process begins. First, the database can undergo preprocessing, if required (e.g., normalization, encoding of categoric variables, among others). The database will be later split into training and testing sets using one of the many available strategies, such as simple split (e.g., 80%|20% - not recommended due to selection bias), cross-validation (k-fold), leave-one-out cross-validation, stratified sampling, bootstrapping, among others, depending on the characteristics of the dataset. In turn, the ML algorithm will be chosen based on the characteristics of the problem and the available data. Although each ML algorithm has advantages and disadvantages, we suggest researchers to compare multiple models to find the most suitable one. The hyperparameters of each ML technique must be adjusted, either manually or by automated processes (e.g., Grid Search, Random Search, Bayesian optimization, and GA). Later, the ML algorithm is fitted to the training dataset, creating the surrogate model. Then, the model is validated by measuring its accuracy using the test and/or validation datasets. Evaluation metrics, such as R^2, MAE, MAPE, and RMSE, will then be used to assess the deviation of surrogate predictions from simulation outcomes. If the surrogate model's performance is unsatisfactory, the model is refined by adjusting the training process, exploring different hyperparameters settings, or incorporating additional data. Finally, when the model is validated, it can be used for application.

Thereupon, the multi-objective optimization process starts. The optimization algorithm needs to be selected and configured to perform the multi-objective optimizations. Comparing different optimization algorithms through different metrics (calculation time, number of Pareto solutions, diversity, convergence, and hypervolume) is advisable to identify the one that is most suitable for the project context. Moreover, it is indicated that more than one round of optimization is performed. In this step, the most influential uncertainty parameters might be considered at their different extreme values to assess their impact on the configuration of the Pareto front. While sensitivity analysis provides insights into the effects of uncertainty parameters on the objective functions, evaluating their impact during optimization is also essential. Doing so can shed light on how uncertainty parameters shape the optimal solutions that define the Pareto front. Thus, conducting multiple optimizations can bring more robustness to the study. After collecting the optimization results, the last step is focused on the decision-making process. The Pareto fronts must be explored by comparing the design variables settings suggested in the optimal solutions. It is recommended that this analysis be performed using boxplot graphs or parallel coordinates to identify the optimal range values for each design variable. Finally, an MCDM method must be chosen to select the optimal solution on the Pareto front. Due to the complexity of building performance, evaluating the variation ranges of results for each objective function is crucial, as different weights might be assigned to each objective based on the project context can yield significantly different results. Therefore, this strategy ensures the selected optimal solution is well-suited.

2.4.2 Directions for future research in the field

Previous tables presented the research gaps identified in the reviewed articles, with some gaps having already been partially addressed. In this section, the authors provide a concise summary of the key synergy between these research gaps found in the SLR, emphasizing their significance as valuable directions for future research in the field. Here are issues and debates deemed more important on this research field nowadays

- Most reviewed articles consider surrogate models specific to a single building or project, but these models could be applied to a wider range of buildings. Developing broader models would require extensive datasets from multiple buildings and the use of data mining techniques to create generalized machine learning models. Data mining is the process of discovering patterns, correlations, and anomalies in large datasets to predict outcomes. It uses algorithms and statistical analysis to extract valuable insights, enabling organizations to make data-driven decisions. This approach would significantly enhance the applicability and effectiveness of multi-objective optimization investigations.
- The appropriate sample size of the dataset remains a subject of investigation, particularly considering its impact on the computational demand, accuracy of the machine learning models and subsequent optimization performance in determining the optimal solution. Although various methods exist for determining the optimal sample size, it depends on the machine learning algorithm's ability to capture input-output interactions. Each modeling context has unique dynamics, requiring a sample size tailored to that specific scenario.
- Developing large datasets with different architectural models might be computationally expensive; therefore, exploring the transfer learning techniques may be the focus for more complex and robust studies. Transfer learning reuses a model developed for one task as the starting point for a related task, leveraging previously learned patterns and features instead of starting from scratch. For instance, an ML model can be retrained with a new dataset from a different architecture model while retaining fundamental knowledge from the previous building.
- Sensitivity analysis needs to be a mandatory step before optimization, to assess the impact of design variables on objective functions and reduce dimensionality (whenever is possible), thus narrowing down the search space for optimization.
- Uncertainty parameters must be included during dataset development for surrogate modeling and optimization. Due to the lower computational cost, several optimizations may be performed considering extreme values for the main uncertainty parameters. This approach allows for identifying and comparing different optimal solutions amidst significant levels of uncertainty.
- There is a growing demand for user-friendly tools based on surrogate models that function as plugins for architectural modeling software or web applications. These tools aim to optimize building design and facilitate rapid performance assessments for professionals and public use. No initiative in this regard was found in the literature so far.
- Further research should include new design variables that go beyond envelope properties, carefully select the objective functions (conflicting as priority), combining with practical issues and boundary conditions (such as interest need and social impact) of the investigated buildings. This could help leverage optimization problems knowledge and promote excellent outcomes.
- During optimization studies, future research needs to consider carbon emissions and other environmental impacts as objective functions. The design and operation of buildings significantly contribute to greenhouse gas emissions (through energy consumption and

material selection), so promoting low-carbon buildings to mitigate climate change is fundamental.

- It is crucial to replicate multi-objective optimization studies based on surrogate models in various climatic contexts to foster the advancement of sustainable building design and facilitate more comprehensive and robust research in the field.
- New algorithms related to machine learning and multi-objective optimization should be introduced and explored due to several reasons: performance improvements, robustness and generalization, innovation and advancements, diversity of perspective, benchmarking, and interpretability.
- Finally, researchers in the field should embrace key ethical practices, including code and data transparency, explicit ethical statements within their papers (clarifying ethical considerations, potential biases, and transparency measures), rigorous validation techniques, and a preference for interpretable models. Adhering to these ethical standards will support a transparent, accountable, and trustworthy research environment.

2.5 Conclusion

This paper presents a systematic literature review on the interplay between multi-objective optimization and machine learning techniques in the context of sustainable building design. It appraises the integration of these methods, highlighting opportunities and challenges found in 54 articles based on simulation data. Specifically, this paper reviews studies employing building performance simulation tools to create databases. These databases then inform machine learning algorithms to develop surrogate models, which are subsequently integrated with multi-objective optimization algorithms to identify optimal design solutions.

The key findings from the systematic literature review are as follows: most studies originate from China, with the humid subtropical climate (Cfa) being the most commonly evaluated weather context. Although the approach can be applied at any design phase, few studies utilize it for retrofit expeditions. Surrogate modeling commonly utilizes Python and MATLAB, with the Latin Hypercube Sampling method widely employed for database generation. Yet, few studies compare machine learning algorithms, with Artificial Neural Networks and Support Vector Regression being the most popular approaches. Hyperparameter optimization is often neglected, and when implemented, genetic algorithms and grid search are commonly used. Sensitivity analysis is present in only half of the studies, mainly focusing on exploring the influence of each design variable while incorporating uncertainty parameters in optimization approaches is limited. Regarding multi-objective optimization, energy consumption, discomfort hours, and construction costs are prominent objective functions, while carbon emissions, daylighting illuminance, and environmental impacts receive less attention. NSGA-II is the most widely used optimization algorithm, and exploring Pareto front settings is common, while few studies adopt decision-making processes to select the optimal preferred solution. Finally, it is important to emphasize that these key findings are shaped by various factors, including complexity and convenience.

Multi-objective optimization based on surrogate models has been attracting significant scientific research attention. Yet, the research findings state that there is still a large unexploited potential and procedures to be incorporated or spread in the evaluated field. While different methods exist for determining the ideal dataset size, it is crucial to ensure the desired level of accuracy in model performance during surrogate modeling and multi-objective optimization. Integrating machine learning with traditional approaches, like sensitivity and uncertainty analyses, enhances robustness and efficiency, especially for complex assessments. Evaluating variation ranges for each objective function and adjusting weights based on the project context is essential to avoid overlooking promising solutions. To develop broader, more versatile, and generalized models, it is essential to obtain large datasets featuring various architectural models. Thus, to mitigate computational costs, future studies should prioritize data mining and transfer-learning strategies. Several key objective functions remain unexplored, including social impacts and aesthetics. Incorporating uncertainty parameters like climate change can enhance resilience in the built environment. In this context, the challenges associated with building decarbonization could drive the adoption of carbon emissions as a key objective function in optimization studies. A user-friendly tool based on surrogate models, capable of functioning as plugins for architectural modeling software or web applications, can help replicate this approach in various climatic contexts to foster the advancement of sustainable building design and facilitate more comprehensive and robust building performance assessment. Finally, the authors emphasize the ethical challenges within the field. This underscores the importance of promoting transparency, data availability, and a stronger commitment to ethical research practices to ensure the integrity and trustworthiness of findings.

Overall, the documents reviewed show that merging optimization methods with surrogate models is a promising technique to enhance sustainable building design, gaining momentum within the scientific community. This synergy enables a higher volume of simulations and parameter assessments with a lower computer cost, ultimately leading to cost-efficient design, technically proficient, and more sustainable building solutions. Nevertheless, designers, policymakers, and researchers must remain vigilant in upholding a realistic, robust, and ethical methodologies.

3. Chapter 3: What lies ahead? The future performance of Global South residential buildings amid climate change: A Systematic Literature Review

Abstract: More than a billion people globally lack affordable and safe housing, with the majority located in the Global South (GS). In these regions, climate change will persistently impact living conditions, reducing thermal comfort and escalating energy consumption. Within this context, this investigation conducts a Systematic Literature Review (SLR) on the use of building performance simulation (BPS) tools for climate adaptation and mitigation through future weather file predictions. By analyzing 47 documents, the study offers suggestions for policymakers and highlights areas that require further research. From policymakers' perspective, standardized metrics can promote better industry understanding and be key indicators for investment funds support climate-resilient developments. Public policies should mitigate overheating risks by moving beyond one-size-fits-all social housing approaches and implement nationwide tools for robust building design. Moreover, real progress in resilience relies on integrating enhanced building design standards with occupant behavior. From an academic perspective, future research should conduct national-level assessments of diverse urban architectural typologies, incorporating new resilience metrics and combining Global and Regional Climate Models to develop ensemble future weather files. New studies should adopt optimization, machine learning, and transfer learning techniques while effectively exploring trade-off procedures. Additionally, Life Cycle Assessment (LCA) and Life Cycle Cost Analysis (LCCA) are indispensable tools for advancing decarbonization efforts and evaluating technology feasibility in the built environment. Lastly, this SLR synthesizes past scientific achievements and current research gaps, providing an understanding of resilience modeling for climate adaptation and mitigation while offering a practical guide for sustainable residential buildings in the GS.

Keywords: Global South, Climate Change, Thermal Comfort, Energy Efficiency, Building Performance Simulation, Sustainable Building Design, Review.

3.1 Introduction

The global housing deficit poses a critical challenge, impacting approximately 1.2 billion people worldwide (UN, 2022, 2023a), primarily located in the Global South (GS). The GS is a geopolitical term referring to the former 'developing countries' of Latin America, Africa, Asia (excluding Israel, Japan, and South Korea), and Oceania (excluding Australia and New Zealand) – see **Figure 10** (DADOS; CONNELL, 2012). These regions grapple with challenges related to rapid urbanization, population growth, and economic disparities. Beyond the lack of shelter, the housing crisis encompasses substandard living conditions and vulnerability to environmental risks, which have been worsened by climate change (BAI et al., 2022; MARÍN-RESTREPO et al., 2023). The Intergovernmental Panel on Climate Change (IPCC) warns that global warming is disproportionately impacting vulnerable communities located in the GS (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). Thus, addressing the global housing deficit requires a multidimensional approach that integrates socio-economic factors combined with climate-resilient building design (SAAD-FILHO; FEIL, 2024).

Within this context, assessing the resilience of buildings becomes crucial and can be achieved through three main approaches: (1) on-site measurements in existing constructions – (Post Occupancy Evaluation - POE), (2) surveys or interviews tailored for existing buildings, and (3) computational modeling and simulation suitable for both new and existing buildings (IPCC, 2022). Building performance simulation (BPS) tools are essential for investigating thermal comfort within the built environment (KRELLING et al., 2023; MENDES et al., 2024a). These tools rely on weather files as vital inputs, with Typical Year (TY) files being widely used. TYs differ in their approach to selecting representative months, with common types being Typical Meteorological Year (TMY), Test

Reference Year (TRY), and Design Summer Year (DSY) (COLE; EVINS; EAMES, 2024; MACHARD et al., 2020). Although weather files like the eXtreme Meteorological Year (XMY) exist, researchers advise against relying on conventional climate data based on 20-to-30-year historical observations (CRAWLEY; LAWRIE, 2019). It is crucial to prioritize forward-looking design, given that modern constructions are expected to last at least 50 years (ANDERSEN; NEGENDAHL, 2023). This caution arises from the impact of rising greenhouse gas (GHG) emissions from human activities, which are altering climate trends. Recognizing this, the IPCC has developed various emissions scenarios within its Assessment Reports (AR) (IPCC, 1990, 1995, 2001, 2007, 2014, 2023), projecting future climate conditions based on different levels of GHG emissions. Consequently, BPS tools are increasingly used in resilience assessments to investigate overheating risks due to climate change, providing valuable insights for building design (COLE; EVINS; EAMES, 2024; CRAWLEY; LAWRIE, 2019; ESCANDÓN et al., 2023; RODRIGUES; FERNANDES; CARVALHO, 2023).

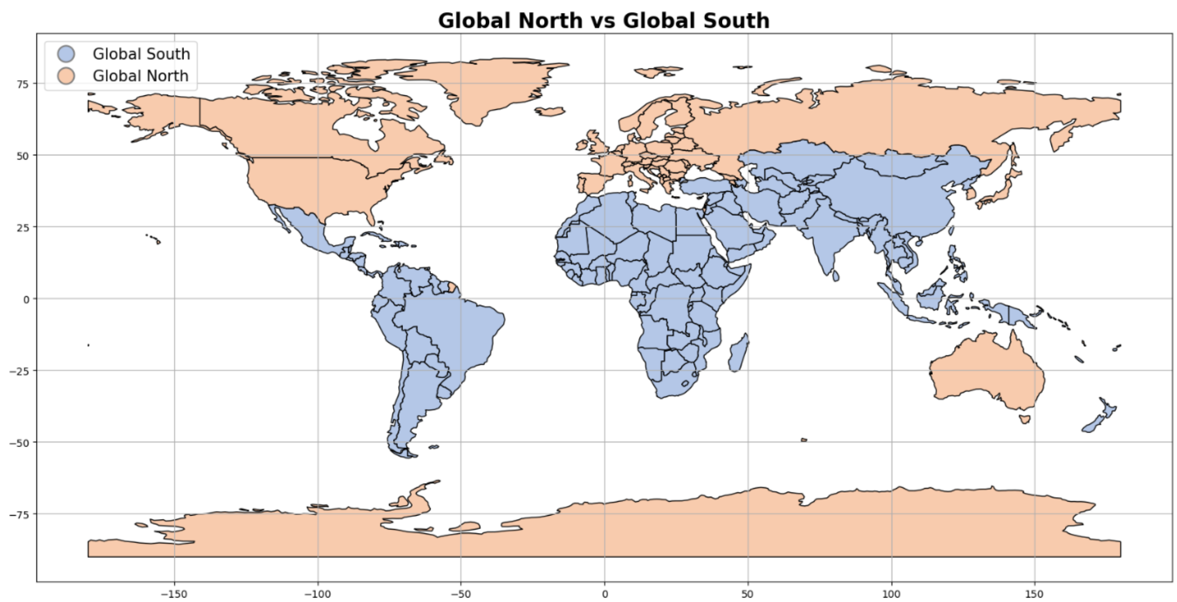


Figure 10. World map illustrating the division between the Global North and Global South.

3.1.1 Main concepts

3.1.1.1 Residential buildings in the Global South

The GS encompasses regions marked by historical colonialism, neo-imperialism, and enduring socio-economic disparities, resulting in high inequality in living standards, life expectancy, and resource access (SAAD-FILHO; FEIL, 2024). Beyond these aspects, the GS features notable climate distinctions, including the highest levels of horizontal solar radiation and temperature (DADOS; CONNELL, 2012). These climatic characteristics profoundly impact architectural practices, evident in structures like Wind Towers in Iran, Arabian house-courtyards for warm-dry climates, vernacular buildings with earthen walls in tropical zones, and architectures utilizing solar protection or ventilated facades (MARÍN-RESTREPO et al., 2023). Moreover, informal settlements are a key aspect of urban architecture in the GS. Often referred to as slums or favelas, these self-built communities commonly use concrete, hollow bricks, corrugated metal sheets, and reclaimed wood due to their affordability, durability, and ease of use, despite their low thermal performance (DADOS; CONNELL, 2012; UN, 2022, 2023a).

Climate change will persistently impact the GS regions, leading to diminished comfort conditions, with over 1 billion people worldwide facing cooling access limitations (IEA, 2022). These phenomena, combined with income growth, are expected to result in over 2.2 billion people purchasing inefficient cooling devices. This surge demand will drive an increase in cooling energy consumption in the world's warmest regions, along with a rise in associated GHG emissions due to the widespread use of HVAC (Heating, Ventilation, and Air Conditioning) systems (IEA, 2018).

While high-heat stress days and nights can lead to building overheating, adopting proper building design strategies can help moderate indoor overheating (IPCC, 2022). Researchers are particularly focused on developing low-cost tools and strategies that prevent the increase in users' energy dependence (R. LEVINSON et al., 2023). Despite the efforts, a gap persists between user-centric design and climate responsiveness, exacerbated by designers' limited understanding of thermal comfort, and sustainability certifications that may not enhance user comfort perception or suit the GS context (MARÍN-RESTREPO et al., 2023). Therefore, given the substantial housing deficits (BUCKLEY, 2005; HELBLE; YOSHINO; ASIAN DEVELOPMENT BANK INSTITUTE), anticipated significant economic growth (ANAND; COMIM; FENNELL, 2020; HELBLE; YOSHINO; ASIAN DEVELOPMENT BANK INSTITUTE), future energy supply challenges (UN, 2022), and increased climate vulnerability (IPCC, 1990, 1995, 2001, 2007, 2014, 2023), urgent climate-resilient measures are imperative in the residential building sector of the GS countries.

3.1.1.2 Climate-resilient building design

Over time, the term "resilience" has evolved, leading to varying interpretations (ATTIA et al., 2021; HOMAEI; HAMDY, 2021; KESIK; O'BRIEN; OZKAN, 2022; MILLER et al., 2021). To comprehensively address building resilience, it is crucial to identify expected features in buildings. In summary, building resilience hinges on four key factors: vulnerability, adaptability, mitigation, and resistance (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). Vulnerability measures a building's susceptibility to harm, damage, or disruption from external stressors (UN, 2022, 2023a). Adaptability involves adjusting to current or anticipated climate conditions and their impacts on humans (IPCC, 2014, 2023). Mitigation encompasses human efforts to reduce GHG emissions or enhance their absorption (IPCC, 2014, 2023). Lastly, resistance denotes a building's ability to endure external stressors without significant damage or loss of functionality (ATTIA et al., 2021). Thus, climate-resilient building design begins by assessing vulnerability, which may inform the development of adaptation and mitigation strategies to enhance resistance against future weather conditions.

Interest in adaptation and mitigation is driven by their interconnectedness and potential for mutual benefits, as highlighted in global policy frameworks such as the Paris Agreement (UN, 2015), the New Urban Agenda (UN, 2017), and the United Nations Sustainable Development Goals (UN, 2023a). Failure to mitigate increases future adaptation costs, while effective adaptation reduces mitigation needs (HAMIN; GURRAN, 2009). Synergy occurs when implementing multiple measures simultaneously yields greater benefits, but trade-offs may arise when one measure negatively impacts the other (HAMIN; GURRAN, 2009; XU et al., 2019). Given the building sector's significant role in GHG emissions, mitigation measures are crucial for improving energy performance while indoor adaptation measures are vital for enhancing thermal comfort (IPCC, 2022). This context involves trade-offs, as seen in potentially increased construction costs for passive design. Affordability concerns may arise for all income groups, and certain passive design measures could escalate embodied carbon emissions due to energy-intensive materials (HAMIN; GURRAN, 2009).

Meanwhile, there is a rising interest in assessing buildings' resilience through codes and regulations. For instance, the RELi™ Rating System is now part of the resilience-related credit strategies of the LEED green building rating system for infrastructures, neighborhoods, and buildings (USGBC, 2021). In addition, the United Nations Environment Programme offers a practical guide for climate-resilient buildings and communities (UN), and initial efforts are established in the ISO 37123 - International standard for resilient cities (ISO, 2019). However, the dynamics within GS contexts, more specifically within informal settlements, further complicate the standardization and understanding of these procedures (DADOS; CONNELL, 2012; UN, 2022, 2023a).

Finally, the narrow window for action is closing swiftly due to urbanization and climate change trends. Delays in integrating adaptation and mitigation strategies into climate action plans may lead to irreversible issues and undesirable outcomes in the built environment (XU et al., 2019). Consequently, this underscores the need for local efforts in the Architecture, Engineering, and Construction (AEC) industry to enhance housing quality through new technologies, innovative practices, strategic public policies, and government incentives (IPCC, 2022; SAAD-FILHO; FEIL, 2024).

3.1.2 Previous studies, research gap, novelty and main contribution

Previous literature reviews have not specifically focused on GS regions. The existing literature is limited in several key aspects: it often narrowly addresses energy performance (SIU et al., 2023; YASSAGHI; HOQUE, 2019), emphasizes quantitative reviews (STAGRUM et al., 2020), primarily examines infrastructure sectors in diverse Global North regions (SHARIFI, 2020), and adopts a broad understanding of resilience (CAMPAGNA; FIORITO, 2022; HONG et al., 2023). While the authors acknowledge the importance of a global perspective, an overly broad context may overlook the nuanced realities of specific regions. Thus, the authors argue that the research gap lies in the holistic and exclusive focus on GS studies, as emphasized in the Adaptation Gap Report by the United Nations Environment Programme (UN, 2023b).

This research introduces novelty by exploring a niche area often neglected. As a consequence, two pivotal questions emerge: (1) What are the research trends, main challenges, and opportunities in resilience modeling for climate adaptation and mitigation in GS residential buildings? (2) What lies ahead regarding the future performance of GS residential buildings amid climate change? To address these questions, this paper examines research on GS residential buildings, specifically assessing resilience through future weather predictions using BPS tools. The investigation is conducted through a Systematic Literature Review (SLR) that provides two significant contributions: first, it identifies a list of research gaps where some issues have been partially addressed; second, it outlines directions for future research in the field and offers suggestions for policymakers. This SLR synthesizes past scientific achievements and current research gaps, providing an understanding of resilience modeling for climate adaptation and mitigation while offering a practical guide for designing more sustainable residential buildings in the GS.

Finally, to provide a clear structure, the remaining sections of this paper are organized as follows: Section 3.2 outlines the research method conducted, explaining the three steps followed to perform the SLR. Section 3.3 presents the findings (quantitative and qualitative results) obtained during the SLR regarding the main topic: “Resilience modeling workflow for climate adaptation and mitigation”. Section 3.4 compares results from prior literature reviews with the current study and offers insights into future research directions in the field and offers suggestions for policymakers. Finally, Section 3.5 presents the conclusions.

3.2 Method

The investigation is conducted through a Systematic Literature Review (SLR) (BRINER; DENYER, 2012; KHAN et al., 2003; KITCHENHAM; CHARTERS, 2007). The SLR approach identifies gaps in the literature, advancing research amid a multitude of conflicting studies. Adhering to explicit methods, ensuring replicability, and synthesizing evidence, it establishes a transparent foundation, aiding theory development, resolving research abundance, and identifying areas requiring study (WATSON; WEBSTER, 2020). Although SLRs reduce bias in selecting source material, they require more time and effort than traditional reviews due to their specific criteria (SIDDAWAY; WOOD; HEDGES, 2019). Building on prior research (BRINER; DENYER, 2012; KHAN et al., 2003; KITCHENHAM; CHARTERS, 2007), the SLR is planned around three key stages: 1) locating scientific studies; 2) selecting papers; and 3) synthesizing and reporting results. **Figure 11** depicts the SLR procedure.

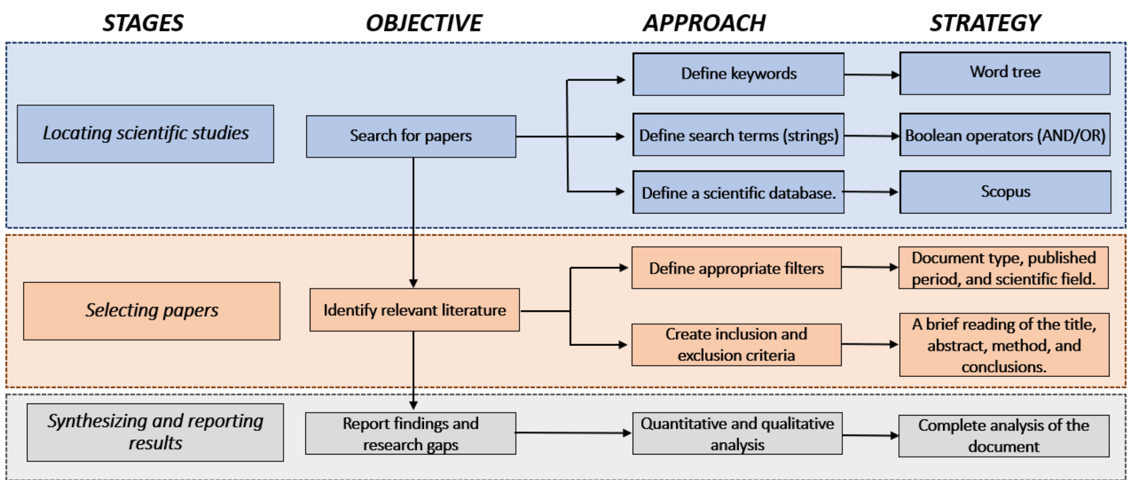


Figure 11. The Systematic Literature Review (SLR) framework.

3.2.1 Locating scientific studies

In the initial stage, studies are located by formulating keywords based on a word tree approach (HART, 1998). Efficient translation of research questions into search terms aids in identifying a maximum number of relevant articles (HALLINGER, 2013). The search string used in the Scopus database was: (Residential OR House OR Dwelling) AND (“Climate change” OR “Global warming” OR Resilience) AND (Simulation OR Performance OR Modeling). Individual or pairwise searching for main topics is omitted due to the goal of identifying synergy between research topics. Finally, Scopus is selected as it is one of the largest multidisciplinary scientific databases, accommodating related terms and variations in spelling.

3.2.2 Selecting papers

Given the emphasis on article selection at this stage, filters are applied using inclusion/exclusion criteria (DENYER; TRANFIELD, 2009; WATSON; WEBSTER, 2020), considering title, abstract, method, and conclusion (SAUNDERS; LEWIS; THORNHILL, 2019). Only peer-reviewed journal articles from the AEC industry, published between 2014 and 2024, are included. This aligns with guidelines prioritizing reliable sources and ensures the inclusion of robust, in-depth studies with substantial contributions (SIDDAWAY; WOOD; HEDGES, 2019). The selected research period aligns with the exponential growth of scientific studies on the topic observed over the past decade.

Finally, given the study's emphasis on building performance simulation, the modeling approach narrows down the number of selected articles specifically related to the AEC industry.

3.2.3 Synthesizing and reporting results

In the third stage, the study synthesizes and reports the findings (BRINER; DENYER, 2012; KHAN et al., 2003; KITCHENHAM; CHARTERS, 2007). Within this context, content analysis emerges as a crucial research tool in research, suitable for both quantitative and qualitative approaches (WATSON; WEBSTER, 2020). Ultimately, the SLR compiles insights from the selected documents, highlighting research gaps, challenges, and opportunities within various approaches and contexts (SIDDAWAY; WOOD; HEDGES, 2019).

3.3 Results

3.3.1 SLR overview

Figure 12 provides an overview of the selected SLR articles in terms of the following categories: (a) study selection, (b) published articles per year, (c) country, (d) climate, (e) building typology, (f) architectural model, (g) performance evaluated, and (h) simulation tool.

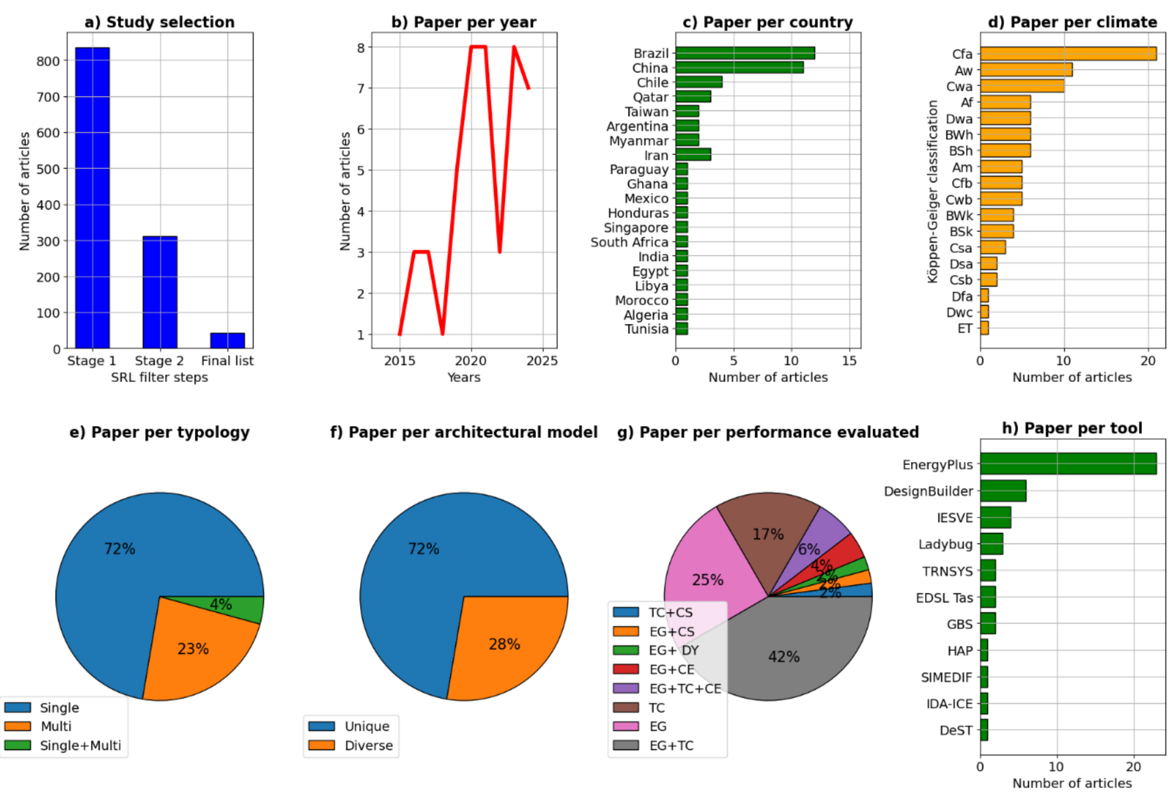


Figure 12. Categorization of selected documents.

Figure 12(a) displays the selection process results from the Scopus database. Documents pertaining to GS countries comprise only 37% of the total found. Therefore, after applying filters and evaluating documents, 47 relevant articles were selected. Figure 12(b) identifies a rising trend in research on the climate resilience of GS residential buildings since 2019, indicative of escalating climate change concerns — a trend mirrored in other AEC sectors. Despite the prevalence of international academic collaborations, Figure 12(c) emphasizes the significant contributions from

Brazil and China to the research field, likely due to their economic potential and corresponding investments in academic research. Figure 12(d) delineates the climate diversity within GS case studies, using the Köppen Geiger classification (BECK et al., 2018). Although it encompasses almost all major climate groups—tropical, dry, temperate, continental, and polar—there is a notable focus on the humid subtropical climate (Cfa) in 20% of cases, followed by the Tropical Savanna (Aw) and Monsoon-influenced humid subtropical climate (Cwa). Moreover, Figure 12(e) and Figure 12(f) detail the models examined, with 72% focusing on single-family typologies, and 74% of these adhering to a single architectural model. Diverse architectural models are scarce, with a singular study considering single and multi-family units. The research spans four performance dimensions—energy (EG), thermal comfort (TC), cost (CS), daylighting (DY), and carbon emissions (CE)—with a majority (around 80%) addressing only energy and thermal comfort performance indicators. Section 3.2.3 provides an in-depth exploration of these objective functions. Figure 12(h) points to EnergyPlus as the predominant BPS tool, aligning with previous findings (MENDES et al., 2024b) due to its credibility and free access, adhering to global standards. Lastly, Table 14 provides a comprehensive list of the articles selected throughout the SLR stages, offering an overview that encapsulates the current research landscape and highlights key documents and contributions within the field.

Table 14. Final list of selected studies from the SLR, including publication year and journal.

Index	Title	Year	Journal	Reference
1	Analysis of the effect of global climate change on ground source heat pump systems in different climate categories	2015	Renewable Energy	(KHARSEH et al., 2015)
2	Future trends of residential building cooling energy and passive adaptation measures to counteract climate change: The case of Taiwan	2016	Applied Energy	(HUANG; HWANG, 2016)
3	Residential buildings' thermal performance and comfort for the elderly under climate changes context in the city of São Paulo, Brazil	2016	Energy and Buildings	(ALVES; DUARTE; GONÇALVES, 2016)
4	The present and future energy performance of the first Passivhaus project in the Gulf region	2016	Sustainability (Switzerland)	(KHALFAN; SHARPLES, 2016)
5	Application of adaptive comfort behaviors in Chilean social housing standards under the influence of climate change	2017	Building Simulation	(RUBIO-BELLIDO et al., 2017)
6	Retrospective analysis of the energy consumption of single-family dwellings in central Argentina. Retrofitting and adaptation to the climate change	2017	Renewable Energy	(FILIPPÍN et al., 2017)
7	Spatial and temporal analysis of urban heat island and global warming on residential thermal comfort and cooling energy in Taiwan	2017	Energy and Buildings	(HWANG; LIN; HUANG, 2017)
8	Should we consider climate change for Brazilian social housing? Assessment of energy efficiency adaptation measures	2018	Energy and Buildings	(TRIANA; LAMBERTS; SASSI, 2018)
9	Effects of climate change for thermal comfort and energy performance of residential buildings in a Sub-Saharan African climate	2019	Buildings	(DODOO; AYARKWA, 2019)
10	Impact assessment of climate change on buildings in Paraguay—Overheating risk under different future climate scenarios	2019	Building Simulation	(SILVERO et al., 2019)
11	Impact of climate change on energy use and bioclimatic design of residential buildings in the 21st century in Argentina	2019	Energy and Buildings	(FLORES-LARSEN;

Index	Title	Year	Journal	Reference
				FILIPPÍN; BAREA, 2019)
12	Impact of Climate Change on the Energy Needs of Houses in Chile	2019	Sustainability (Switzerland)	(ROUAULT et al., 2019)
13	Low carbon heating and cooling of residential buildings in cities in the hot summer and cold winter zone - A bottom-up engineering stock modeling approach	2019	Journal of Cleaner Production	(LI et al., 2019)
14	Overheating risk in Mediterranean residential buildings: Comparison of current and future climate scenarios	2020	Applied Energy	(RODRIGUES; FERNANDES, 2020)
15	Design and application of cellular concrete on a Mexican residential building and its influence on energy savings in hot climates: Projections to 2050	2020	Applied Sciences (Switzerland)	(BORBON-ALMADA et al., 2020)
16	Development and application of future design weather data for evaluating the building thermal-energy performance in subtropical Hong Kong	2020	Energy and Buildings	(LIU et al., 2020b)
17	Effectiveness of passive design strategies in responding to future climate change for residential buildings in hot and humid Hong Kong	2020	Energy and Buildings	(LIU et al., 2020a)
18	Effects of climate change on variations in climatic zones and heating energy consumption of residential buildings in the southern Chile	2020	Energy and Buildings	(VERICHEV; ZAMORANO; CARPIO, 2020)
19	The influence of climate change on renewable energy systems designed to achieve zero energy buildings in the present: A case study in the Brazilian Savannah	2020	Sustainable Cities and Society	(GUARDA et al., 2020)
20	The vulnerability of homes to overheating in Myanmar today and in the future: A heat index analysis of measured and simulated data	2020	Energy and Buildings	(ZUNE; RODRIGUES; GILLOTT, 2020b)
21	Vernacular passive design in Myanmar housing for thermal comfort	2020	Sustainable Cities and Society	(ZUNE; RODRIGUES; GILLOTT, 2020a)
22	A simulation-based method to predict the life cycle energy performance of residential buildings in different climate zones of China	2021	Building and Environment	(ZOU et al., 2021b)
23	Adaptation and mitigation to climate change of envelope wall thermal insulation of residential buildings in a temperate oceanic climate	2021	Energy and Buildings	(VERICHEV et al., 2021)
24	Bermed earth-sheltered wall for low-income house: Thermal and energy measure to face climate change in tropical region	2021	Applied Sciences (Switzerland)	(CALLEJAS et al., 2021)
25	Evaluation of dry wall system and its features in environmental sustainability	2021	Journal of Cleaner Production	(ARAB; FARROKHZAD; HABERT, 2021)
26	Passive cooling design strategies as adaptation measures for lowering the indoor overheating risk in tropical climates	2021	Energy and Buildings	(GAMERO-SALINAS et al., 2021)
27	The impact of climate change on the thermal-energy performance of the SCIP and ICF wall systems for social housing in Brazil	2021	Indoor and Built Environment	(CRUZ; CUNHA, 2022)
28	The recent residential apartment buildings' thermal performance under the combined effect of the global and the local warming	2021	Energy and Buildings	(ALVES; GONÇALVES; DUARTE, 2021)

Index	Title	Year	Journal	Reference
29	The viability of solar photovoltaic powered off-grid Zero Energy Buildings based on a container home	2021	Journal of Cleaner Production	(KRISTIANSEN et al., 2021)
30	Data-driven prediction and optimization of residential building performance in Singapore considering the impact of climate change	2022	Building and Environment	(YAN; JI; YAN, 2022b)
31	Effects of climate change in the thermal and energy performance of low-income housing in Brazil—assessing design variable sensitivity over the 21st century	2022	Renewable and Sustainable Energy Reviews	(NUNES; GIGLIO, 2022)
32	The energy performance and passive survivability of high thermal insulation buildings in future climate scenarios	2022	Building Simulation	(WANG et al., 2022)
33	Investigation of urban heat island and climate change and their combined impact on building cooling demand in the hot and humid climate of Qatar	2023	Urban Climate	(KAMAL et al., 2023a)
34	A multi-objective optimization framework for building performance under climate change	2023	Journal of Building Engineering	(LI et al., 2023b)
35	Climate change and ideal thermal transmittance of residential buildings in Iran	2023	Journal of Building Engineering	(RODRIGUES et al., 2023)
36	Energy Performance Assessment of the Container Housing in Subtropical Region of China upon Future Climate Scenarios	2023	Energies	(SUO et al., 2023)
37	Heat stress: adaptation measures in South African informal settlements	2023	Buildings and Cities	(HUGO, 2023)
38	Predicting climate change and occupants' behaviour impact on thermal-energy performance of global south housing: Case study in Brazil	2023	Indoor and Built Environment	(CRUZ; BASTOS, 2024)
39	Predicting the response of heating and cooling demands of residential buildings with various thermal performances in China to climate change	2023	Energy	(XIONG et al., 2023)
40	Study on Summer Overheating of Residential Buildings in the Severe Cold Region of China in View of Climate Change	2023	Buildings	(YU et al., 2023)
41	Ventilative cooling of residential buildings in China: A simulation-based evaluation of lightweight modular integrated constructions considering climate change	2024	Energy and Buildings	(HU et al., 2024)
42	Diminishing benefits of thermal mass in Iranian climate: Present and future scenarios	2024	Applied Energy	(RODRIGUES et al., 2024)
43	Building for tomorrow: Analyzing ideal thermal transmittances in the face of climate change in Brazil	2024	Applied Energy	(RODRIGUES; PARENTE; FERNANDES, 2024)
44	Defining weather scenarios for simulation-based assessment of thermal resilience of buildings under current and future climates: A case study in Brazil	2024	Sustainable Cities and Society	(KRELLING et al., 2024)
45	Impact of climate change on the heating and cooling load components of an archetypical residential room in major Indian cities	2024	Building and Environment	(ARUL BABU; SRIVASTAVA; RAI, 2024)
46	Multiple regional climate model projections to assess building thermal performance in Brazil: Understanding the uncertainty	2024	Journal of Building Engineering	(BRACHT et al., 2024)
47	Multiscale modeling to optimize thermal performance design for urban social housing: A case study	2024	Applied Thermal Engineering	(GONÇALVES et al., 2024)

3.3.2 Resilience modeling workflow for climate adaptation and mitigation

A practical workflow for resilience modeling using BPS tools starts with defining the building design problem clearly and establishing key parameters (see **Figure 13**). These include the building's operational mode, relevant metrics, IPCC emissions scenarios with the future horizon encompassed by the prediction method/engine, and analysis settings to explore different design variables. Firstly, the process begins by choosing an appropriate BPS tool from options like EnergyPlus, DesignBuilder, eQuest, or IESVE. The next step involves creating a 'baseline model'. This model allows for in-depth analysis. Building operation assumptions play a crucial role in resilience assessments as they shape expectations for indoor environmental quality. The choice between mechanically conditioned, naturally ventilated (occupant-controlled), or mixed-mode operation will pre-define the expected context of resilience metrics. Unlike traditional simulations, resilience analysis requires consideration of a variety of contexts that could affect building performance, taking into account various IPCC emission scenarios and future horizons available from different prediction methods/engines. Furthermore, the goal extends beyond simply evaluating resilience. It also includes the identification of design strategies for climate adaptation and mitigation. This comprises architectural designs that bolster the resilience of the built environment through minimizing vulnerability and enhancing resistance. Within this context, different approaches employ mathematical methods and process automation to efficiently evaluate a wide range of design variables. It focuses on optimizing one or more metrics —often referred to as objective, cost or fitness functions—which can be either minimized or maximized depending on various constraints. Frequently, the results yield multiple optimal solutions, necessitating a trade-off procedure between adaptation and mitigation strategies. This enables a comprehensive exploration of design solutions, maximizing the potential for efficient climate-resilient building design.

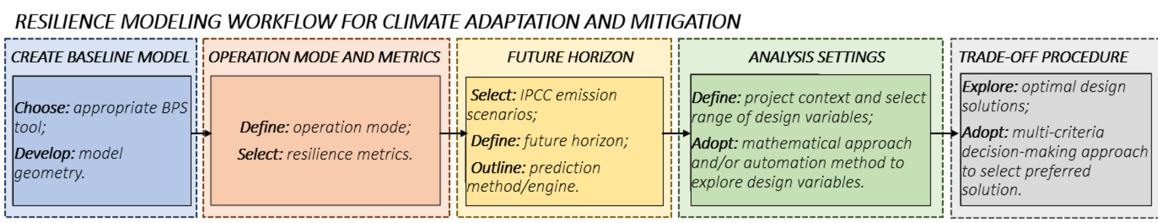


Figure 13. Workflow for resilience modeling.

3.3.2.1 Operation modes and Metrics

As noted, building operations can be categorized into three main modes: a) mechanically conditioned, b) naturally ventilated (controlled by occupants), or c) a combination of both (mixed-mode) (ELI et al., 2021). When the building envelope fails to maintain thermal comfort, reliance on an HVAC system often becomes necessary. Yet, HVAC systems depend on a consistent power supply, which may be compromised by unexpected grid failures (UN, 2022). Additionally, the adoption and utilization of HVAC systems are influenced by cultural and socio-economic factors (MARÍN-RESTREPO et al., 2023). In GS regions experiencing energy poverty, residents might lack the financial and basic infrastructure resources to operate HVAC systems effectively (UN, 2022, 2023a). Concurrently, despite a preference for natural ventilation (free-running buildings) (MARÍN-RESTREPO et al., 2023), rising living standards (BUCKLEY, 2005; HELBLE; YOSHINO; ASIAN DEVELOPMENT BANK INSTITUTE) and comfort expectations in GS countries are driving an increased demand for HVAC systems, revealing a significant oversight in contemporary energy discussions (IEA, 2018).

A possible solution to promote energy efficiency and thermal comfort is to combine both operation modes (mechanically and naturally ventilated) (ELI et al., 2021; KRELLING et al., 2024). For instance, several studies suggest that the HVAC system should be activated only when indoor temperatures fall outside an acceptable comfort range (CRUZ; CUNHA, 2022; DODOO; AYARKWA, 2019; LIU et al., 2020a; NUNES; GIGLIO, 2022), or that air conditioning operates exclusively during specific times, such as nighttime hours to facilitate comfortable sleeping conditions (XIONG et al., 2023). Although the first approach displays high energy-saving potential, it can yield unrealistic dynamics. Typically, once activated, occupants tend to turn off the HVAC system based on personal preference rather than at the precise moment when the temperature returns to the designated comfort threshold (ELI et al., 2021; KRELLING et al., 2024). Building standards and energy codes typically adopt either natural or mechanical ventilation and advise specific occupancy patterns that may not fully reflect actual occupant behavior, highlighting a significant literature gap in user interactions with HVAC systems in the Global South (MENDES et al., 2024b).

Nonetheless, the interaction between mechanically and naturally ventilated operation modes is not always straightforward in terms of building design. For instance, while enhancing thermal insulation typically improves a building's energy efficiency, it can also elevate the risk of overheating in the summer unless coupled with effective passive and adaptive cooling strategies (CRUZ; BASTOS, 2024; CRUZ; DE CARVALHO; DA CUNHA, 2020). This underscores the critical need to integrate both natural and mechanical ventilation considerations in resilience assessments. However, a key question arises: How can we effectively assess the resilience of different operating modes? For mechanically conditioned periods, the increase in energy demand (ED) and peak of energy demand (PD) could serve as a straightforward metric (DODOO; AYARKWA, 2019; LIU et al., 2020b, 2020a). Yet, researchers might argue that this metric is more indicative of energy performance than resilience. In this article, "metric" refers to any parameter that characterizes a specific condition or state (HOMAEI; HAMDY, 2021). Metrics, also called objective functions in BPS studies, can be derived from one or more variables or parameters, offering insightful data that enhance understanding of resilience beyond mere raw measurements.

For naturally ventilated periods, numerous metrics are available for assessing resilience. The choice of these metrics often depends on considerations such as user-friendliness and relevance to the study context (HOMAEI; HAMDY, 2021). While some metrics can be calculated using only environmental data or processed hourly data, others necessitate assumptions regarding occupant behavior, including clothing choices and physical activity levels (ATTIA et al., 2021; HOMAEI; HAMDY, 2021; KESIK; O'BRIEN; OZKAN, 2022; MILLER et al., 2021). For a comprehensive understanding, **Table 15** organizes several metrics into four key categories (KRELLING et al., 2023): intensity, frequency, duration, and severity, providing a structured framework for their comparison and application.

Table 15. Overview of resilience metrics for naturally ventilated operation mode: Descriptions, highlights, and limitations.

Category	Metrics	Description	Highlight	Limitation	Reference
Intensity	• Max/Min values for Operative temperature (OT).	Combination of the dry-bulb and mean radiant temperatures with air velocity.	Characterize the most severe thermal conditions.	Do not illustrate how often it occur.	(ALVES; GONÇALVES; DUARTE, 2021; SILVERO et al., 2019)
	• Max/Min values for the standard effective temperature (SET).	Combination of air velocity, humidity, occupant metabolic rate, and clothing insulation.			(KRELLING et al., 2023, 2024)
Frequency	• Thermal autonomy (TA).	Percentage of occupied hours within the upper/lower limit temperature.	Analyze the frequency of a specific condition.	Do not state how far conditions are from limits.	(GONÇALVES et al., 2024)
Duration	• Hours of safety (HS). • Recovery time (RT).	Length of time before a building becomes uninhabitable or the	Important for evaluating the impact of thermal	Alone, it does not fully define resilience in year-round analysis.	(KRELLING et al., 2024)

Category	Metrics	Description	Highlight	Limitation	Reference
		time required to recover from an extreme condition.	environments on human health.		
Severity	• Degree hours (DH). • Indoor Overheating Degree (IOD).	Cumulative temperature deviation from a reference point over a period.	Compile data considering both intensity and frequency.	Results' significance is unclear without a defined acceptable range for indoor temperatures.	(GAMERO-SALINAS et al., 2021; LI et al., 2019)

For simplicity, the table lists only the most popular metrics and those frequently mentioned in articles. Other metrics, such as the Heat Index, Wet Bulb Globe Temperature (WBGT), and Ambient Warmness Degree (AWD), are primarily concerned with the outdoor environment. Although these metrics are valuable, they are less effective in directly assessing the resilience of buildings (ATTIA et al., 2021; HOMAEI; HAMDY, 2021; KESIK; O'BRIEN; OZKAN, 2022; MILLER et al., 2021). Within this context, the Equivalent Performance Index (EPI) facilitates a comprehensive evaluation of building performance (NUNES; GIGLIO, 2022). This metric assesses both thermal aspects and energy requirements, effectively integrating these factors into a single index. Such a unified approach is particularly valuable for studies that examine buildings with mixed-mode operations. Equation 3.1 illustrates how to calculate the EPI metric.

$$EPI = \left(\frac{(DH_h + DH_c)}{(DH_h + DH_c)_{max}} + \frac{(ED_h + ED_c)}{(ED_h + ED_c)_{max}}\right) * 0.5 \qquad (3.1)$$

Where EPI represents the Equivalent Performance Index; DH_h and DH_c denote the equivalent degree-hours for heating and cooling, respectively, measured in °C·h; ED_h and ED_C refer to the annual heating and cooling energy demand, expressed in kWh/year; and max is the max value of the sum of the performance criteria, dependent on the sample (NUNES; GIGLIO, 2022).

Furthermore, the acceptable range for indoor temperatures is often derived from various standards, regulations, and models. The comfort standards and models mentioned in the SLR articles are: ASHRAE Standard 55 (GONÇALVES et al., 2024; WANG et al., 2022), CCS (VERICHEV et al., 2021; VERICHEV; ZAMORANO; CARPIO, 2020), CIBSE (YU et al., 2023; ZUNE; RODRIGUES; GILLOTT, 2020a, 2020b), PMV/PPD (DODOO; AYARKWA, 2019; KHALFAN; SHARPLES, 2016; YAN; JI; YAN, 2022b), EN15251 (RUBIO-BELLIDO et al., 2017; SILVERO et al., 2019), JGJ 134/449 (LI et al., 2019; SUO et al., 2023), Humphreys (ALVES; DUARTE; GONÇALVES, 2016), IRAM11549 (FILIPPÍN et al., 2017), and ISO13790 (ROUAULT et al., 2019). Each presents different formulas to calculate maximum acceptable indoor air temperature. Within this context, Alves et al. (ALVES; DUARTE; GONÇALVES, 2016) investigated the vulnerability of elderly people living in São Paulo by evaluating two adaptive thermal comfort indices: ASHRAE Standard 55 and Humphreys. These indices assess individuals' physiological and behavioral adaptations to their environment (in contrast to the static comfort models such as PMV/PPD). The findings indicate that Humphreys demonstrates greater adaptability to internal operative temperature variations due to its stronger correlation between external and internal temperatures compared to the ASHRAE Standard 55. Despite both models showing a tendency towards heat sensation, uncertainties persist regarding the limits of human adaptation, warranting further investigation.

3.3.2.1.1 SLR overview – Operation modes and Metrics

Figure 14 shows the section's overview in terms of the following categories: (a) operation modes, (b) combined metrics, (c) metrics categories, and (d) thermal comfort standards from the selected articles.

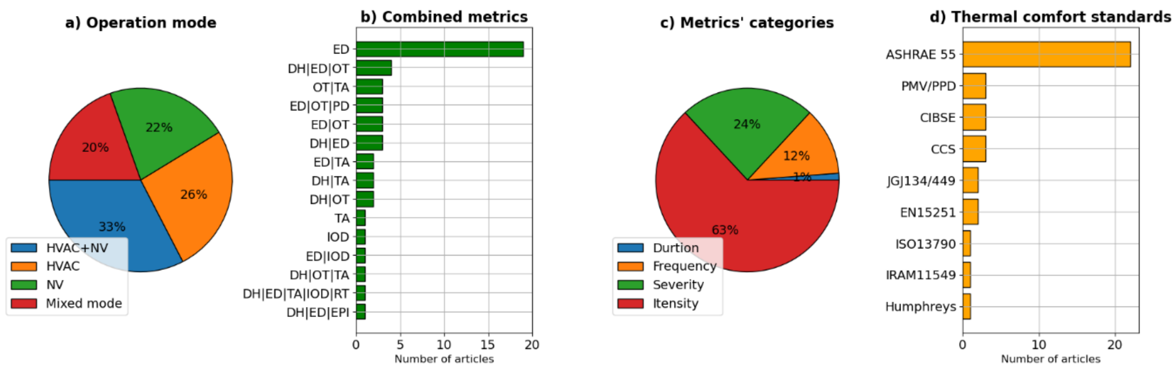


Figure 14. Overview of findings for the 'Operation modes and Metrics' section.

Figure 14(a) illustrates that the most common operation mode emphasizes buildings that are either naturally ventilated and/or mechanically ventilated (accounting for 80% of cases), without combining these modes into a mixed operation mode. Although attempting to understand the optimal design for both modes is a good approach, it may overlook the potential benefits of a mixed operation mode. Surprisingly, while the exclusive use of naturally ventilated mode is predominant in the GS, it is featured in fewer than 22% of the studies. Figure 14(b) delves into the combinations of metrics, highlighting the common pairing of degree-hours with energy demand and operative temperature. Notably, two critical but underrepresented metrics are Indoor Overheating Degree and Peak Energy Demand, which appear in fewer than 10% of the studies. Moving on to Figure 14(c), it categorizes the metrics used in these studies, where energy demand and peak energy demand are interpreted as intensity and severity, respectively. The results highlight the prominence of intensity and severity categories, likely due to their straightforward analysis and interpretation. However, the duration category, which is critical for assessing the safety of the built environment, warrants more attention due to its direct relevance. Lastly, Figure 14(d) illustrates the adoption of comfort standards in the studies, showing that despite the diversity of standards, the ASHRAE Standard 55 is predominantly adopted in the studies.

3.3.2.1.2 Research gaps – Operation modes and Metrics

Table 16 summarizes the challenges, opportunities, demands, and suggestions identified in the selected SLR articles related to this section on 'Operation modes and Metrics'. In addition, research gaps that have been partially addressed by existing studies are highlighted and categorized into two different contexts: a) Occupant Behavior and b) Operation Mode.

Table 16. Research gaps pointed out and partially addressed related to 'Operation modes and Metrics'.

Index	Category	Challenges, opportunities, demands and suggestions.	Pointed out by	Partially addressed by
1	a	Further studies should explore the impact of occupant behaviors and preferences.	(GAMERO-SALINAS et al., 2021; GONÇALVES et al., 2024; LI et al., 2019; RODRIGUES	(CRUZ; BASTOS, 2024; LI et al., 2019)

Index	Category	Challenges, opportunities, demands and suggestions.	Pointed out by	Partially addressed by
			et al., 2024; RUBIO-BELLIDO et al., 2017; TRIANA; LAMBERTS; SASSI, 2018; ZUNE; RODRIGUES; GILLOTT, 2020b)	
2	b	The lack of defined thermal neutrality in free-running buildings across certain regions limits thermal comfort research and affects overheating definitions.	(ALVES; GONÇALVES; DUARTE, 2021; GAMERO-SALINAS et al., 2021; ZUNE; RODRIGUES; GILLOTT, 2020b)	(ALVES; DUARTE; GONÇALVES, 2016)
3		Advanced ventilation systems such as displacement ventilation (underfloor air distribution) and mixed-mode operation will become more essential.	(ALVES; DUARTE; GONÇALVES, 2016; ALVES; GONÇALVES; DUARTE, 2021; ARUL BABU; SRIVASTAVA; RAI, 2024; GAMERO-SALINAS et al., 2021; HUGO, 2023; LIU et al., 2020b; RODRIGUES et al., 2024)	(DODOO; AYARKWA, 2019; LIU et al., 2020a; NUNES; GIGLIO, 2022)
4		Research should focus on enhancing passive strategies while preventing mold and condensation in various climate contexts.	(GAMERO-SALINAS et al., 2021; ZUNE; RODRIGUES; GILLOTT, 2020a, 2020b)	None

Studies show that occupants' behavior significantly affects building performance. Actions like opening a window can increase noise or security issues, undermining passive strategies and increasing HVAC dependence. Thus, merely elevating construction standards will not necessarily enhance comfort; it is essential to consider occupants' behavioral impact on ventilation and thermal comfort. Real progress lies in aligning improved building standards with behavioral insights. Furthermore, introducing new resilience indicators could deepen our understanding of occupant preferences and behavior, leading to better building designs, particularly in the GS.KRELLING et al., (2023, 2024) introduced a resilience assessment framework employing specific metrics over three stages: first, the resistance stage evaluates thermal autonomy, energy consumption, and indoor overheating; second, the robustness stage assesses failures and feature breakdowns using annual maximum operative temperature; and finally, the recovery stage measures function re-establishment time. However, a notable question remains: can studies using alternative metrics/definitions produce divergent construction guidelines? The absence of an accepted definition for thermal neutrality in free-running buildings across GS areas limits thermal comfort research and affects overheating characterization. For instance, research shows that giving occupants flexible control over their environment, through means like effective shading and ventilation, can greatly improve comfort levels. In addition, natural ventilation in the tropics faces challenges with hot and humid air, underscoring the need for advanced approaches and systems like displacement ventilation (underfloor air distribution) and mixed-mode operation. Finally, the role of relative humidity in thermal comfort requires further investigation. Future research should aim to enhance passive strategies to prevent mold and condensation, ensuring year-round comfort in various GS climates.

3.3.2.2 Future Horizon

BPS tools depend on weather files as vital inputs. While simulating building performance with historical weather data provides valuable insights, designing for future conditions is imperative (COLE; EVINS; EAMES, 2024; CRAWLEY; LAWRIE, 2019; ESCANDÓN et al., 2023; RODRIGUES; FERNANDES; CARVALHO, 2023). This caution stems from the impact of rising GHG emissions from human activities, which are altering climate trends. Taking this into account, the IPCC has developed various emissions scenarios within its Assessment Reports (AR) (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). These scenarios, presented in Table 17, project diverse potential futures based on different levels of GHG emissions, along with considerations such as population dynamics, economic trends, and technological advancements. Surprisingly, only two studies diverge from using the IPCC emission scenarios. Zune et al. (ZUNE; RODRIGUES; GILLOTT, 2020a, 2020b) utilized the Climate Risks in Myanmar report to predict future climate conditions.

Table 17. Description of IPCC emission scenarios by Assessment Report.

Index	AR	Emission scenarios	Description	Reference
1	AR1 (1990)	Scientific Assessment (SA)	• SA90: Initial attempts to model future emissions.	(IPCC, 1990)
2	AR2 (1995)	IPCC Scenario (IS)	• IS92a-f: Set of scenarios to model future emissions.	(IPCC, 1995)
3	AR3 + AR4 (2001-2007)	Special Report on Emissions Scenarios (SRES)	• A1*: Rapid growth, global population peaks mid-century and declines, rapid adoption of new efficient technologies (A1F1, A1B, A1T). • A2: Nations operate independently, sustain population growth, less focus on rapid economic development. • B1: Convergent world, global population like A1, rapid shift to service and information economy. • B2: Emphasis on local solutions for economic, social, environmental sustainability.	(IPCC, 2001, 2007)
4	AR5 (2014)	Representative Concentration Pathways (RCP)	• RCP2.6: Aims to keep global warming likely below 2°C above pre-industrial temperatures. • RCP4.5: Intermediate scenarios. • RCP6.0: Intermediate scenarios. • RCP8.5: A high greenhouse gas emissions scenario.	(IPCC, 2014)
5	AR6 (2021)	Shared Socioeconomic Pathways (SSP)	• SSP1: Sustainability – Prioritizing Green Path: Prioritizing sustainability, easing challenges in mitigation and adaptation. • SSP2: Middle Road: Continuation of trends with limited sustainability progress. • SSP3: Regional Rivalry – Rising Nationalism: Increased nationalism hinders mitigation and adaptation. • SSP4: Inequality – Divided Path: Growing inequalities pose challenges, especially for the poorest. • SSP5: Fossil-fueled Development – High-Speed Highway: Economic growth fueled by fossil fuels, driving high emissions.	(IPCC, 2023)

In general, weather predictions rely on Global Climate Models (GCMs) (RODRIGUES; FERNANDES; CARVALHO, 2023). These are highly complex computer programs that simulate interactions across various environmental elements such as the atmosphere, ocean, and land surface (CAMPAGNA; FIORITO, 2022). Numerous GCMs have been crafted by diverse climate research institutions globally, exhibiting differing levels of performance depending on the region and variable under examination (EYRING et al., 2016). GCMs furnish data at broad spatial (ranging from 50 km to 250 km) and temporal resolutions (between 6 hours to 1 day), thereby amplifying the ambiguity in model results (EYRING et al., 2019). Once validated with historical data, GCMs utilize IPCC emissions scenarios as starting points for forecasting (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). However, directly applying GCM outputs in BPS tools is discouraged due to their limited resolution and inherent data biases (RODRIGUES; FERNANDES; CARVALHO, 2023). To address this, methods for downscaling temporally and spatially GCM outputs have been developed (COLE; EVINS; EAMES, 2024). These techniques fall into two main categories: statistical (such as the stochastic or imposed offset method) and dynamical approaches, both capable of generating weather files suitable for BPS tools (CAMPAGNA; FIORITO, 2022).

While the stochastic and dynamical methods require significant computational resources, the statistical imposed-offset method, also known as the morphing method, is computationally efficient (COLE; EVINS; EAMES, 2024). It produces weather files consistent with historical observations, yet its usefulness for future projections may be hindered by limited data availability (BRACHT et al., 2024). Despite its efficiency, the morphing method has drawbacks, including its inability to account for the increasing severity and frequency of extreme weather events, tendency to overestimate extremes, inconsistencies in climate variable relationships, and limitations on applicability to weather records with similar baseline periods (RODRIGUES; FERNANDES; CARVALHO, 2023). However, for building resilience assessment, the morphing method remains a viable option (CAMPAGNA; FIORITO, 2022; ESCANDÓN et al., 2023; MACHARD et al., 2020). In addition, the Regional Climate Models (RCMs) are employed to refine the outputs of GCMs through dynamic downscaling, furnishing more granular insights into climate simulations and projections of climate change (BRACHT et al., 2024; CAMPAGNA; FIORITO, 2022). GCMs simulate Earth's climate globally with coarse resolution, capturing large-scale processes while RCMs focus on smaller areas with higher resolution. Therefore, the adoption of RCMs improves the simulation of mesoscale weather processes and enhances reliability (BRACHT et al., 2024). Yet, it can be computationally intensive, requiring large volumes of data and high levels of expertise, which limits accessibility to various stakeholders and the scientific community (KRELLING et al., 2024).

Furthermore, numerous engines facilitate the production of future weather data. **Table 18** provides a concise overview of these engines used in SLR articles, detailing their main features such as resources (IPCC report, emission scenarios, and future horizons), advantages and limitations.

Table 18. Description of prediction engines for future weather conditions: Resources, advantages, and limitations.

Tool	Resources	Advantages	Limitations	Reference
Climate Change World Weather File Generator	• III IPCC AR: SRES A2. • Morphing method. • Baseline (1961–1990). • Future horizon: 2020 – 2080. • CMIP2. • HadCM3 grid.	• Available at no cost (Free). • Details of its use are outlined in the user guide. • Morphs weather data from any global location.	• Outdated baseline and Emission scenario. • Utilizes two world grids with mismatched large resolutions. • No interpolation. averages nearest four grid points. • Does not determine the typical/extreme periods.	(GONÇALVES et al., 2024; NUNES; GIGLIO, 2022)

Tool	Resources	Advantages	Limitations	Reference
			• Closed implementation, no longer maintained.	
Meteonorm	• III IPCC AR: SRES A2 (v7). • V IPCC AR: RCP 2.6, 4.5 and 8.5 (v8). • Stochastic method. • Baseline (1961–1990). • Baseline (200–2019). • Future horizon: 2020 – 2100. • CMIP5.	• Easy user interface. • Platform independent. • Produces weather data from any global location.	• Available at a high cost. • Outdated baseline and emission scenarios.	(GAMERO-SALINAS et al., 2021; YU et al., 2023)
Future Weather Generator	• VI IPCC AR: SSP1, SSP2, SSP3 and SSP5. • Morphing method. • Baseline (1961–1990). • Future horizon: 2050 – 2080. • CMIP6. • EC-Earth3 grid.	• Available at no cost (Free). • Details of its use are outlined in the user guide. • Determine the typical/extreme periods. • Morphs weather data from any global location. • Open-source and cross-platform.	• Based only in GCM, RCM would increase the accuracy and discretization of the tool.	(RODRIGUES et al., 2023; RODRIGUES; PARENTE; FERNANDES, 2024)

Ultimately, the effectiveness of these approaches hinges on data availability and the proximity of weather stations. Data sourced from distant stations, often located outside urban centers, may not accurately reflect local conditions due to urban heat island effects (VERICHEV et al., 2021; VERICHEV; ZAMORANO; CARPIO, 2020). Alternative strategies include utilizing nearby stations, applying tools like the Urban Weather Generator (UWG) (KAMAL et al., 2023a), employing regression for missing data estimation, leveraging cloud cover data for solar radiation, and integrating satellite data (ALVES; GONÇALVES; DUARTE, 2021; KRELLING et al., 2024; ZUNE; RODRIGUES; GILLOTT, 2020a, 2020b).

3.3.2.2.1 SLR overview – Future Horizon

Figure 15 shows the overview in terms of the following categories: (a) Assessment Report, (b) Emissions scenarios, (c) Future horizons, and (d) Prediction method/engine from the selected articles during the SLR.

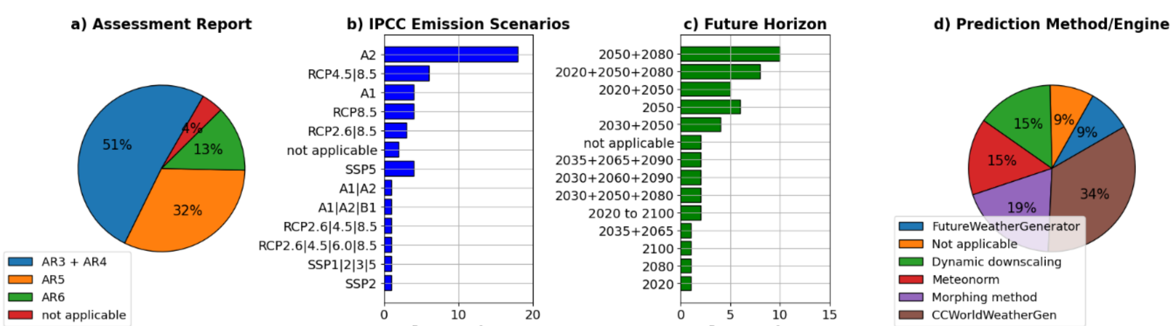


Figure 15. Overview of findings for the 'Future Horizon' section.

In **Figure 15**(a), it is evident that a significant proportion, approximately 51%, of studies rely on AR3 and AR4 as their primary references. This preference aligns logically, with AR6 being the latest publication by the IPCC, therefore, appearing last in the ranking. **Figure 15**(b) provides insights into the combinations and specific IPCC emissions scenarios utilized. Notably, approximately 65% of studies opt to assess only one emission scenario, while the remaining 35% examine results across multiple projections. Among the individual scenarios, A2, A1, and RCP8.5 emerge as the most prevalent, representing approximately 38%, 11%, and 10%, respectively. The prevalent combination of scenarios observed is RCP4.5 and RCP8.5. Surprisingly, despite the potential for more precise predictions in newer ARs, none of the studies opted to blend IPCC emissions scenarios from various reports. This could be interpreted as a research gap, given the relevance of evaluating diverse climate projections. **Figure 15**(c) sheds light on the combinations and specific future horizons evaluated. A notable trend is that the majority of studies, approximately 76%, opt to assess more than one period, indicating a comprehensive approach. Among studies focusing on a single horizon, the year 2050 emerges as the most commonly evaluated, featured in 62% of cases. As for combinations, the years 2020, 2050, and 2080 stand out, comprising 20% of studies that analyze multiple future horizons. Additionally, **Figure 15**(d) depicts the methods/engines employed to transform climate data into future projections. Notably, CCWorldWeatherGen tool and morphing method emerge as the preferred engine/method, utilized in 33% and 21% of cases, respectively. An ideal tool ought to be cost-free, accessible, adaptable across various platforms, customizable, and easy to maintain. However, the popularly mentioned tools fail to meet these criteria entirely. One potential solution is the proposed Future Weather Generator tool, which is currently only discussed in a few studies (RODRIGUES; FERNANDES; CARVALHO, 2023).

3.3.2.2.2 Research gaps – Future Horizon

Table 19 summarizes the challenges, opportunities, demands, and suggestions identified in the selected SLR articles related to this section on ‘Future Horizon’. In addition, research gaps that have been partially addressed by existing studies are highlighted and categorized into two different contexts: a) Future weather predictions and b) Regulations, building codes and standards.

Table 19. Research gaps pointed out and partially addressed related to ‘Future Horizon’.

Index	Category	Challenges, opportunities, demands and suggestions.	Pointed out by	Partially addressed by
1	a	Investigating the future weather predictions across different IPCC emission scenarios is essential.	(ALVES; DUARTE; GONÇALVES, 2016; ARUL BABU; SRIVASTAVA; RAI, 2024; CALLEJAS et al., 2021; FILIPPÍN et al., 2017; KAMAL et al., 2023a; LI et al., 2019; LIU et al., 2020a; NUNES; GIGLIO, 2022; RODRIGUES; PARENTE; FERNANDES, 2024; YAN; JI; YAN, 2022b)	(ARUL BABU; SRIVASTAVA; RAI, 2024; BORBON-ALMADA et al., 2020; BRACHT et al., 2024; HUANG; HWANG, 2016; LIU et al., 2020b, 2020a; SILVERO et al., 2019; VERICHEV et al., 2021; VERICHEV; ZAMORANO; CARPIO, 2020; XIONG et al., 2023; YU et al., 2023; ZOU et al., 2021b)

Index	Category	Challenges, opportunities, demands and suggestions.	Pointed out by	Partially addressed by
2		Analyzing and combining various Global Climate Models (GCMs) and Regional Climate Models (RCMs) will enhance the reliability of future climate predictions.	(ARUL BABU; SRIVASTAVA; RAI, 2024; KAMAL et al., 2023a; LI et al., 2023b; RODRIGUES; PARENTE; FERNANDES, 2024)	(ARUL BABU; SRIVASTAVA; RAI, 2024; BRACHT et al., 2024; LIU et al., 2020b, 2020a; ZOU et al., 2021b)
3		Accuracy of climate-resilient building design relies on the quality of current weather data.	(ARUL BABU; SRIVASTAVA; RAI, 2024; RODRIGUES; PARENTE; FERNANDES, 2024)	None
4		Future research should explore the impacts of urban morphology, microclimate, heatwaves, and urban heat island effects on building performance.	(GUARDA et al., 2020; LIU et al., 2020b, 2020a; RODRIGUES; PARENTE; FERNANDES, 2024)	(ALVES; DUARTE; GONÇALVES, 2016; ALVES; GONÇALVES; DUARTE, 2021; GONÇALVES et al., 2024; HWANG; LIN; HUANG, 2017; KRELLING et al., 2024)
5		Adopting a probabilistic approach would strengthen results by recognizing climate data variability.	(ARUL BABU; SRIVASTAVA; RAI, 2024)	None
6	b	Policymakers need to update regulations to address the escalating climate change risks.	(ALVES; DUARTE; GONÇALVES, 2016; FILIPPÍN et al., 2017; RODRIGUES et al., 2023; RODRIGUES; PARENTE; FERNANDES, 2024; ROUAULT et al., 2019; SILVERO et al., 2019; WANG et al., 2022; YAN; JI; YAN, 2022b; YU et al., 2023)	(YU et al., 2023)
7		Applying a social housing prototype nationwide without considering local climate differences is inadequate.	(FLORES-LARSEN; FILIPPÍN; BAREA, 2019)	None

Given the uncertainties of future weather conditions, it is imperative to assess various projections combined with different urban morphologies, heatwaves, and urban heat island effect. For example, the ensemble of weather files generated from diverse climate model projections should be utilized to evaluate associated uncertainties. Considering the vast array of possibilities, adopting a probabilistic approach is recommended to explore the diverse IPCC emission scenarios derived from different Assessment Reports, as well as from various GCMs and RCMs. Furthermore, access to reliable climate data is paramount to support research efforts. However, limitations in certain GS regions hinder data availability, impeding the scientific community's ability to address climate change and slowing scientific progress. Nonetheless, this data scarcity underscores the importance of shaping new construction regulations in these regions. Within this discussion, public policies should address climate change-induced overheating risks by moving away from a one-size-fits-all regulatory approach. Implementing a social housing prototype nationwide without accounting for local climate nuances proves inadequate. Hence, a viable alternative involves developing nationwide tools freely accessible to support building design while considering local climate variations and escalating climate change risks.

3.3.2.3 Analysis Settings

As mentioned earlier, in the resilience modeling workflow, the main objective is typically to formulate climate adaptation and mitigation strategies for building design. This involves identifying design variables that enhance building resilience by decreasing vulnerability and increasing resistance, with a focus on optimizing one or more metrics, which may need to be minimized or maximized based on different constraints. Often, this process yields multiple optimal solutions, requiring a trade-off between adaptation and mitigation strategies.

In BPS studies, automation strategies are frequently employed to streamline the evaluation process. BPS tools are often integrated with automation software such as MATLAB and jEPlus (CRUZ; BASTOS, 2024; GONÇALVES et al., 2024), or programming languages like Python and R (LI et al., 2023b; YAN; JI; YAN, 2022b). This integration significantly enhances the efficiency of exploring various design variables during the building design process. According to the selected SLR articles, three analysis approaches were identified: parametric analysis, sensitivity analysis, and optimization. **Table 20** effectively summarizes the advantages, limitations, and recommendations for each approach.

Table 20. Description of different analysis approaches.

Approach	Advantages	Limitations	Recommendations	Reference
Parametric analysis	• Flexibility: Allows for the examination of how changes in parameters affect outcomes. • Comprehensiveness: Can cover a wide range of scenarios by varying key parameters.	• Time-consuming: Requires multiple runs, which can be computationally expensive. • Data Overload: Can generate large amounts of data, making it difficult to interpret results.	• To employ data management techniques to organize and analyze results effectively.	(CRUZ; CUNHA, 2022; LI et al., 2019; TRIANA; LAMBERTS; SASSI, 2018)
Sensitivity analysis	• Prioritization: Helps identify which parameters most significantly influence the performance. • Resource Efficiency: Focuses efforts and resources on the most impactful variables.	• Complexity: Can be complex to set up. • Assumption Based: Often depends on assumptions about parameter independence and linearity which may not hold.	• To use robust statistical tools to interpret the results. • To ensure a clear understanding of interactions between parameters.	(GAMERO-SALINAS et al., 2021; HWANG; LIN; HUANG, 2017; LIU et al., 2020a; NUNES; GIGLIO, 2022; ZOU et al., 2021b)
Optimization	• Target-Oriented: Seeks the best possible solution according to specified criteria. • Cost-Effective: Optimizes resources and operational costs in the design and development phases.	• Complexity and Cost: Can be a complex and costly simulation approach due to computational needs. • Solution limitation: May converge on local optima rather than global optima, depending on the algorithm used.	• To employ advanced algorithms that are capable of escaping local optima.	(CRUZ; BASTOS, 2024; GONÇALVES et al., 2024; LI et al., 2023b; YAN; JI; YAN, 2022b)

A promising alternative among the selected articles is optimization based on surrogate models (LI et al., 2023b; LÓPEZ-GUERRERO et al., 2024; YAN; JI; YAN, 2022b). These models, also known as meta, statistical, or response surface approximation models, initially learn the relationship between the input and output variables by analyzing previously recorded data, and subsequently, mimic the behavior of the original model to quickly predict the outputs according to the newly-given inputs with high accuracy (WESTERMANN; EVINS, 2019). Furthermore, the surrogate model can be combined with an optimization algorithm for performing several evaluations (LI et al., 2023b; LÓPEZ-GUERRERO et al., 2024; YAN; JI; YAN, 2022b). Instead of coupling a BPS tool with an automation platform (CRUZ; BASTOS, 2024; GONÇALVES et al., 2024), the surrogate model can replace the simulation engine to streamline design optimization and minimize computational expenses (WESTERMANN; EVINS, 2019). In this new approach, the simulation tool primarily generates a database that will be used by a machine learning algorithm to develop the surrogate model(LÓPEZ-GUERRERO et al., 2024). Then, this surrogate model is integrated with a multi-objective optimization algorithm to find the optimal design solution (CRUZ et al., 2024a). In this context, Yan et al. (YAN; JI; YAN, 2022b) utilized a transfer learning technique to predict the performance of multiple building typologies while boosting computational efficiency throughout their study. The transfer learning technique allows the effective retraining of the machine learning model with a new dataset of a distinct architectural model, while the model preserves the fundamental knowledge derived from the data of the prior building. In other words, transfer learning is a machine learning approach where the knowledge obtained from training on one task is employed to enhance learning and performance on a separate, related task, often by reusing pre-existing models or learned representations (KO; PARK, 2021a; LI et al., 2021).

Furthermore, design variables are parameters or attributes that directly impact a building's performance. These variables usually encompass architectural, mechanical, and electrical aspects of the building's design. While some authors categorize design variables into separate mitigation and adaptation strategies, the IPCC emphasizes their interconnected nature (BAI et al., 2022). In addition, other variables can also influence the assessment and interpretation of building performance, often referred to as uncertainty parameters. They can lead to variations in energy demand and thermal comfort, reflect occupant preferences, and influence the development of optimal construction guidelines (EISENHOWER et al., 2012). These parameters identified in the SLR, can be categorized into two main groups (excluding those related to future weather predictions): system settings and occupant behavior. The system settings category includes: 1) Pre-cooling approach, where HVAC systems are activated one hour before occupancy (KRELLING et al., 2024); 2) HVAC setup, which refers to different setpoint temperatures and the availability of mixed operation mode (CRUZ; BASTOS, 2024; KRELLING et al., 2024); and 3) Ventilation availability, which denotes varying schedules for ventilation accessibility (CRUZ; BASTOS, 2024; FILIPPÍN et al., 2017; HU et al., 2024). The occupant behavior category includes: 1) Occupancy patterns, which denote variations in the timing and duration of occupancy throughout the day (CRUZ; BASTOS, 2024; LI et al., 2019); 2) Occupancy density, referring to fluctuations in the number of occupants present (FILIPPÍN et al., 2017); and 3) Thermal comfort standards, indicating variations in the acceptable range of comfort temperatures (ALVES; DUARTE; GONÇALVES, 2016; CRUZ; CUNHA, 2022; RUBIO-BELLIDO et al., 2017).

The SLR articles span five performance dimensions—energy, comfort, cost, daylighting, and carbon emissions. Energy is typically related to HVAC system energy demand, while discomfort hours are normally assessed using thermal comfort standards, which define acceptable temperature ranges for occupants. Construction costs are usually measured using Life Cycle Cost Analysis (LCCA). Studies examining daylighting illuminance typically focus on useful daylight illuminance (UDI), which measures the percentage of occupied hours annually with daylight levels ranging from 100 to 3000 lux, ensuring spaces are neither too dim nor too bright (YAN; JI; YAN, 2022b). Finally, carbon emissions are usually measured by a global warming indicator expressed in $kgCO_2eq$, which refers to GHG emissions. Most of the studies focus solely on carbon emissions from a building's energy consumption, converting energy demand (normally expressed in kWh) into $kgCO_2eq$ using a specific factor (ARAB; FARROKHZAD; HABERT, 2021; BORBON-ALMADA et al., 2020; KRISTIANSEN et al., 2021). However, Verichev et al. (2021) extended their analysis to include emissions from additional phases such as material production, transportation, and the construction and demolition stages. These broader evaluations (also known as "cradle to grave") employ a Life Cycle Assessment (LCA) to capture the full impact. **Figure 16** is a heatmap summarizing the envelope design variables considered across different metrics (objective functions) and their respective frequencies in the SLR articles. It highlights the proportion of studies that employed each design variable for each objective function. The count of studies associated with each objective function is displayed on the right, next to the corresponding labels.

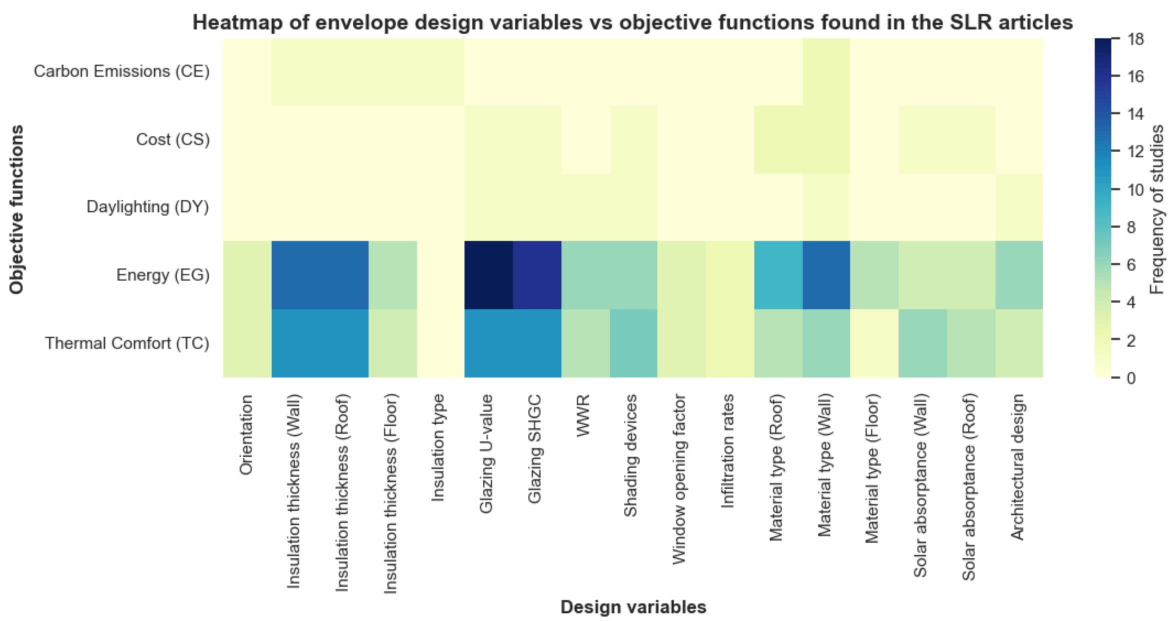


Figure 16. Heatmap showing the relationship between envelope design variables and objective functions.

The heatmap reveals that design variables such as insulation thickness (Wall and Roof) and glazing properties (U-value and SHGC) are the main features for popular objective functions such as energy consumption and thermal comfort. However, their high costs make them unlikely to be implemented in practice, highlighting the incompatibility of many evaluated envelope variables. Future investigations should prioritize building design possibilities within the GS context that are more realistic and feasible. Still, it is important to highlight studies that evaluate unconventional or innovative construction systems, as well as those particularly popular in specific GS regions. These systems are hidden in the heatmap. Thus, **Table 21** lists these construction systems, providing a concise technical description along with key findings.

Table 21. Overview of unconventional, innovative, and particularly popular construction systems.

Index	Construction systems	Description	Key findings	References
1	• Cool roofs/walls	• Coating/Painting material designed to reflect more sunlight and absorb less heat. • It reduces heat transfer into buildings, lowering indoor temperatures while reducing the need for air conditioning.	In future climates, applying cool coating/painting in the building's envelope may require additional passive strategies for optimal thermal comfort. (Climates: Cfa and Cwa)	(HUGO, 2023; KRELLING et al., 2024)
2	• Dry wall systems	• Panels made from gypsum plaster pressed between layers of paper. • It offers easy installation, fire resistance, and sound insulation.	In both current and future climates, buildings constructed with traditional materials exhibit higher energy consumption and carbon emissions. (Climate: BSk)	(ARAB; FARROKHZAD; HABERT, 2021)
3	• Structural Concrete Insulated Panels (SCIP) • Insulated Concrete Form (ICF)	• Thick layer of foam insulation sandwiched between two layers of concrete (SCIP). • Modular units, made of insulating materials, stacked and filled with concrete (ICF). • It offers rapid construction, structural elements, and improved energy efficiency.	The SCIP/ICP strategy promises energy mitigation by reducing consumption and enhancing indoor thermal comfort in future weather conditions. (Climate: Aw)	(CRUZ; CUNHA, 2022)
4	• Thatched roofs with gable vents • Raised floors	• Thatched roofs with ventilated attic spaces bring insulation to prevent intense solar radiation while facilitating air exchange. • Raised floors protect against floods, prevent moisture penetration, allow ventilation through floor cracks, and reduce radiated heat gain from hot, dry ground.	Traditional houses featuring thatched roofs with gable vents, and raised floors may encounter challenges in maintaining indoor thermal comfort under future weather conditions. (Climates: Am, Aw and Cwa)	(ZUNE; RODRIGUES; GILLOTT, 2020a, 2020b)
5	• Cellular concrete (foam or aerated concrete)	• Modular unit composed of cement, water, and a foaming agent. • It offers lightweight properties and thermal insulation.	The unit could lower energy consumption in future climates, highlighting the need to promote lightweight materials for mitigating climate change. (Climates: BWh, Dwa, and Cfa)	(BORBON-ALMADA et al., 2020; HU et al., 2024)
6	• Shipping containers	• Standardized metal box used for transporting goods across long distances via ships, trucks, and trains. • When used as a shelter/building, it offers high durability, affordability, and modularity.	In future weather conditions, containers equipped with advanced ventilation control strategies can enhance thermal comfort while reducing heating demands. (Climate: Cfa)	(KRISTIANSEN et al., 2021)

Index	Construction systems	Description	Key findings	References
7	• Bermed Earth-Sheltered Walls	• Construction technique where walls are underground/covered with earth. • This method offers: thermal stability, durability, and noise reduction.	When combined with other passive strategies serves as a climate-responsive approach for addressing global warming effects. (Climate: Aw)	(CALLEJAS et al., 2021)

The combination of various design variables can lead to three distinct types of interactions between adaptation and mitigation strategies: co-benefits or synergies, conflicts, and trade-offs. Co-benefits or synergies occur when implementing an adaptation measure also results in additional mitigation gains, or vice versa. Conflicts arise when two measures are incompatible, making simultaneous implementation impractical. Trade-offs occur when implementing an adaptation measure leads to negative effects on mitigation, or vice versa (HAMIN; GURRAN, 2009; XU et al., 2019). When addressing trade-offs in building design, often referred to as resolving conflicting objectives (metrics), several approaches can be employed. These include: 1) Subjective selection based on the priorities, preferences, and expertise of stakeholders involved in building design; 2) Weighted sum, where the problem is transformed into a single objective by assigning weights to each objective; 3) Constraint-based methods, which focus on solutions that meet defined constraints or acceptable thresholds set by decision-makers; and 4) Multi-criteria decision methods (MCDM) (EVINS, 2013; MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). One prominent MCDM method is the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which ranks alternatives based on their proximity to an ideal solution and their distance from a negative ideal solution (SHIH; SHYUR; LEE, 2007; YANG; CHEN; HUNG, 2007). Another widely used MCDM approach is the Analytic Hierarchy Process (AHP), which structures decision problems hierarchically and uses pairwise comparisons to derive weights for criteria and alternatives (BRUNELLI, 2015). These approaches help decision-makers select the optimal solution based on varying preferences and priorities.

Although MCDMs provide frameworks to assess complex building design alternatives across criteria like energy efficiency, thermal comfort, and environmental impact, none of the SLR articles applied MCDM to perform a trade-off between adaptation and mitigation. The most common approaches identified in the SLR include subjective selection (CRUZ; BASTOS, 2024), comparison of optimal solution configurations for each metric (objective function) (GONÇALVES et al., 2024), and investigation of Pareto front settings (LI et al., 2023b; YAN; JI; YAN, 2022b). For instance, Gonçalves et al., (2024) evaluated optimal solutions using three distinct approaches: minimizing costs, maximizing benefits, and optimizing cost-benefit ratios. The cost-minimization approach prioritizes solutions with minimal construction investments. The benefit-maximization approach emphasizes achieving the highest comfort levels. Lastly, the cost-benefit optimization approach aims to balance costs against average comfort levels among the optimal solutions.

3.3.2.3.1 SLR overview – Analysis settings

Figure 17 shows the overview in terms of the following categories: (a) analysis approaches, (b) design variables' categories, (c) objective functions, (d) trade-off procedure from the selected articles during the SLR.

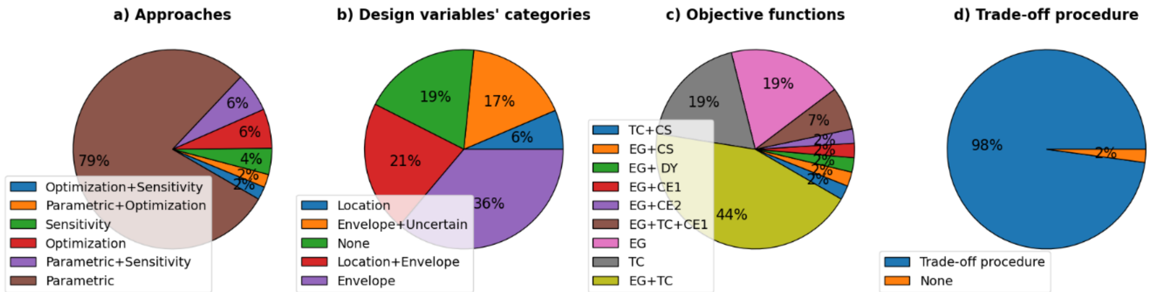


Figure 17. Overview of findings for the 'Analysis Settings' section, illustrating the distribution of approaches, design variable categories, objective functions, and the prevalence of trade-off procedures.

Figure 17(a) illustrates the analysis approaches used in the studies, with parametric analysis being the most prevalent at approximately 76%. However, optimization offers a more efficient way to explore a broader range of variables and conduct robust studies. Best practices involve starting with a sensitivity analysis to identify key variables and streamline the optimization process by eliminating redundancies. Despite these benefits, only 4% of studies incorporate optimization, and only one study combines sensitivity analysis with optimization. Figure 17(b) highlights that envelope-related categories dominate the studies, accounting for 74%. This focus aligns with goals extending beyond resilience to include strategies for climate adaptation and mitigation. Nevertheless, about 26% of studies adopt a narrower scope, focusing solely on climate projections (expressed as "none" in the graph) and/or diverse locations. Accurately predicting increased energy consumption is crucial for discussions on grid failure/overload and national energy supply. While these predictions are valuable, studies should not be confined to these uncertainty analyses due to the potential for significant contributions in related climate-resilient building design discussions. Furthermore, as noted in section 3.1, the majority of studies focus solely on energy demand and thermal comfort indicators. Less than 14% of studies address carbon emissions, revealing a significant scientific gap given the close relationship between carbon emissions due to energy-intensive materials and mitigation efforts. In other words, nearly 90% of the studies focus solely on adaptation strategies for climate change, neglecting mitigation efforts. Figure 17(c) distinguishes between studies considering emissions solely from energy consumption (CE_1) and those accounting for emissions across all stages of material production (CE_2). Surprisingly, only one study conducted a Life Cycle Assessment (LCA) (VERICHEV et al., 2021), further highlighting the limited consideration of carbon emissions and mitigation efforts in the current research field. Lastly, Figure 17(d) lists studies that employed a trade-off procedure, with only one study using a method to select the preferred solution from available design options.

3.3.2.3.2 Research gaps – Analysis Settings

Table 22 summarizes the challenges, opportunities, demands, and suggestions identified in the selected SLR articles related to this section on 'Analysis Settings'. In addition, research gaps that have been partially addressed by existing studies are highlighted and categorized into two different contexts: a) Analysis method and b) Building design.

Table 22. Research gaps pointed out and partially addressed related to 'Analysis Settings'.

Index	Category	Challenges, opportunities, demands and suggestions.	Pointed out by	Partially addressed by
1	a	Future study should incorporate uncertainty analysis into the design decision support process.	(BRACHT et al., 2024)	None
2	a	Incorporating optimization approaches in future studies could greatly improve the building design.	(GUARDA et al., 2020; LIU et al., 2020b, 2020a; TRIANA; LAMBERTS; SASSI, 2018)	(CRUZ; BASTOS, 2024; GONÇALVES et al., 2024; LI et al., 2023b; YAN; JI; YAN, 2022b)
3	a	Further research should discuss machine learning models combined with optimization algorithms.	(YAN; JI; YAN, 2022b)	(LI et al., 2023b)
4	a	While applying trained predictive models to multiple building types through transfer learning is feasible, their scalability remains constrained.	(YAN; JI; YAN, 2022b)	None
5	b	Future research should explore diverse and complex building typologies in new locations for a realistic representation of architectural variety.	(ARUL BABU; SRIVASTAVA; RAI, 2024; FLORES-LARSEN; FILIPPÍN; BAREA, 2019; GUARDA et al., 2020; KAMAL et al., 2023a; LI et al., 2023b; LIU et al., 2020b; NUNES; GIGLIO, 2022; RODRIGUES et al., 2023, 2024; RODRIGUES; PARENTE; FERNANDES, 2024; TRIANA; LAMBERTS; SASSI, 2018)	(KRELLING et al., 2024)
6	b	Performing a life cycle assessment (LCA) offers a broader perspective on environmental impacts and decarbonization concerns in the built environment.	(BORBON-ALMADA et al., 2020; CALLEJAS et al., 2021; DODOO; AYARKWA, 2019; GAMERO-SALINAS et al., 2021; KRISTIANSEN et al., 2021; LI et al., 2023b; NUNES; GIGLIO, 2022; RODRIGUES et al., 2024; TRIANA; LAMBERTS; SASSI, 2018)	(VERICHEV et al., 2021)
7	b	Conducting a Life Cycle Cost Analysis (LCCA) to compare adaptation investments against energy savings and thermal comfort improvements, aiming to assess the payback period.	(BORBON-ALMADA et al., 2020; CALLEJAS et al., 2021; GAMERO-SALINAS et al., 2021; LI et al., 2023b; RODRIGUES et al., 2024; SUO et al., 2023; TRIANA; LAMBERTS; SASSI, 2018)	(GONÇALVES et al., 2024; LI et al., 2023b)
8	b	A paradigm shift in building design and the mindset of designers and engineers is necessary to incorporate adaptation and mitigation issues.	(ALVES; DUARTE; GONÇALVES, 2016; LIU et al., 2020a; RODRIGUES et al., 2023)	None
9	b	The increased energy demand from climate change underscores the challenges for zero energy buildings.	(GUARDA et al., 2020; KHALFAN; SHARPLES, 2016; KRISTIANSEN et al., 2021)	None
10	b	Conducting field tests would validate the practical benefits of the climate-resilient building design.	(CALLEJAS et al., 2021; HUGO, 2023; LI et al., 2023b)	(KRISTIANSEN et al., 2021; LI et al., 2019)

Future simulation studies should integrate uncertainty and sensitivity analyses with optimization techniques into the design process to surpass parametric analysis limitations and improve building designs. Employing machine learning alongside optimization algorithms can make the design process more efficient and reduce computational costs. Transfer learning proves scalable and effective when design parameters across building types remain consistent or building performance goals are unchanged, facilitating the exploration of varied and complex building typologies in new locations for an accurate illustration of architectural diversity. Unfortunately, there are limitations to this technique for multiple building types. For instance, the predictive performance of transfer learning may deteriorate when the design parameters of various building types differ significantly or when the building performance metric change. For instance, Rodrigues et al. (RODRIGUES et al., 2023, 2024; RODRIGUES; PARENTE; FERNANDES, 2024) applied the EPSAP algorithm as alternative to generate diverse building geometries. Furthermore, incorporating LCA and LCCA into climate-resilient studies can enhance decarbonization of the built environment and evaluate the feasibility of technologies in the Global South. The impact of climate change on building design necessitates a paradigm shift in design approaches and designer mindset, emphasizing the importance of identifying the relationships between passive design elements and building energy efficiency. This approach empowers architects to apply these strategies more effectively from the early stages of design.

3.4 Discussions

3.4.1 Synergies and disparities compared to previous work

In this section, the authors critically examine and compare findings from prior literature reviews to identify synergies and underscore disparities with the current study. The previous review studies reveal several synergies, primarily emphasizing the urgent need for resilience research on Global South cities (CAMPAGNA; FIORITO, 2022; SHARIFI, 2020), while also highlighting that certain climates have been under-evaluated (STAGRUM et al., 2020). Moreover, there is a growing need to adapt public policies, as delays caused by urban infrastructure inertia could lead to irreversible and undesirable outcomes (SHARIFI, 2020). For instance, updating housing laws based on future weather predictions could introduce new regulations, enhance comfort, and exceed minimum standards, thus leading to climate-resilient building design (HONG et al., 2023).

In summary, the following main synergies are identified:

- **From a methodological perspective:** Common findings include reliance on outdated weather data, use of obsolete emission scenarios from old IPCC Assessment Reports, and prevalent use of the morphing method to generate future weather files for simulation tools (CAMPAGNA; FIORITO, 2022).
- **From a practical perspective:** Occupant participation in resilience strategies is widely recognized as dependent on an understanding of local social conditions and demographic factors influencing engagement (SIU et al., 2023). Elements like community cohesion, economic stability, and age influence occupants' willingness and ability to engage, making it essential to tailor strategies to each community’s unique needs.
- **From a computational perspective:** there is a pressing need for automation tools capable of accommodating diverse emission scenarios (SIU et al., 2023; YASSAGHI; HOQUE, 2019), managing extensive output data volumes (SIU et al., 2023), and applying probabilistic methods to address high levels of uncertainties (YASSAGHI; HOQUE, 2019).

On the other hand, previous studies also reveal significant disparities, highlighting that many cities in the Global North are creating action plans to address climate change adaptation and mitigation (SHARIFI, 2020), with discussions on trade-offs being relatively well-established (SHARIFI, 2020; YASSAGHI; HOQUE, 2019).

In summary, the following main disparities are identified:

- **From the AEC industry perspective:** Establishing comprehensive metrics, data sharing systems, and labeling systems is crucial to quantify resilience, facilitate benchmarking, and enhance communication across diverse stakeholders (HONG et al., 2023).
- **From a software perspective:** the development of new tools should involve collaboration between building modelers, researchers, and stakeholders to ensure integration of best practices, accompanied by clear guidance for interpreting results and acknowledging simulation methodology limitations in graphical and analytical outputs (SIU et al., 2023).
- **From a conceptual perspective:** A significant challenge in resilience research is defining the optimal level required, tailored to location-specific needs and associated costs. Resilience demands vary by factors like local climate, socioeconomic conditions, and exposure to environmental risks, which influence feasibility and effectiveness (HONG et al., 2023). While studies often address cost and feasibility concerns, few provide precise benchmarks or clear resilience requirements, leaving uncertainty in determining adequate levels of long-term planning.

3.4.2 Future research directions and suggestions for policy makers

Here, the authors provide a concise summary of the key synergies between these research gaps found in the SLR, emphasizing their significance as valuable directions for future research in the field. Here are issues and debates deemed more important in this research field today:

- Expanding and diversifying climate resilience studies for residential buildings in the Global South across different locations, architectural typologies, and operational modes is critical. National-level assessments would significantly elevate the quality and impact of these studies, informing evidence-based public policies for diverse weather contexts. Despite single-family homes being predominant, urban centers increasingly feature verticalization. Hence, it is essential to diversify architectural designs and assess whether findings are universally applicable across different building types. Additionally, examining various operational modes is vital. While natural ventilation is favored, constraints such as infrastructure and financial limitations often limit reliance on HVAC systems. Thus, exploring both operational modes can uncover energy-saving opportunities, reduce dependence on artificial systems, and enhance living standards in emerging economies.
- Diversifying resilience metrics can broaden the perspective of the scientific community and simultaneously challenge the prevailing norms. Therefore, from a scientific perspective, the exploration of diverse and novel metrics should be prioritized in new studies. Specifically, it is important to understand whether studies using alternative metrics/definitions lead to conflicting conclusions or divergent construction guidelines. Introducing new resilience indicators could deepen our understanding of resilience, ultimately leading to more effective building designs, especially in Global South regions. From a regulatory and policy perspective, certain standardized metrics such as thermal autonomy, degree hours, overheating degree, energy consumption, and peak energy demand should be prioritized. This approach will promote their widespread adoption and understanding within the AEC industry (stakeholders).
- To delve into the dynamics of occupants' behavior in resilience studies, it is crucial to incorporate probabilistic models for occupancy patterns, window openings, and the control

of lighting and HVAC systems. Factors such as limitations on opening windows can compromise passive strategies and lead to greater dependence on HVAC systems. From the perspective of policymakers, simply raising construction standards may not effectively enhance comfort. It is crucial to recognize the impact of occupants' behavior on thermal comfort. Real progress lies in integrating enhanced building design standards with insights into occupant behavior. Therefore, new simulation studies necessitate the inclusion and exploration of these dynamics through complex probabilistic approaches to effectively support the development of new regulations and standards.

- To effectively address uncertainties in future weather conditions, it is crucial to assess multiple climate projections, ensure access to reliable climate data, develop new public policies based on future scenarios, and establish nationwide tools that are freely accessible to support climate-resilient building design. New studies should integrate emissions scenarios from various IPCC Assessment Reports and assess their uncertainties and impacts using an ensemble of weather files generated from diverse Global Climate Models and Regional Climate Models. In addition, it is imperative to assess projections combined with different urban morphologies, heatwaves, and the urban heat island effect. Access to reliable climate data is essential for supporting research efforts. However, data limitations in certain regions of the Global South hinder progress in addressing climate change. Lastly, public policies should mitigate overheating risks by moving away from a one-size-fits-all approach for social housing prototypes, instead implementing nationwide tools that consider local climate variations and support better building design.
- Climate resilience studies for Global South residential buildings should advance beyond unsuitable envelope variables, integrating sophisticated approaches such as optimization based on machine learning models and employing transfer learning methods, while also incorporating comprehensive assessments like Life Cycle Assessment (LCA) and Life Cycle Cost Analysis (LCCA) to ensure holistic sustainability across the buildings' lifespan. It is imperative to investigate envelope design variables that are realistic and feasible within the GS context. Future simulation studies should incorporate uncertainty and sensitivity analyses with optimization techniques to overcome limitations of parametric analysis and enhance building designs. By employing machine learning alongside optimization algorithms, the design process can become more efficient and cost-effective, while transfer learning offers scalability and effectiveness, enabling the exploration of various complex building typologies. Finally, integrating LCA and LCCA into climate-resilient studies is indispensable for advancing decarbonization efforts in the built environment and evaluating the sustainability and feasibility of technologies specifically in the Global South.

3.5 Conclusion

This paper presents a Systematic Literature Review (SLR) on resilience assessment of residential buildings located in the Global South (GS) using future weather file predictions within building performance simulation (BPS) tools. By analyzing 47 documents, key findings reveal a growing research field led by Brazil and China. Studies predominantly focus on humid subtropical, tropical savanna, and monsoon-influenced climates, emphasizing single-family homes with limited architectural diversity. Performance dimensions include energy, thermal comfort, cost, daylighting, and carbon emissions. Operation modes focus primarily on natural or mechanical ventilation separately, rather than in an integrated manner, with common evaluation metrics including degree-hours, energy demand, and operative temperature. Outdated IPCC emission scenarios from Assessment Reports 3 and 4 are the main references, whereas CCWorldWeatherGen software and the morphing method are the preferred tool/method for future weather file predictions. Parametric analysis dominates analysis settings. While many studies assess envelope strategies for climate-resilient design, few focus solely on climate projections or specific locations. Surprisingly, nearly all studies exclusively address adaptation strategies, overlooking mitigation efforts. Furthermore, this study aims to address two pivotal questions: (1) What are the research trends, main challenges, and opportunities in resilience modeling for climate adaptation and mitigation in GS residential buildings? (2) What lies ahead regarding the future performance of GS residential buildings amid climate change?

The answer to the first question reflects a solid scientific perspective. While there are notable insights, it is clear that the GS scientific community are still in the early stages of climate-resilient building design. This study offers suggestions for policymakers and identifies areas needing further research. From a policymakers' point of view, certain standardized metrics such as thermal autonomy, degree hours, overheating degree, energy consumption, and peak energy demand should be prioritized to promote their widespread adoption and understanding within the AEC industry. In fact, both private and public banks and investment funds that finance new residences in the Global South should use these metrics as key indicators to not only sponsor new construction but also support climate-resilient developments. Furthermore, public policies should mitigate overheating risks by moving beyond one-size-fits-all social housing approaches and implementing nationwide tools to support of climate-resilient building design. From an academic point of view, future research should conduct national-level assessments for diverse urban architectural typologies and operation modes to support as many climate contexts as possible, provide suitable findings for the urban built environment, and uncover energy-saving opportunities while enhancing living standards in emerging economies. Introducing new indicators could deepen scientific understanding of resilience, leading to more effective GS building design. Still, it is crucial to assess how different metrics can influence our understanding of building performance. Furthermore, new studies should integrate the dynamics of occupants' behavior into resilience assessments, as they play a crucial role in improving the indoor thermal comfort. Research using diverse Global Climate Models and Regional Climate Models for developing ensemble future weather files are essential as well as ensuring reliable access to climate data across all GS regions. Finally, future robust studies should effectively explore the trade-off between adaptation and mitigation in construction systems. Optimization, machine learning and transfer learning techniques, Life Cycle Assessment (LCA), and Life Cycle Cost Analysis (LCCA) are indispensable for advancing decarbonization efforts and evaluating technology feasibility in the built environment.

The answer to the second question reveals that current construction practices in the Global South lack the resilience needed to adapt to future climate conditions, resulting in increased discomfort in naturally ventilated buildings and heightened reliance on artificial systems due to extreme outdoor temperatures. However, several studies demonstrate that optimizing passive design strategies can enhance resilience and effectively adapt to future climate conditions. Thus, adjustments to current construction practices can foster climate-resilient design, providing both the public and private sectors with an opportunity to sponsor new construction that not only reduces the housing deficit but also supports climate-resilient developments. Finally, this synthesis of past scientific achievements provides an understanding of resilience modeling for climate adaptation and mitigation, supporting the design of more sustainable and equitable urban residential buildings in the Global South for future generations.

4. Chapter 4: How can we promote climate-resilient building design within the Global South context? A simulation-based procedure for the Latin America residential sector

Abstract: Climate change is disproportionately impacting vulnerable communities in the Global South, underscoring the need for policymakers to update building regulations to address overheating risks. Within this discussion, this investigation proposes a procedure for developing construction guidelines to support climate-resilient building design in the Global South's residential sector. This study compares future climate projections for five Latin American cities and generates future urban weather files by integrating IPCC emissions scenarios with urban heat island (UHI) effects. Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) are applied and compared as surrogate models leveraging transfer learning techniques to efficiently explore three architectural designs. Subsequently, these surrogate models are integrated with the Adaptive Geometry Estimation-based Multi-objective Evolutionary Algorithm (AGE-MOEA) to enhance thermal comfort and reduce energy demand. The procedure—comprising contextualization, investigation, and definition—employs an optimization loop, cluster analysis, heatmaps, and frequency analysis to establish design thresholds for transparent and opaque building components. Results indicate a strong similarity in climate projections across cities when comparing Special Report on Emissions Scenarios (SRES) and Shared Socioeconomic Pathways (SSP) scenarios, with future urban weather conditions trending towards higher dry-bulb temperature, relative humidity, and global horizontal radiation. XGBoost and ANN demonstrated a comparable performance, with transfer learning proving beneficial. Design thresholds were established targeting three key building components: walls, roofs, and windows — with certain configurations consistently emerging as favorable, including low solar absorptance, small and shaded windows, and low thermal transmittance and thermal capacity for roofs. Finally, these findings highlight the procedure's potential to deliver valuable insights, supporting Latin American policymakers in developing construction guidelines for climate-resilient building design within the residential sector.

Keywords: Global South, Latin America, Climate Change, Building Performance Simulation, Machine Learning, Optimization.

4.1 Introduction

Construction regulation guidelines for improving building thermal-energy performance can help reduce energy demand on a national scale while promoting thermal comfort (EVOLA; LUCCHI, 2024). However, developing countries are currently introducing such legislation amidst rapid construction growth and economic expansion (IWARO; MWASHA, 2010). Parallel to this, climate change disproportionately affects vulnerable communities in the Global South (GS) (IPCC, 1990, 1995, 2001, 2007, 2014, 2023), which includes developing countries in Latin America, Africa, Asia (excluding Israel, Japan, and South Korea), and Oceania (excluding Australia and New Zealand) (DADOS; CONNELL, 2012). As a result, over 2.2 billion people are expected to resort to purchasing inefficient cooling devices, while more than 1 billion will face significant cooling access risks (IEA, 2018, 2022). Therefore, construction regulations are essential not only for improving energy efficiency and thermal comfort but also for addressing the vulnerabilities posed by climate change, rapid urbanization, and population growth in fast-developing regions (CRUZ et al., 2024b).

Latin America (See **Figure 18**), stands out in the GS context for its recent social and economic growth, driven by economic diversification into manufacturing, services, and technology, supported by increased foreign direct investment and favorable trade agreements (LUBBOCK; VIVARES, 2022; WORLD BANK, 2024). Nonetheless, the housing deficit in Latin America remains significant, affecting millions, where informal settlements, often called slums or favelas, are common (OECD, 2015).

Construction methods across Latin America share common features shaped by the region's history, climate, and economic conditions (VIGEVANI; RAMANZINI JUNIOR, 2022). The widespread use of concrete and masonry, driven by the affordability of raw materials like limestone and clay, is a key characteristic (INTER-AMERICAN DEVELOPMENT BANK, 2022). Low labor costs support labor-intensive construction, and informal settlements are predominantly composed of self-built housing to meet urgent housing needs (LUBBOCK; VIVARES, 2022; MARÍN-RESTREPO et al., 2023). Unfortunately, this often results in poor thermal-energy performance and substandard structural integrity (UN, 2022, 2023a). In conjunction, public policies often attempt to address the housing deficit by implementing a standardized social housing prototype nationwide (FLORES-LARSEN; FILIPPÍN; BAREA, 2019). However, this one-size-fits-all regulatory approach frequently overlooks local climate variations and the growing risk of overheating due to climate change (ALVES; DUARTE; GONÇALVES, 2016; ALVES; GONÇALVES; DUARTE, 2021; FILIPPÍN et al., 2017; RODRIGUES et al., 2023; RODRIGUES; PARENTE; FERNANDES, 2024; ROUAULT et al., 2019; SILVERO et al., 2019; WANG et al., 2022; YU et al., 2023) . Therefore, effectively addressing the housing deficit in Latin America requires incorporating construction guidelines to support climate-resilient building designs, ensuring long-term thermal comfort and structural integrity for vulnerable populations (CRUZ et al., 2024b).

While regulations for building thermal-energy performance exist across Latin America, their

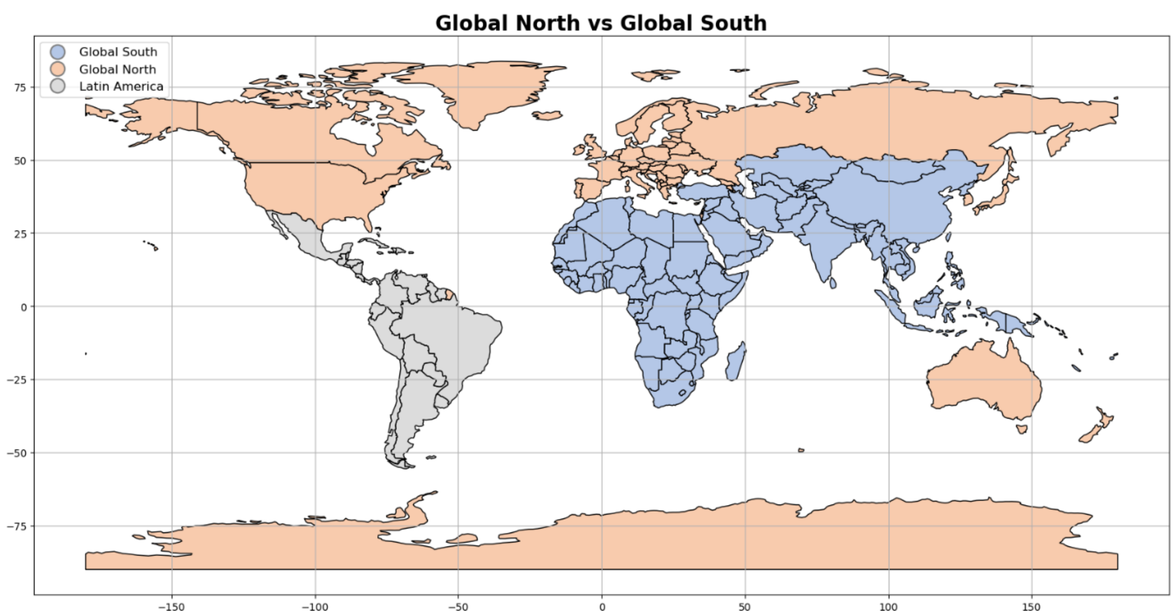


Figure 18. The word map division between the Global North and Global South contexts, highlighting Latin America.

implementation and enforcement vary significantly between countries. **Table 23** provides a brief overview of the current regulations on building thermal-energy performance in major emerging economies and the most populous nations in Latin America, including Brazil, Mexico, Argentina, Colombia, Chile, and Peru.

Table 23. Characteristics of thermal-energy performance regulations in Latin America's major emerging economies and most populous nations, including mandatory requirements.

Current regulations' characteristics	Brazil	Mexico	Argentina	Colombia	Chile	Peru
Divides the territory into bioclimatic zones	x	x	x	x	x	x

Establishes minimum thermal properties of opaque construction systems	x	x	x		x	x
Establishes minimum thermal properties of transparent construction systems		x	x		x	
Determines the minimum size for ventilation openings	x					
Establishes window solar shadowing requirements/values		x	x			
Establishes air permeability values to prevent infiltration through closed doors/windows			x		x	x
Determine the requirements or procedures to prevent condensation			x		x	x
Establishes lighting comfort requirements	x					x
Simulation methods to evaluate building performance	x					
Mandatory	x	x	x		x	
References	(BRAZIL, 2023)	(MEXICO, 2011)	(ARGENTINA, 2001)	(COLOMBIA, 2015)	(CHILE, 2024)	(PERU, 2014)

When analyzing Table 23, Brazil and Mexico stand out for their well-established features, while countries like Colombia and Peru have yet to implement effective strategies to improve construction quality, particularly in terms of thermal-energy performance. Although standards exist across the region, they are often non-mandatory and typically presented in a simplified format to ensure accessibility for professionals and ease of dissemination. The primary issue, however, is that none of these regulations adequately address the increasing risk of overheating caused by climate change.

4.1.1 Literature review

Climate-resilient building design begins by assessing vulnerability, which may inform the development of adaptation and mitigation strategies to enhance resistance against future weather conditions (ATTIA et al., 2021; HOMAEI; HAMDY, 2021; KESIK; O'BRIEN; OZKAN, 2022; MILLER et al., 2021). In this context, simulation studies play a crucial role in extending research findings beyond the limitations of traditional experiments, such as small scale and location constraints. Building performance simulation (BPS) tools are increasingly used in resilience assessments to examine overheating risks from climate change, providing valuable insights for building design (CRAWLEY; LAWRIE, 2019). Instead of relying solely on traditional historical climate data, researchers recommend modifying weather files to reflect climate change trends (COLE; EVINS; EAMES, 2024; MACHARD et al., 2020). The Intergovernmental Panel on Climate Change (IPCC) has developed various emissions scenarios within its Assessment Reports (AR), projecting future climate conditions based on different greenhouse gas (GHG) emissions levels (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). By utilizing these scenarios, BPS tools can provide detailed analyses of how buildings may perform under different future climates, aiding in the development of strategies to enhance building resilience (COLE; EVINS; EAMES, 2024; CRAWLEY; LAWRIE, 2019; ESCANDÓN et al., 2023; RODRIGUES; FERNANDES; CARVALHO, 2023).

New AR frequently introduce updated projections such as the Special Report on Emissions Scenarios (SRES) from AR3(IPCC, 2001) and AR4(IPCC, 2007), the Representative Concentration Pathways (RCP) from AR5(IPCC, 2014), and the Shared Socioeconomic Pathways (SSP) from AR6(IPCC, 2023). Although uncertainty remains regarding which pathway will prevail, all scenarios indicate a trend toward a warmer climate by the end of the 21st century. Huang; Hwang, (2016) examined future cooling energy demand trends in residential buildings in Taipei, Taiwan, using the SRES for three time periods: the 2020s, 2050s, and 2080s. Their simulations predicted increases in cooling energy demand of 31%, 59%, and 82%, respectively. Similarly, studies by Guarda et al. (2020), Borbon-Almada et al. (2020), and Dodoo; Ayarkwa (2019) projected significant increases in energy demand in Cuiaba, Brazil; Hermosillo, Mexico; and Accra and Kumasi, Ghana. By 2080, energy demand in Brazil is expected to rise by 40%, while Mexico could see a 61% increase by 2050, and Ghana's demand may increase by up to 50% by 2050.

Furthermore, climate data sourced from distant stations, often removed from urban centers, may not accurately reflect local conditions due to urban heat island (UHI) effects (VERICHEV et al., 2021; VERICHEV; ZAMORANO; CARPIO, 2020). Alternative strategies include utilizing nearby urban stations or applying tools like the Urban Weather Generator (UWG) to predict the UHI effects (KAMAL et al., 2023a). Several studies have used the UWG to assess how UHI affects building performance (LÓPEZ-GUERRERO et al., 2022). Ma; Yu, (2024) reported a 6% increase in cooling loads for high-rise residential buildings in Hong Kong, while Lima; Scalco; Lamberts (2019) found a 3% increase in office buildings in Maceió, Brazil. Similarly, Palme et al. (2017) observed a 15% to 200% rise in thermal loads in various residential buildings across four coastal cities in South America, and Litardo et al. (2020) found a 30% to 70% increase in cooling loads in Duran, Ecuador. In comparable climates, Liu et al., (2017) reported a 4% to 11% increase in energy consumption for residential buildings in Singapore, and Kumari et al. (2020) noted a 6% to 16% rise in educational buildings in Delhi, India. Given that modern constructions are expected to last at least 50 years (ANDERSEN; NEGENDAHL, 2023), it is crucial to incorporate forward-thinking design strategies that evaluate a range of climate projections, various urban morphologies, and the UHI effect to inform long-term climate-resilient building design.

The primary goal of resilience modeling is often to develop climate adaptation and mitigation strategies for building design (ATTIA et al., 2021; HOMAEI; HAMDY, 2021; KESIK; O'BRIEN; OZKAN, 2022; MILLER et al., 2021), focusing on design variables that directly influence thermal-energy performance (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). Flores-Larsen et al. analyzed future energy demand using SRES projections in residential buildings across Argentine cities, finding that shading devices, reduced glass solar heat gains, and natural ventilation were the most effective strategies against climate change. Liu et al (2020a), using the RCP projections, also identified solar protection as key to energy performance in Hong Kong's residential buildings. Similarly, Rodrigues; Fernandes (2020) studied 16 Mediterranean locations using SRES projections, recommending lower U-values to offset heating and cooling demands, except in Casablanca, Morocco, where higher U-values pose an overheating risk. In Honduras, Gamero-Salinas et al. (2021), based on SRES projections, found that natural ventilation, wall absorptance, solar heat gain coefficients, and shading devices significantly reduce overheating in vertical social housing.

In many cases, BPS tools are integrated with automation software, such as MATLAB or jEPlus, to streamline analyses using parametric, sensitivity, or optimization techniques. Gonçalves et al. (GONÇALVES et al., 2024) optimized social housing in Belem, Brazil to enhance thermal performance and reduce life cycle costs. Using SRES, they found a 40% reduction in thermal comfort due to climate change, but optimization results achieved 95% thermal autonomy and a 31% reduction in investment costs. Krelling et al. (2024) evaluated overheating risks in buildings in Florianopolis, Brazil using RCP projections. Their findings suggest cooling energy consumption could rise by 48% by the 2050s, but optimization results showed that passive strategies like shading and cool coatings could significantly mitigate heat stress.

Although optimization is a promising technique, it can be computationally intensive if they still require BPS tools to run energy simulations in each iteration. An alternative is optimization based on surrogate models (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019). These models, also known as meta, statistical, or response surface approximation models, initially learn the relationship between the input and output variables by reading the previously recorded data, and subsequently, mimic the behavior of the original model to be able to fast predict the outputs according to the newly-given inputs with high accuracy (AMASYALI; EL-GOHARY, 2018; SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017). Furthermore, the surrogate model can be combined with an optimization algorithm for performing several evaluations. Li et al. (2023b) optimized the design of a residential building in Huangshan, China, using RCP projections. Different machine learning algorithms were tested to predict heating, cooling, and cost based on envelope parameters, and were subsequently integrated with the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) for optimization. Results showed that optimal roof insulation increases from 40 mm to 90 mm by 2050, while thermal transmittance decreases from 0.38 to 0.19 W/m²K. Similarly,Yan; Ji; Yan (2022b) applied NSGA-II to optimize the design of two residential buildings in Singapore using SSP projections. The optimization results indicated a need for improved wall and envelope insulation to adapt to future warming conditions. YAN; JI; YAN (2022b) utilized the XGBoost algorithm combined with transfer learning technique to predict the performance of these two building typologies. The transfer learning technique allows the effective retraining of the machine learning model with a new dataset of a distinct architectural model, while the model preserves the fundamental knowledge derived from the data of the prior building (HOSNA et al., 2022; KO; PARK, 2021b). In other words, transfer learning is a machine learning approach where knowledge gained from training on one task is applied to improve learning and performance on a separate yet related task, often by reusing pre-existing models or learned representations (LAGUNAS et al., 2023; PAN; YANG, 2010). Consequently, combining machine learning models with optimization algorithms can identify the most effective design strategies for energy efficiency and thermal comfort while accounting for future climate uncertainties, making it a powerful tool for shaping construction regulations that prioritize long-term resilience in buildings.

4.1.2 Novelty and main contribution

In Latin America, the housing deficit (INTER-AMERICAN DEVELOPMENT BANK, 2022; VIGEVANI; RAMANZINI JUNIOR, 2022), common construction methods (UN, 2022, 2023a), shared socioeconomic conditions (MARÍN-RESTREPO et al., 2023; OECD, 2015), and regional agreements (LUBBOCK; VIVARES, 2022; WORLD BANK, 2024) create an ideal environment for collaboration to address climate change in the building sector. This offers an opportunity for neighboring countries to exchange technical knowledge and expertise, fostering the development of climate-resilient building policies that transcend national boundaries. However, developing construction guidelines demands greater generalizability and scalability of evaluation results, compared to most studies that focus on individual cities or building typologies (CRUZ et al., 2024b).

Within this discussion, this investigation proposes a procedure for developing construction guidelines to support climate-resilient building design in the Global South’s residential sector. This study compares future climate projections for five Latin American cities and generates future urban weather files by integrating IPCC emissions scenarios with urban heat island (UHI) effects. Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) are applied and compared as surrogate models leveraging transfer learning techniques to efficiently explore three architectural designs, reducing the resource intensity and time demands associated with training standalone models. Subsequently, these surrogate models are integrated with the Adaptive Geometry Estimation-based Multi-objective Evolutionary Algorithm (AGE-MOEA) to enhance thermal comfort and reduce energy demand. The procedure — comprising contextualization, investigation, and definition—employs optimization loop, cluster analysis, heatmaps, and frequency analysis to establish design threshold for transparent and opaque building components. Lastly, this research introduces two key novel contributions: 1) a macro-level geopolitical perspective that fosters international collaboration, and 2) a simulation-based procedure integrating machine learning with optimization techniques to develop construction guidelines to support climate-resilient building design.

Finally, to provide a clear structure, the remaining sections of this paper are organized as follows: Section 4.2 outlines the research method conducted, explaining all the actions related to future urban weather predictions, surrogate modeling, and the procedure for developing construction guidelines. Section 4.3 illustrates the prediction findings, simulations results and established guidelines. Section 4.4 discusses the results and compares them with prior studies. Finally, Section 5 presents the conclusions and directions for future research in the field.

4.2 Method

Table 24 outlines the research method for this study, breaking it down into distinct steps. Each step highlights the objectives, approaches, design variables, and metrics considered.

Table 24. Key features of the research method for each stage, categorized by objectives, approaches, design variables, and metrics.

Step	Description	Goal	Approach	Design variables	Metrics
1	Future urban weather prediction	Predict future weather conditions in the urban environment	• Morphing method. • UHI modeling.	• Location. • Future horizon. • Emission scenarios. • Urban context.	• Percentage deviation • Dry-bulb temperature. • Relative humidity. • Global horizontal radiation.
2	Surrogate modeling	Develop a machine learning models to predict thermal-energy performance indicators	• XGBoost • ANN • Transfer learning	• Weather data. • Envelope properties. • Occupant behavior. • Architectural design	• R^2, MAE, and MAPE. • Degree-hours. • Energy demand.
3	Construction guidelines development	Define design threshold for transparent and opaque components to support climate-resilient building design	• AGE-MOEA algorithm. • K-Means Clustering Algorithm. • Frequency analysis		• Inertia and silhouette scores. • Thermal properties

The first step involves comparing future climate projections and predicting urban weather conditions for the selected cities by integrating IPCC emissions scenarios and UHI effects into historical weather data. The SRES scenarios are compared to the SSPs from the latest IPCC AR through percentage deviation, while the UWG is used to incorporate UHI effects into the weather data. In this phase, the key metrics used to evaluate future urban weather conditions are dry-bulb temperature, relative humidity, and global horizontal radiation.

The second step focuses on developing machine learning models to predict the thermal-energy performance of residential buildings. XGBoost and ANN are applied and compared as surrogate models leveraging transfer learning techniques to efficiently explore three architectural designs, reducing the resource intensity and time demands associated with training standalone models. These designs include a simplified model, a detached house, and a low-rise apartment and key thermal-energy metrics considered are degree-hours and energy demand.

Finally, in the third step, the procedure is proposed — comprising contextualization, investigation, and definition. The present method employs optimization loop, cluster analysis, heatmaps, and frequency analysis to develop construction guidelines that promote climate-resilient building design. This step integrates the developed surrogate models with the AGE-MOEA algorithm to optimize building design under future urban weather conditions, aiming to enhance thermal comfort and reduce energy demand. This is accomplished by assessing various envelope properties in combination with diverse occupant behaviors, such as occupancy patterns and HVAC setpoint preferences, across the mentioned three distinct architectural designs. Subsequently, the Pareto fronts are evaluated using the K-means clustering algorithm and heatmaps to group similar design configurations and reveal common optimal values. Frequency analysis identifies the most common values in each cluster and the overall dataset, translating them into thermal properties of construction elements. Therefore, the procedure's key output is design thresholds for transparent and opaque building components.

4.2.1 Future urban weather predictions

This study incorporated future urban weather predictions for five cities across four Latin American countries, selected based on their status as major urban centers in emerging economies, high housing deficit indices, and diverse climates. Weather files for historical climate conditions refer to the Typical Meteorological Year (TMY) (CLIMATE.ONEBUILDING.ORG). **Table 25** and Figure 19. Weather data for the evaluated cities, featuring monthly averages of dry-bulb temperature, relative humidity, and global horizontal radiation. present key climate parameters, including dry-bulb temperature (DBT), relative humidity (RH), and global horizontal radiation (GHR) for the assessed locations.

Table 25. Weather data for the evaluated cities, including Köppen-Geiger classification, and average, maximum, and minimum values of dry-bulb temperature, relative humidity, and global horizontal radiation.

City	Country	Koppen-geiger	DBT (°C)			RH (%)	GHR (Wh/m²)
			Average	Max	Min	Average	Average
Rio de Janeiro (RJ)	Brazil	Aw	24	38	13	82	209
São Paulo (SP)	Brazil	Cfa	19	33	7.5	82	213
Santiago (ST)	Chile	Csb	15	33	-6	71	204
Bogota (BG)	Colombia	Cfb	13	24	0	80	184
Lima (LM)	Peru	BWh	19	30	11	81	178

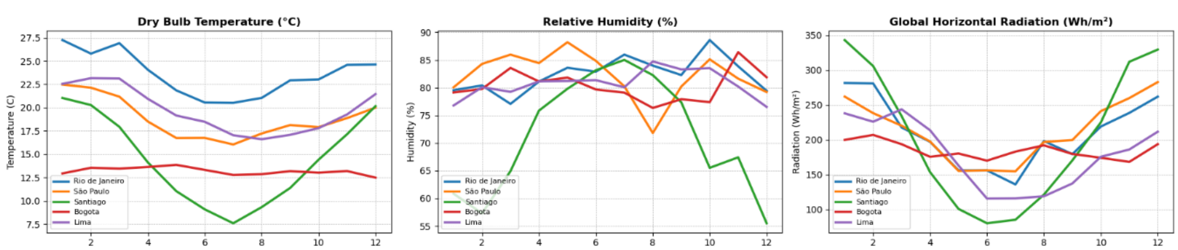


Figure 19. Weather data for the evaluated cities, featuring monthly averages of dry-bulb temperature, relative humidity, and global horizontal radiation.

Future weather predictions typically rely on Global Climate Models (GCMs) (RODRIGUES; FERNANDES; CARVALHO, 2023), which simulate interactions between the atmosphere, ocean, land surface, and more (CAMPAGNA; FIORITO, 2022; EYRING et al., 2016). After validation with historical data, GCMs use IPCC emissions scenarios to forecast future conditions (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). However, due to low resolution and data biases, direct use of GCM outputs in BPS tools is discouraged (RODRIGUES; FERNANDES; CARVALHO, 2023). To improve this, downscaling techniques are used, either statistical (e.g., stochastic or imposed offset methods) or dynamical (COLE; EVINS; EAMES, 2024). Regional Climate Models (RCMs) refine GCM outputs through dynamic downscaling, providing more detailed climate context, focusing on smaller areas with higher resolution, improving mesoscale weather simulations and reliability (BRACHT et al., 2024; CAMPAGNA; FIORITO, 2022). While stochastic and dynamical methods require significant computing power, the statistical imposed offset method (also called morphing method) is more efficient (CAMPAGNA; FIORITO, 2022; ESCANDÓN et al., 2023; MACHARD et al., 2020).

To address uncertainties in future projections, this study considered multiple IPCC Emission Scenarios and used two tools to generate future weather files: Climate Change World Weather File Generator(JENTSCH et al., 2013) and the Future Weather Generator (RODRIGUES; FERNANDES; CARVALHO, 2023). Both tools are based on the morphing method. Climate Change World Weather File Generator, based on the older CMIP2 model, offers the A2 scenario from SRES for 2020, 2050, and 2080. The Future Weather Generator, based on CMIP6, offers all SSP scenarios for 2050 and 2080. In this study, both tools are used to compare the future climate projections from different IPCC Emission Scenarios through a metric called percentage deviation. This metric quantifies the relative difference between two values by expressing their absolute difference as a percentage of their average (See Equation 4.1):

$$Percentage\ deviation = \frac{|P_2 - P_1|}{\left(\frac{|P_1| + |P_2|}{2}\right)} x\ 100 \tag{4.1}$$

Where, P_1 and P_2 represent the two values being compared. This metric is particularly useful when there is no clear baseline, as it provides a symmetric and unbiased measure of the difference. By normalizing the difference to the average of the two values, percentage deviation offers a balanced perspective on how much the values differ relative to their combined magnitude.

Additionally, this study employed the open-access Urban Weather Generator (UWG) tool to integrate UHI effects into the weather data. This tool has been extensively validated by previous researchers (BUENO et al., 2014; MAO et al., 2017; SALVATI et al., 2019). The UWG requires inputs such as microclimate data, urban features, vegetation, and building characteristics. These parameters were defined based on the typical low- and medium-rise residential urban fabric in Latin American cities. Two key criteria were used to define the primary urban parameters. First, the urban configuration was determined using the Local Climate Zone (LCZ) classification system (STEWART; OKE, 2012), selecting the compact low-rise class (LCZ3). The LCZ classification categorizes 17 local climate zones, 10 of which describe urban areas based on characteristics such as density, vegetation cover, soil permeability, and surface properties (STEWART; OKE, 2012). Secondly, building on the first criterion and drawing from prior studies that utilized the UWG software in Latin American cities (LITARDO et al., 2020; LÓPEZ-GUERRERO et al., 2024; PALME et al., 2017), the key urban parameters were uniformly defined for all evaluated cities (LÓPEZ-GUERRERO et al., 2024; SALVATI et al., 2019). These parameters included a green coverage (GC) of 0.2, a site coverage ratio (SCR) of 0.65, a façade-to-site ratio (FSR) of 0.75, and anthropogenic heat from traffic (AHT) of 25 W/m². To ensure consistency and comparability of the urban fabric, this configuration was applied uniformly across all cities. Additionally, acknowledging that residential neighborhoods in low- and medium-income areas in Latin America may exhibit higher SCR or lower GC (DA SILVA; LIMA; SAITO, 2023; FERNÁNDEZ; KOPLOW-VILLAVICENCIO; MONTOYA-TANGARIFE, 2023; LIMA; SCALCO; LAMBERTS, 2019; VÁSQUEZ et al., 2019), the parameters were conservatively set to prevent overestimation of the Urban Heat Island Intensity (UHII). Finally, by combining future climate projections with UHI effect, a hypothetical future urban weather dataset was generated to assess how climate change may influence construction guidelines for climate-resilient building design in urban centers.

4.2.2 Surrogate modeling

Creating a surrogate model using simulation data involves key steps (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019). First, clearly define the building design problem, identifying the inputs (design variables) and outputs (objective functions). Next, simulate an initial high-fidelity baseline model by varying design variables and collecting results in a dataset. This dataset is then preprocessed and split into training and test sets or using cross-validation techniques (WANG; SRINIVASAN, 2017). In the third step, select an appropriate machine learning algorithm to train the surrogate model on the training data to learn the relationship between inputs and outputs. Validate the model by comparing its predictions against the test set by using evaluation metrics to measure accuracy (SUN; HAGHIGHAT; FUNG, 2020). If the model's performance is inadequate, refine it by adjusting training, exploring hyperparameters, or adding new data (AMASYALI; EL-GOHARY, 2018). Finally, once validated and refined, the surrogate model can be applied for tasks like optimization or real-time predictions, offering fast and efficient approximations of the original model (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019).

4.2.2.1 Architectural designs

In this study, three typical architectural designs are selected for evaluation: a simplified model, a detached house, and a low-rise apartment (see **Figure 20** for 3D views and floorplans). All models have a ceiling height of 3 meters, with floor areas of 16 m², 56 m², and 62 m², respectively. Although detached houses dominate the residential building stock, urban centers are increasingly characterized by vertical developments (ARUL BABU; SRIVASTAVA; RAI, 2024; GUARDA et al., 2020; LI et al., 2023b; LIU et al., 2020b; NUNES; GIGLIO, 2022; TRIANA; LAMBERTS; SASSI, 2018). Therefore, it is crucial to diversify the architectural designs analyzed to determine whether the findings can be broadly applied across different building types.

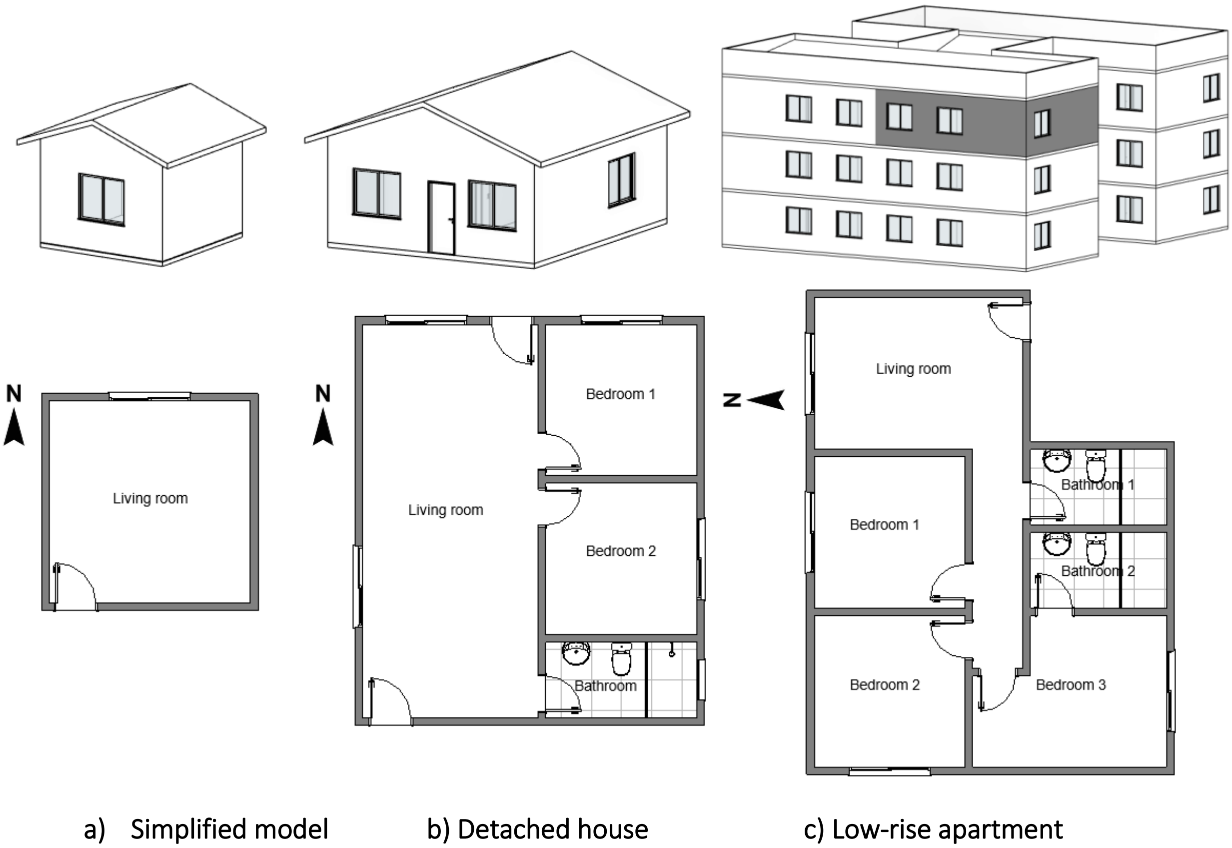


Figure 20. 3D views and floor plans for each architectural design analyzed in this study: (a) Simplified model, (b) Detached house, and (c) Low-rise apartment.

To ensure the accuracy of simulation results and minimize discrepancies with field measurements, especially during the design phase when the building is not yet constructed, it is crucial to employ effective strategies. Without the possibility of calibration, confidence in the results can be enhanced by using validated software, precise input data, and comparisons to a baseline (CRUZ; BASTOS, 2024). These measures help identify potential errors in input data or model assumptions. In this study, the detached house model was calibrated based on a previously published study (LÓPEZ-GUERRERO et al., 2024; LOPEZ-GUERRERO et al., 2024), while these additional methods were also applied to ensure reliable outcomes for the other two evaluated models. The models were developed using EnergyPlus, a validated tool, with all major inputs aligned with building regulation guidelines and calibrated simulation results (BRAZIL, 2023). For instance, the thermal zones considered two to four people with a metabolic rate of 108 W/person, an installed lighting power density of 6 W/m², and a constant internal load for equipment of 1.5 W/m² (BRAZIL, 2023).

4.2.2.1.1 Operation mode and performance metrics

When the building envelope fails to maintain thermal comfort, reliance on HVAC systems becomes necessary. However, HVAC adoption in Latin America is often limited by cultural and socio-economic factors, such as lack of financial resources and infrastructure (INTER-AMERICAN DEVELOPMENT BANK, 2022; LUBBOCK; VIVARES, 2022; OECD, 2015; VIGEVANI; RAMANZINI JUNIOR, 2022; WORLD BANK, 2024). While natural ventilation is preferred, rising living standards and comfort expectations are increasing HVAC demand (IEA, 2018, 2022). For mechanically conditioned periods, energy demand and peak demand offer straightforward performance metrics, while for naturally ventilated periods, metrics like operative temperature, thermal autonomy, degree-hours, and indoor overheating degree are available (KRELLING et al., 2023).

The interaction between mechanical and natural ventilation modes can complicate building design (MENDES et al., 2024a, 2024b). For example, improving thermal insulation boosts energy efficiency but may increase overheating risk in summer without effective passive or adaptive cooling (CRUZ; BASTOS, 2024; CRUZ; CUNHA, 2022; CRUZ; DE CARVALHO; DA CUNHA, 2020). This highlights the importance of incorporating both ventilation modes in resilience assessments. Therefore, this study examines two operation modes: natural and mechanical ventilation. For the naturally ventilated mode, the performance metric includes degree-hours (DH), while for mechanical ventilation, energy demand (ED) is used (see Equations 4.2 and 4.3). DH measures the total number of hours outside the upper or lower temperature limits — indicating discomfort hours, whereas ED refers to the energy demand required by the HVAC system to maintain all zones within the comfort temperature range. Therefore, for both metrics, low values are desirable.

$$DH = \frac{\sum H_{Discomfort}}{N_{tz}} \tag{4.2}$$

$$ED = \frac{\sum ED_{HVAC}}{A_{total}} \tag{4.3}$$

Where, for equation 4.2: $H_{discomfort}$ is the number hours of the year with operative temperature outside the thermal comfort range without the assistance of HVAC system for each thermal zone, and N_{tz} is the number of thermal zones. For equation 4.3, ED_{HVAC} refers to the total energy demand of the HVAC system, and A_{total} represents the total floor area of the building.

The natural ventilation mode was set to operate during occupancy hours, using EnergyPlus' Airflow Network, with windows opening when indoor air temperature exceeds 19°C and is higher than the outdoor temperature. Thermal comfort follows the ASHRAE Adaptive Comfort model, based on 90% acceptability limits for outdoor temperatures between 10°C and 33.5°C, allowing a ±2.5°C deviation from optimal comfort, respectively. The Zone System Unitary HVAC template within EnergyPlus was used to model mechanical ventilation, operating during occupancy with a COP of 3.24. The setpoint temperature is specified in section 2.2.2. (BRAZIL, 2023).

4.2.2.1.2 Design variables

The design variables explored in this study fall into three categories: envelope properties, occupant behavior, and architectural design. For the envelope, these variables include glazing properties (U-value and SHGC), wall, roof and ceiling type, thermal insulation thickness for wall and roof, shading device depth, window size and opening factor, absorptance values for wall and roof, ground contact context, and orientation. The wall and roof types listed in Table 26 represent the most commonly used construction systems in Latin America. Although various shading devices are available, this study focused on overhangs and side fins to simplify the modeling process. The ground context refers to the influence of soil temperature. In detached houses, ground temperature plays a significant role in thermal-energy performance, but in apartments, this heat exchange may be less relevant since the residential unit is not necessarily in contact with the ground (CRUZ; BASTOS, 2024; CRUZ; CUNHA, 2022). Thus, two contexts are considered: one using the soil temperature defined by the EnergyPlus Slab Program and another under adiabatic conditions.

Occupant behavior is a key factor in thermal-energy studies, particularly in residential buildings where adaptability is higher (LI et al., 2019; RODRIGUES et al., 2024; RUBIO-BELLIDO et al., 2017; ZUNE; RODRIGUES; GILLOTT, 2020b). Overgeneralizing this behavior can lead to inaccurate assessments of thermal-energy performance. This study addresses occupant behavior by exploring varying occupancy patterns and HVAC setpoint preferences (CRUZ; BASTOS, 2024). Three occupancy patterns are examined: 1) occupants at home only in the evening, 2) part-time workers, and 3) occupants always at home, representing those who work from home (see **Figure 21**). To capture different comfort requirements, this study also considers two setpoint temperature for heating and cooling within HVAC operation mode. Finally, the architectural design category refers to the considered housing projects within this study - simplified model, detached house and low-rise apartment. The complete list of design variables, along with their respective value ranges, is further detailed in

Table 27.

Table 26. Thermal properties of the construction systems examined in this research, including wall, roof, and ceiling types.

Component	Index	Construction system	Description (Layers)	Thickness (m)	Specific gravity (kg/m³)	Thermal conductivity (W/mK)	Specific heat (kJ/kgK)
Wall	1	Traditional masonry	Coating mortar	0.02	1950	1.15	1.00
			Ceramic blocks (horizontally perforated)	0.09	459	0.47	0.93
			Coating mortar	0.02	1950	1.15	1.00
			Construction system's properties: U-value = 2.77 W/(m²K) and TC = 117 kJ/(m²K)				
	2	Structural masonry	Coating mortar	0.02	1950	1.15	1.00
			Concrete blocks (vertically perforated)	0.14	840	1.01	1.00
			Coating mortar	0.02	1950	1.15	1.00
			Construction system's properties: U-value = 2.73 W/(m²K) and TC = 195 kJ/(m²K)				
	3	Concrete wall	Cast-in-situ concrete panel	0.10	2300	1.75	1.00
			Construction system's properties: U-value = 4.40 W/(m²K) and TC = 230 kJ/(m²K)				
Roof	1	Clay tile		0.01	1500	1.15	1.00
	2	Fiber cement tile		0.006	1700	0.65	0.84
Ceiling	1	Wooden lining		0.01	650	0.15	2.30
	2	Plaster panel		0.01	900	0.35	0.87
	3	Polyvinyl chloride (PVC) board		0.01	273	0.2	0.96

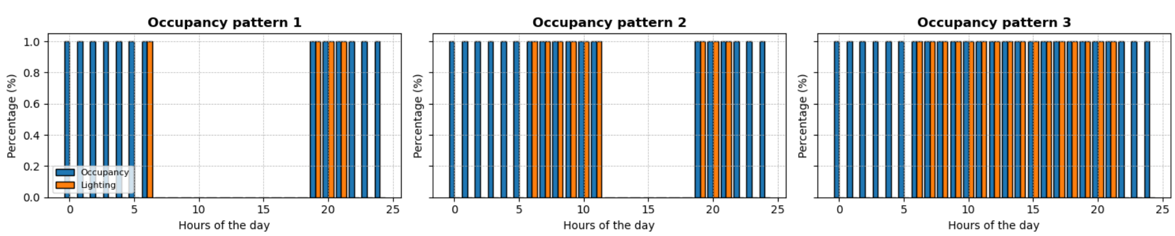


Figure 21. Occupancy patterns and lighting schedules.

Table 27. Description of design variables, including their units and ranges considered in the study.

Category	ID	Description	Unit	Range
Envelope	DV1	Glazing U-value	W/m²K	{1.02, 1.64, 2.27, 2.89,3.51, 4.13, 4.76, 5.38}
	DV2	Glazing SHGC	Dimensionless	{0.19, 0.28, 0.37, 0.46, 0.54, 0.63, 0.72, 0.81}
	DV3	Wall type	Dimensionless	{1, 2, 3} – See Table 4
	DV4	Roof type	Dimensionless	{1, 2} – See Table 4

	DV5	Ceiling type	Dimensionless	{1, 2, 3} – See Table 4
	DV6	Insulation - Walls	m	{0, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10}
	DV7	Insulation - Roof	m	{0, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10}
	DV8	Shading device depth	m	{0, 0.4, 0.8, 1.2}
	DV9	WWR	%	{20, 30, 40, 50, 60}
	DV10	Opening factor	%	{50, 60, 70, 80, 90}
	DV11	Absorptance value - Wall	Dimensionless	{0.2, 0.3, 0.4, 0.50, 0.6, 0.7, 0.80}
	DV12	Absorptance value - Roof	Dimensionless	{0.2, 0.3, 0.4, 0.50, 0.6, 0.7, 0.80}
	DV13	Building orientation	(°)	{0, 45, 90, 135, 180, 225, 270, 315}
	DV14	Ground contact context	Dimensionless	Y/N
Occupant behavior	DV15	Occupancy patterns	%	{1, 2, 3} – See Figure 4
	DV16	Set point temperature	(°)	{21°C -23°C} or {20°C -25°C}
Architectural design	DV17	Housing project	Dimensionless	Detached, low-rise apartment and simplified model

4.2.2.2 Dataset

The dataset creation step aims to select design points that maximize information gain per simulation while minimizing sampling time. Common methods include Monte Carlo, Sobol's, and Latin Hypercube Sampling (LHS) (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019). Sobol's method was chosen for its efficiency in high-dimensional problems, generating quasi-random sequences that provide better coverage and faster convergence with fewer samples. It delivers reproducible results and scales well with increasing dimensions, making it ideal for simulations requiring accuracy and efficiency (CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023).

In this study, we focus on three distinct building types, each requiring the development of a corresponding dataset. All combinations of design variables listed in Table 5 resulted in a total of 65 x 10^9 scenarios for each architectural design. However, generating this dataset for each case is both resource-intensive and time-consuming. To optimize the balance between simulation time and data requirements for transfer learning, different sample sizes were assigned to each architectural design. Specifically, the datasets consist of 1,000 samples for the detached house, 500 samples for the low-rise apartment, and 500 samples for the simplified model. Following a previous study (YAN; JI; YAN, 2022b), this approach was adopted because the detached house, with its intermediate level of complexity, serves as an effective source domain in the transfer learning process. Specifically, the detached house has three thermal zones, while the simplified model and low-rise apartment have one and four thermal zones, respectively.

Subsequently, each dataset was pre-processed to prevent features with larger values from disproportionately influencing predictions. To ensure all features had equal weight, we applied z-score normalization (see Equation 4.4), which scales each feature to the same range, where μ is the mean of all the x values and σ is their standard deviation.

$$z = \frac{x - \mu}{\sigma} \tag{4.4}$$

Furthermore, instead of relying on a simple split into training and test datasets, this study employed cross-validation techniques to evaluate the regression model's performance more robustly. Cross-validation involves dividing the dataset into multiple folds, where the model is trained on a subset of the data (training folds) and validated on the remaining fold (validation fold). This process is repeated multiple times, ensuring that every data point is used for both training and validation at least once. By averaging the results across all folds, cross-validation provides a more reliable estimate of the model's generalizability, reducing the risk of overfitting or underfitting that might arise from a single train-test split (SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017). Overfitting happens when a model learns patterns from the training data too precisely, causing poor performance on new, unseen data.

4.2.2.3 Transfer learning technique

As previously discussed, we implemented transfer learning as a solution for predicting outcomes across two different building types, as training independent models for each case would be both resource-intensive and time-consuming. This technique leverages a pre-trained model that has learned general features from a large dataset, which are then reused or fine-tuned for a new, smaller dataset. It is most efficient when tasks are similar, as the model can transfers knowledge from the source task to the target task (KO; PARK, 2021b).

The procedure begins with a source task, T_s, and a target task, T_t along with their respective datasets D_s and D_t (HOSNA et al., 2022). In the context of supervised learning, a task T consists of two main components: the label space Y (output space) and a predictive function $f(x)$ that maps an input x to an output y. The goal is to leverage the knowledge learned from the source task to improve performance on the target task. The model trained on the source task, $f_s(x)$, typically extracts useful features from the source data. These features, represented as $h(x)$, are then transferred and reused to create a new model for the target task, $f_t(x)$, that combines the feature extractor and a new task-specific head, $g(.)$ (see Equation 4.5) (LAGUNAS et al., 2023; PAN; YANG, 2010). In practice, the pre-trained model's parameters, ϑ_s, are fine-tuned for the target task. The fine-tuning process involves minimizing a loss function, L (See Equation 4.6), that updates a subset of the model's parameters, denoted as ϑ_t, while retaining the general knowledge captured by ϑ_s. In other words, the objective is to minimize the loss over the target dataset, D_t, expressed in Equation 6, where $l(.)$ is the loss function for each target sample (LAGUNAS et al., 2023; PAN; YANG, 2010).

$$f_t(x) = g\big(h(x)\big) \tag{4.5}$$

$$L(f_t(x_t), y_t) = \frac{1}{N_t}\sum_{j=1}^{N_t} l(f_t\big(x_t^j\big), y_t^j) \tag{4.6}$$

The transfer learning process consists of two main steps: (1) training in the source domain, and (2) fine-tuning the model in the target domain with a small dataset (KO; PARK, 2021b). In this study, the detached house served as the source domain, while the low-rise apartment and simplified model were used as target domains. The detached house dataset provides an intermediate level of complexity, allowing the model to learn more generalized features (YAN; JI; YAN, 2022b). By retraining on a progressively simpler model (simplified model) and a more complex model (low-rise apartment), the model fine-tunes its knowledge to adapt to other building types.

Furthermore, two machine learning algorithms were evaluated for transfer learning: XGBoost and ANN. XGBoost is a robust gradient boosting algorithm that builds decision trees sequentially, each correcting the errors of the previous ones. Its optimization of a custom loss function, combined with regularization, improves accuracy while preventing overfitting (CHEN; GUESTRIN, 2016). When applying transfer methods, it leverages ensemble learning to predict errors between domains. However, transfer learning is more commonly associated with deep learning models, where layers of learned features can be transferred, so ANN was tested as well. For instance, ANN are composed of an input layer, one or more hidden layers, and an output layer. Each layer contains interconnected neurons that process and transform data through activation functions (HASTIE; FRIEDMAN; TIBSHIRANI, 2001). It offers the ability to reuse learned features by freezing earlier layers and fine-tuning later ones, enabling efficient adaptation to new tasks. This built-in capability allows the ANN model to retain general knowledge while focusing on task-specific patterns (HOSNA et al., 2022).

Hyperparameter settings significantly influence the performance of surrogate models. Common optimization methods include grid search, random search, Bayesian optimization, and evolutionary algorithms(CRUZ et al., 2024a). This study employed random search for its simplicity, scalability, and efficiency in high-dimensional spaces, outperforming grid search while avoiding the complexity of Bayesian and evolutionary approaches. For XGBoost, the hyperparameters included the number of trees, maximum tree depth, and learning rate (CHEN; GUESTRIN, 2016), while for the ANN, they included the number of hidden layers, neurons per layer, activation functions, and learning rate (HASTIE; FRIEDMAN; TIBSHIRANI, 2001). Finally, for this stage, the following Python libraries were utilized: TensorFlow, Scikit-learn, and XGBoost.

4.2.2.4 Performance evaluation of machine learning models

The evaluation step of machine learning models involves assessing their performance on unseen data by comparing predicted outputs to actual outcomes. Common metrics like coefficient of determination (R^2), root mean square error (RMSE), mean square error (MSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) are used to measure performance (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019).

R^2 measures the proportion of variance in the output variable that is predictable from the input variables. It ranges from 0 to 1, where values closer to 1 indicate that the model explains a large proportion of the variance, making it a useful metric for assessing the overall fit of the model. MAE calculates the average absolute difference between predicted and actual values, providing a straightforward measure of prediction accuracy in the same units as the target variable. Lastly, MAPE offers a relative error metric by expressing the prediction error as a percentage of the actual values. It is particularly valuable when comparing model performance across datasets with varying scales or when evaluating proportional errors. By considering R^2, MAE, and MAPE together, we can evaluate the goodness-of-fit, absolute accuracy, and relative accuracy of a model, ensuring a balanced and nuanced assessment of its predictive performance. These metrics are calculated using Equation 4.7 to 4.9, where n is the total number of the test target samples; y_i' is the actual value; y_i is the arithmetic mean of y; and y_i'' is the predicted value of the model.

$$R^2 = 1 - \frac{\sum_i^n (y_i - y_i')^2}{\sum_i^n \left(y_i - y_i''\right)^2} \tag{4.7}$$

$$MAE = \frac{1}{n}\sum_i^n |y_i - y_i'| \tag{4.8}$$

$$MAPE = \frac{1}{n}\sum_i^n \left|\frac{y_i - y_i'}{y_i}\right| \tag{4.9}$$

4.2.3 Procedure for developing construction guidelines

The proposed procedure for developing construction guidelines to support climate-resilient building design comprises three steps: contextualization, investigation, and definition. **Figure 22** outlines the methods and objectives of each step.

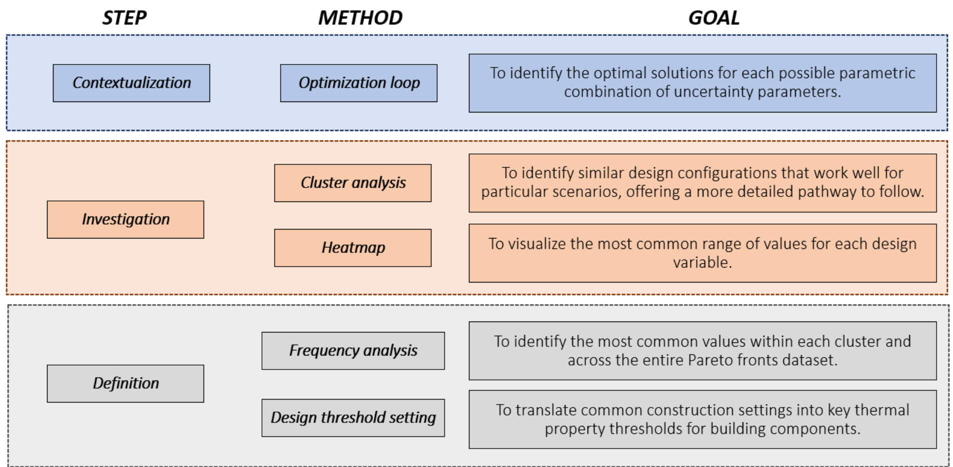


Figure 22. Procedure for construction guidelines development to support climate-resilient building design.

Initially, a comprehensive assessment of various building contexts is essential. This analysis considers multiple parameters defining the building context, which often impact performance and are known as uncertainty parameters. Consequently, this stage involves an optimization loop to identify the optimal solutions across all possible combinations of these parameters. Once the optimal solution database is established, the next step is to examine these solutions using cluster analysis and heatmap. The clustering process groups similar design configurations, helping to identify specific collections of variables that consistently perform well across different contexts. Heatmap visualization highlights common ranges and frequently optimal values for each design variable, regardless of any specific uncertainty parameter. In the final step, frequency analysis identifies the most common values in each cluster and the overall dataset, translating them into thermal properties of construction elements. Therefore, the procedure's key output is design thresholds for transparent and opaque building components.

4.2.3.1 Contextualization: Optimization

In this first step, contextualization focuses on three key elements: site context, occupant behavior, and architectural design. These elements are selected because ground temperature is less relevant in apartments compared to houses (CRUZ; BASTOS, 2024; CRUZ; CUNHA, 2022), building orientation is site-dependent, occupancy varies with individual routines (CRUZ; BASTOS, 2024), and comfort levels are highly personal, resulting in significant variability (LI et al., 2019; RODRIGUES et al., 2024; RUBIO-BELLIDO et al., 2017; ZUNE; RODRIGUES; GILLOTT, 2020b). Thus, this stage involves an optimization loop to identify the Pareto front for each possible parametric combination of these uncertainty parameters. This optimization loop step aims to improve building design by enhancing thermal comfort and reducing energy demand, all while considering future weather conditions. A common method for solving multi-objective problems is the Pareto front. This method generates a set of non-dominant solutions, allowing decision-makers to choose the most appropriate or preferred option from these optimal solutions (EVINS, 2013; MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). Therefore, this approach can help in identifying the optimal range of values for each design variable, supporting the development of climate-resilient building design construction guidelines. Considering the range of values for each key uncertain parameter—building orientation (DV13), ground contact context (DV14), occupancy patterns (DV15), setpoint temperature (DV16), and housing project (DV17) (see Table 5)—there are 288 possible parametric combinations. This implies that at this stage, 288 optimizations—one for each building context—are required.

Algorithms like the Strength Pareto Evolutionary Algorithm 2 (SPEA2) and Multi-Objective Particle Swarm Optimization (MOPSO) have been widely used in building performance optimization (EVINS, 2013; MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). However, NSGA-II, a population-based evolutionary algorithm known for solving complex, non-linear problems and identifying optimal solutions, remains a preferred choice for its robustness and efficiency (DEB et al., 2002). While emerging algorithms like the Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D), the Constrained Multi-objective Evolutionary Algorithm with an Improved Two-Archive Strategy (C-TAEA), Multi-objective Manta Ray Foraging Optimizer (MOMRFO), Adaptive Weighted Genetic Algorithm (awGA), and Reference Vector Evolutionary Algorithm (RVEA) show promise results (ALSHARIF et al., 2023; CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023; SHEN; PAN, 2023; SHI et al., 2024), they are underutilized in this field. To address this gap, this study adopts the Adaptive Geometry Estimation based Multi-objective Evolutionary Algorithm (AGE-MOEA) (PANICHELLA, 2019). AGE-MOEA builds on the NSGA-II framework but modifies the crowding distance calculation to focus on well-distributed solutions near the Pareto front by adapting to its geometry. The algorithm balances exploration and convergence by dynamically adjusting its search based on the objectives' geometry, ensuring broad solution space coverage. Non-dominated fronts are sorted, with the first front used to normalize the objective space and estimate the Pareto front geometry. The Minkowski p-norm is calculated from the closest solution to the front's midpoint, and it computes a survival score considering both neighbor distance and proximity to the ideal point (PANICHELLA, 2019). Finally, the Python library named Pymoo was used to apply the AGE-MOEA with the following parameters setup, a population size of 100 was used, with random sampling, simulated binary crossover with a probability of 0.9 and an eta of 15, polynomial mutation with an eta of 20, and an age-based survival mechanism, and the algorithm ran for 200 generations.

4.2.3.2 Investigation: Clustering and Heatmap

In the second step, we explore the Pareto front database, excluding all the uncertainty parameters, examining all optimal solutions through cluster analysis and heatmap. Clustering can reveal patterns in design configurations, helping to identify groups of design variables that work well across different contexts. In this study, we applied the K-means algorithm, a popular clustering method that partitions data into clusters based on similarity (MACQUEEN, 1967). To determine the optimal number of clusters, we used two metrics: inertia and the silhouette score. Inertia measures the compactness of the clusters by calculating the distance between data points and their assigned cluster centers; lower inertia values indicate tighter, more cohesive clusters (RYKOV et al.). The silhouette score evaluates how well each data point fits within its cluster compared to others, with higher values suggesting clearer separation between clusters (THINSUNGNOEN et al., 2015). Together, these metrics helped identify the ideal number of clusters for meaningful analysis.

A heatmap is a visual representation of data where values are depicted through color gradients. It is often used to show the intensity or frequency of certain values within a dataset. For instance, a heatmap can display ranges of optimal values for design variables, with colors indicating how frequently certain configurations perform well. This makes it easy to identify trends and patterns across different parameters at a glance.

4.2.3.3 Definition: Frequency analysis and design threshold setting

In the final step, a frequency analysis is conducted to identify the most common values within each cluster defined in the previous step, as well as across the entire Pareto fronts dataset. By determining the most frequent values, these can be translated into key thermal properties of construction elements, including thermal transmittance, thermal capacity, solar absorptance, and solar heat gain coefficient. Consequently, the procedure's main output is a set of design thresholds for transparent and opaque construction elements.

4.3 Results

4.3.1 Future urban weather predictions results

This study utilizes future urban weather predictions for five cities across four Latin American countries to assess how climate change projections might shape construction guidelines for climate-resilient building design. Future weather data were generated using the Climate Change World Weather File Generator and the Future Weather Generator tools, while the Urban Weather Generator was employed to integrate UHI effect. Initially, the future weather data from the different tools were compared to analyze and validate the future projections to some extent. Subsequently, the future weather data were modified to incorporate urban context.

In the first step, the study focused on the years of 2050 and 2080 with the worst-case emission scenario. Specifically, the A2 scenario from SRES (AR 3 + AR 4) and the SSP5-8.5 scenario (AR 6) were applied for the year of 2050 and 2080. **Figure 23** illustrates the monthly average values of DBT, RH, and GHR for each city, while **Table 28** presents the percentage deviations of these metrics across the four future weather datasets.

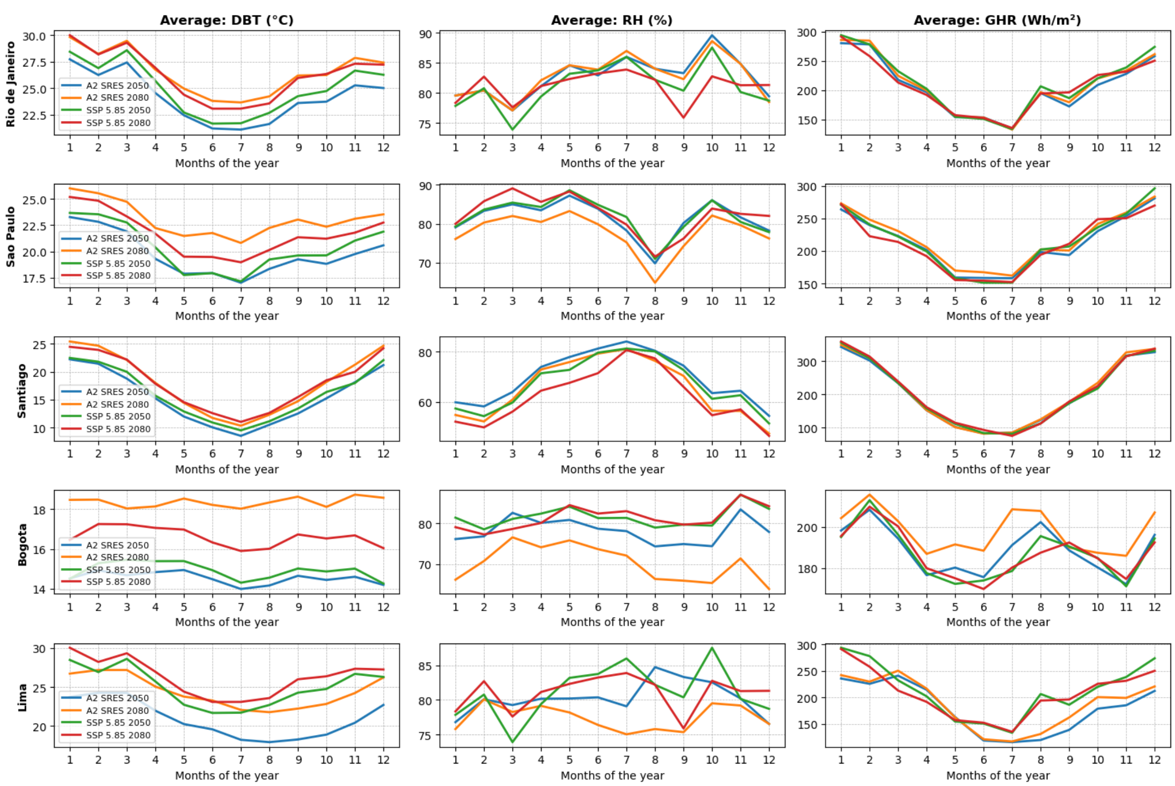


Figure 23. Comparison between climate parameters for future climate projections A2 SRES and SSP5.85, including monthly average values for dry-bulb temperature, relative humidity, and global horizontal radiation.

Table 28. Percentage deviation when comparing results for future climate projections A2 SRES and SSP5.85 for dry-bulb temperature, relative humidity, and global horizontal radiation.

Location	Percentage deviation (%) by metric					
	DBT		RH		GHR	
	2050	2080	2050	2080	2050	2080
Rio de Janeiro	3.5%	1.6%	2.4%	3.5%	9.4%	10%
São Paulo	3.4%	6.5%	1.7%	6.5%	6%	9%
Santiago	8%	5%	4.1%	7%	2.8%	5%
Bogota	2.8%	10%	4.7%	10%	2.1%	6%
Lima	3.6%	6%	2%	5.5%	3%	6%

Table 28 showed a high degree of similarity in the projections for all cities evaluated, regardless of the tool used, as the percentage deviations for each metric are fairly low. No metric exhibited a percentage deviation greater than 10%, indicating that both tools were valid for studying the impact of climate change. This suggests that the A2 and SSP5-8.5 scenarios provide comparable climate projections for both 2050 and 2080.

To streamline the analysis, the study focused exclusively on the year 2080 under the SSP5-8.5 scenario, as it represents the most severe future climate context. Additionally, only the latest emission scenario proposed by AR6 was used to enhance the diversity of analysis with new projections, since this is the most recent available projection. Figure 5 showed that future weather predictions indicate a sharp escalation in the analyzed parameters by 2080 when compared to historical data. The DBT is projected to increase by 2.71°C in Rio de Janeiro, 2.85°C in Sao Paulo, 3.63°C in Santiago, 3.4°C in Bogota, and 3.36°C in Lima. RH is expected to rise by 1.39% in Rio de Janeiro, 1.2% in Sao Paulo, 9.2% in Santiago, 2.4% in Bogota, and 1.4% in Lima. Similarly, GHR will increase by 2.3 Wh/m² in Rio de Janeiro, 2.0 Wh/m² in Sao Paulo, 5.3 Wh/m² in Santiago, 2.5 Wh/m² in Bogota, and 2.2 Wh/m² in Lima.

Furthermore, the LCZ class 3 was applied to incorporate UHI effects into the weather data. This urban configuration, including aspects like density, vegetation cover, soil permeability, and other surface properties, were assumed to ensure consistency and comparability across all evaluated cities. **Figure 24** presents the DBT for the historical, future, and future urban weather contexts for all analyzed cities.

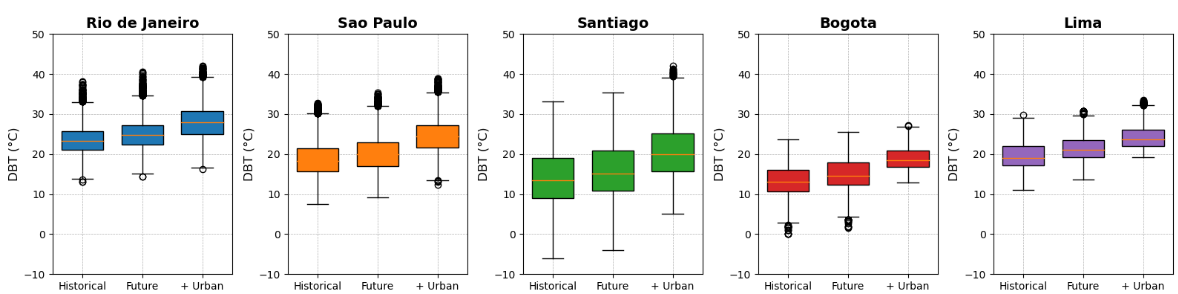


Figure 24. Comparison between the distribution of values for historical, future and future urban predicted dry-bulb temperature.

As expected, historical weather files, based on data from rural meteorological stations or sourced from distant stations (often removed from urban centers), exhibited the lowest DTB values compared to those derived from future projections and UHI models. The average difference in DTB values between historical and future climates is approximately 2 °C across all cities. However, these values increase notably when the UHI effect is incorporated, reaching deviations up to 5 °C when comparing future climates with future climates that include urban influence. This illustrated the compounded influence of both climate change and urbanization on local temperature dynamics, particularly when comparing future climate scenarios with and without urban influence. Such findings emphasize the critical need for urban-specific climate models to accurately project temperature variations and their implications for climate-resilient building design.

4.3.2 Surrogate modeling results

In this study, datasets for each architectural design were generated using Sobol's method. Different sample sizes were assigned to each design to optimize the balance between simulation time and data requirements for transfer learning. Subsequently, XGBoost and ANN were employed and compared as surrogate models, utilizing transfer learning techniques to efficiently explore three distinct architectural designs. To prevent overfitting, we applied cross-validation (10-fold) and evaluated the models using R^2, MAE, and MAPE. The following sections present the results, detailing dataset analysis and the performance evaluation of the machine learning models.

4.3.2.1 Analysis of datasets

Figure 25 presents the degree-hours (DH) and energy demand (ED) results from the simulated dataset for each city analyzed under future urban conditions. The graphs summarize the distribution of these metrics across the simplified model, detached house, and low-rise apartment, respectively.

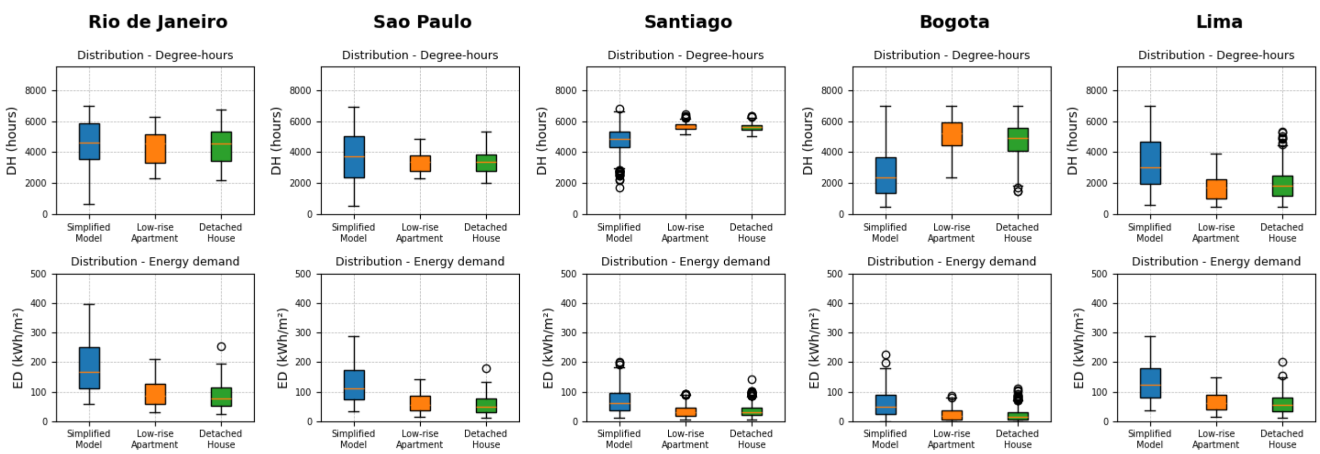


Figure 25. Distribution of degree-hours and energy demand values for each dataset generated.

Figure 25 illustrates distinct metric distributions for each city, reflecting variations in climate contexts considered in this study. Despite these differences, the detached house and low-rise apartment datasets displayed similar performance ranges, often aligning with each other. In contrast, the simplified model exhibited a notably different pattern, with more dispersed data points, only occasionally overlapping with the other datasets. Overall, Santiago and Bogotá demonstrated the lowest DH performance but achieved the lowest ED values, likely due to the effectiveness of passive design strategies in improving energy efficiency. Conversely, Rio de Janeiro, São Paulo, and Lima reported the highest ED values, likely influenced by the elevated temperatures typical of their climates.

4.3.2.2 Performance evaluation of machine learning models

In this study, XGBoost and ANN were evaluated in combination with transfer learning techniques. This study utilized random search to determine the optimal hyperparameter settings. For

XGBoost, the hyperparameters included the number of trees, maximum tree depth, and learning rate, while for the ANN, they included the number of hidden layers, neurons per layer, activation functions, and learning rate. **Table 29** presented the performance evaluation of each model across all cities, with the detached house as the source domain and the low-rise apartment and simplified model as target domains 1 and 2, respectively.

Table 29. Performance results evaluated using R², MAE, and MAPE, across the source domain, target domain 1, and target domain 2 for each city in this study.

City	Algorithm	Metric	Source domain			Target domain 1			Target domain 2		
			R^2	MAE	MAPE	R^2	MAE	MAPE	R^2	MAE	MAPE
RJ	XGBoost	DH	0.967	148	4	0.965	146	3	0.836	255	13
		ED	0.977	4	5	0.97	5	6	0.960	12	7
	ANN	DH	0.929	208	5	0.927	205	4	0.803	306	16
		ED	0.943	7	8	0.935	8	10	0.930	17	11
SP	XGBoost	DH	0.945	116	3	0.936	108	3	0.875	439	16
		ED	0.973	3	6	0.971	4	6	0.965	8	7
	ANN	DH	0.908	163	4	0.899	152	4	0.840	483	17
		ED	0.935	5	8	0.933	6	8	0.927	10	9
ST	XGBoost	DH	0.903	52	1	0.869	55	1	0.826	66	2
		ED	0.933	3	10	0.925	4	12	0.913	9	15
	ANN	DH	0.867	73	2	0.835	77	2	0.810	73	3
		ED	0.896	5	12	0.888	6	15	0.895	12	17
BG	XGBoost	DH	0.865	293	6	0.825	303	7	0.809	337	12
		ED	0.930	3	1	0.937	3	1	0.910	9	7
	ANN	DH	0.831	323	8	0.809	334	9	0.801	371	14
		ED	0.912	4	2	0.919	4	2	0.901	10	8
LM	XGBoost	DH	0.925	191	12	0.892	195	13	0.874	217	16
		ED	0.962	4	7	0.961	4	8	0.945	10	8
	ANN	DH	0.907	211	15	0.875	215	16	0.866	239	18
		ED	0.943	5	9	0.942	5	10	0.936	11	9

Table 29 highlights the similar performance of XGBoost and ANN in surrogate modeling. Particularly, XGBoost achieved slightly better results for R^2, MAE, and MAPE metrics across DH and ED models in all cities. Overall, both algorithms consistently delivered R^2 values above 80%, MAE below 500 hours for DH and 20 kWh/m² for ED, and MAPE below 20% for both outputs. The application of transfer learning, which fine-tunes a pre-trained model from a larger dataset to a smaller one, proved beneficial. A clear trend emerged: performance metrics for the source domain and target domain 1 were comparable, while a slight decrease was observed for target domain 2. Despite identical input parameters, the simplified model's performance metrics differed from those of the detached house and low-rise apartment models. Notably, the detached house and low-rise apartment datasets showed similar performance ranges (see Figure 25), enhancing transfer learning efficacy. In contrast, the distinct performance pattern of the simplified model slightly reduced the effectiveness of transfer learning in that case. Finally, XGBoost was selected for the optimization stage due to its fast-training speed and interpretability. In machine learning, an interpretable model allows its predictions or decisions to be easily understood and explained by humans. While ANN produced comparable results, it requires longer training times and lacks interpretability.

4.3.3 Procedure's results for developing construction guidelines

Finally, the procedure—comprising contextualization, investigation, and definition—employed an optimization loop, cluster analysis, heatmaps, and frequency analysis to develop construction guidelines that promote climate-resilient building design. The following sections illustrated the results for each step of the procedure.

4.3.3.1 Contextualization results

In the first step, the contextualization involved a loop to conduct 288 optimizations, considering parametric combinations of three key factors: site context, occupant behavior, and architectural design. **Figure 26** illustrated the Pareto front database generated for each analyzed city within this loop, with each architectural design labeled accordingly.

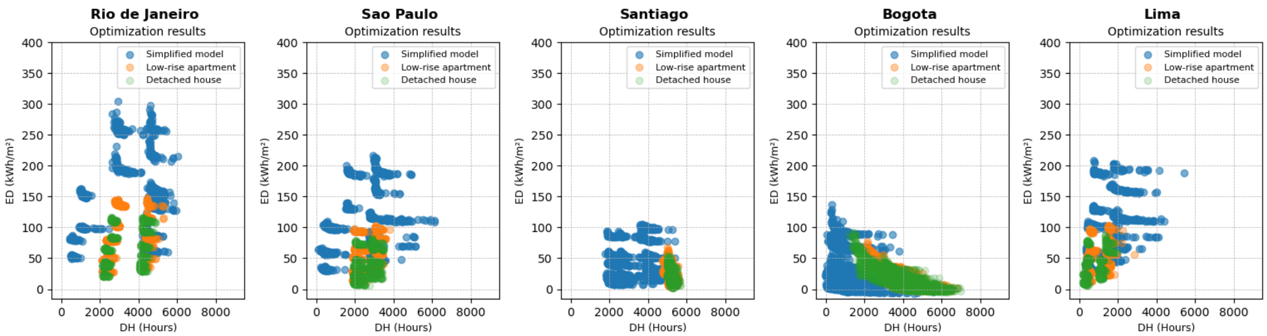


Figure 26. Pareto front results from each optimization loop, categorized as outcomes for the simplified model, detached house, and low-rise apartment.

The Pareto front distributions reflected the impact of climate variations across the cities studied. For Rio de Janeiro, Sao Paulo, and Lima, the dots formed by the Pareto fronts are more distinct and dispersed, suggesting that variations in site context, occupant behavior, and architectural design strongly influence performance. On the other hand, the data points for Santiago and Bogota show a tighter relationship, even when accounting for the shift in the simplified model, indicating more consistent results despite varying conditions. Notably, the detached house and low-rise apartment datasets showed overlapping performance ranges in many cities, though low-rise apartments occasionally yielding slightly poorer outcomes in terms of ED and DH. For the simplified model, the performance often deviated significantly, especially in cities with more diverse climatic conditions like Rio de Janeiro, Sao Paulo and Lima.

4.3.3.2 Investigation results

In the second step, the analysis explored the Pareto front database without considering the uncertainty parameters, examining all optimal solutions through cluster analysis and heatmap. Clustering was used to group similar data points based on specific characteristics. In this study, the K-means algorithm was applied and determined the optimal number of clusters using two metrics:

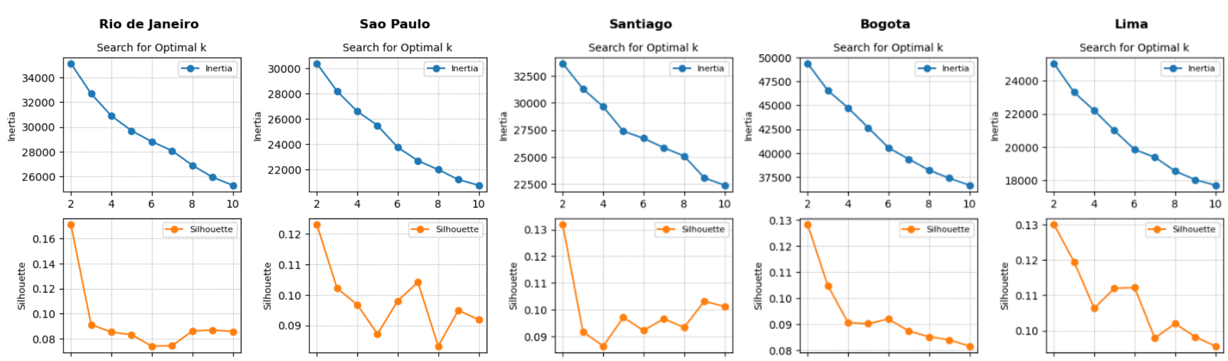


Figure 27. Clustering analysis results presented as inertia and silhouette score curves for each analyzed city.

inertia and silhouette score. In **Figure 27**, clustering performance metrics—inertia and silhouette score—are presented for each city to identify the optimal number of clusters in the dataset.

The inertia metric shows a consistent decrease as the number of clusters increases, reflecting improved within-cluster compactness. However, this reduction diminishes after a certain point, indicating a potential "elbow" that suggests an optimal number of clusters. The silhouette score, which evaluates cluster quality based on cohesion and separation, peaks at specific values, providing additional guidance for determining the optimal number of clusters. Considering the inertia score, the optimal number of clusters would be excessively high, rendering the development of generalized guidelines impractical. Therefore, the silhouette score was used as the primary criterion to determine the optimal number of clusters. Across all cities, two emerges as the optimal number of clusters. This suggests a consistent clustering pattern in each dataset, likely driven by shared characteristics. Furthermore, **Figure 28** labeled the Pareto front according to the defined clusters, providing a clear illustration of the distribution dynamics within each cluster.

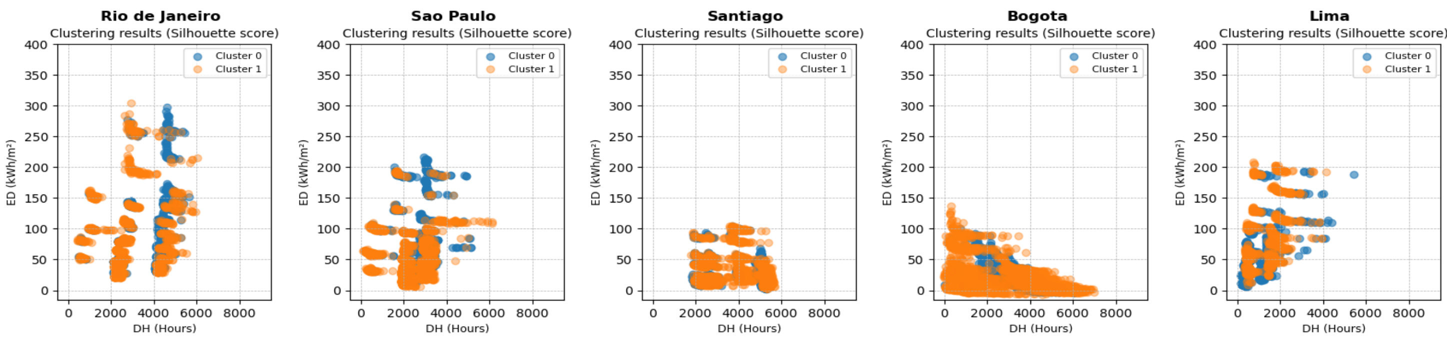


Figure 28. Pareto front results labeled based on cluster analysis definitions for each analyzed city.

When analyzing Figure 28, a common trend was the overlapping behavior of the clusters. Specifically, Santiago and Bogota exhibit identical results for both clusters. Additionally, minor deviations are observed for Rio de Janeiro, Sao Paulo, and Lima, where Cluster 0 shows worse performance in terms of DH, while ED results remain nearly identical between the clusters. Overall, this high level of performance similarity suggests that despite distinct design configurations, when subjected to varying conditions, produced comparable performance outcomes.

Furthermore, **Figure 29** presents a heatmap, illustrating the frequency of specific values across the entire dataset for each analyzed city. These heatmaps allow for quick identification of trends and patterns across various parameters. To ensure clarity and consistency in the graphical representation, the range of possible values for each variable is normalized to a scale of 1 to 10. However,

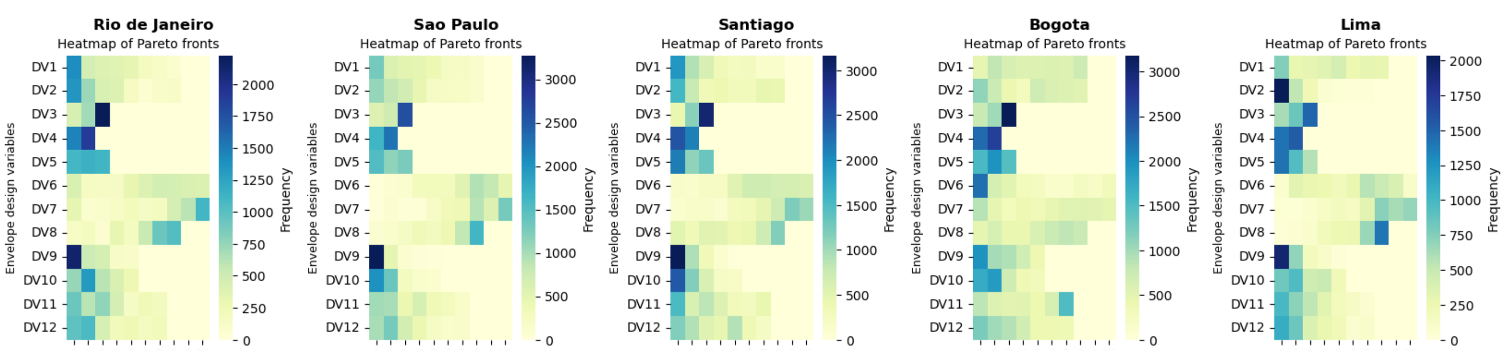


Figure 29. Heatmap of Pareto front database for each city analyzed.

Table **27** provides the actual range of values for each variable. This ensures that while the heatmaps use a standardized scale for visualization, the corresponding actual values can be referenced in

Table **27**.

When considering clustering classification, heatmaps can be generated for each cluster (Cluster 0 and Cluster 1). The distribution of values within these distinct heatmaps reveals that the most frequent configurations in Clusters 0 and 1 are highly similar. In Rio de Janeiro, Sao Paulo, and Santiago, the heatmaps are nearly identical, making them reliable indicators for defining construction guidelines. Conversely, in Bogota and Lima, slight variations in values complicate the interpretation of results and the formulation of guidelines. To simplify the analysis and ensure consistency, this study focused on analyzing the entire dataset. Generally, low solar absorptivity for walls and roofs, along with small, shaded windows, are common favorable configurations across cities. High-performance glazing is widely preferred, with some variation in Sao Paulo, Bogota, and Lima. Roof insulation is recommended in all cities except Bogota, while wall insulation is primarily beneficial in Sao Paulo, Santiago and Lima.

4.3.3.3 Definition Results

Finally, by determining the most frequent values, these characteristics can be translated into key thermal properties of construction elements, including thermal transmittance, thermal capacity, solar absorptance, and solar heat gain coefficient. Consequently, the main output is a set of design thresholds for transparent and opaque building components that support climate-resilient building design. In this study, three options were considered: the most frequent configurations of Cluster 0, Cluster 1, and the entire Pareto front dataset. However, due to the similarity of results across these classifications, the analysis focused on the entire dataset. **Table 30** provided the design thresholds for transparent and opaque construction elements for each analyzed city.

Table 30. Design thresholds for climate-resilient buildings in each analyzed city.

Index	Component	Property	City				
			Rio de Janeiro	Sao Paulo	Santiago	Bogota	Lima
1	Wall	U-value W/(m^2K)	2.1	1.0	1.0	2.1	1.0
		TC kJ/(m^2K)	240	241.5	241.5	240	50.3
		SA	0.2	0.2	0.5	0.8	0.2
2	Roof	U-value W/(m^2K)	0.5	0.5	0.9	2.1	1
		TC kJ/(m^2K)	31.3	31.3	20.7	26.4	22.5
		SA	0.2	0.2	0.5	0.2	0.2
3	Window	WWR	20%	20%	20%	20%	20%
		U-value W/(m^2K)	1.02	2.27	1.02	1.65	2.89
		SHGC	0.19	0.28	0.19	0.19	0.19
		Opening factor	90%	60%	50%	50%	90%
		Shading devices	Large	Large	Large	Large	Large

Table 30 outlined the design thresholds for climate-resilient building components, focusing on three key elements: walls, roofs, and windows. Specifically, it presents optimal values for thermal transmittance, thermal capacity, and solar absorptance for opaque elements (walls and roofs). For transparent elements (windows), it includes window-to-wall ratio, thermal transmittance, solar heat gain coefficient, opening factor, and shading devices. Variations in design thresholds are observed across cities due to differing climatic contexts. However, certain favorable configurations are consistent, such as low solar absorptance for walls and roofs, high-performance glazing, small, and shaded windows. Low thermal transmittance and thermal capacity for roofs are recommended for all cities except Bogota, while these properties are suggested for walls only in Sao Paulo, Santiago, and Lima.

4.4 Discussions

Building performance simulation (BPS) tools are essential for extending insights beyond experimental limitations, especially when dealing with uncertain issues such as climate change. Given the unpredictability of which climate scenario will ultimately materialize, this study stands apart from others (CRUZ; BASTOS, 2024; CRUZ; CUNHA, 2022) by addressing this uncertainty through a comparative analysis of multiple IPCC emission scenarios. Yet, the projection results align well with existing literature (BRACHT et al., 2024; CRAWLEY; LAWRIE, 2019; GONÇALVES et al., 2024; VERICHEV; ZAMORANO; CARPIO, 2020). Additionally, considering the diverse climatic conditions across various locations was deemed a highly effective approach. As seen in previous studies (BRACHT et al., 2024; RODRIGUES; FERNANDES, 2020; RODRIGUES; PARENTE; FERNANDES, 2024), it enables a more comprehensive evaluation of the proposed method, demonstrating its adaptability and potential.

Furthermore, considering the urban context is vital, especially in Latin American cities, where significant urban population growth is projected in the coming decades (LUBBOCK; VIVARES, 2022; WORLD BANK, 2024), a focus increasingly highlighted in recent studies (FELIX KRIESTEN et al., 2024; HOSTEIN et al., 2024; KAMAL et al., 2023b; MA et al., 2023). The urban climate was modeled using the Local Climate Zone (LCZ) classification system, for the compact low-rise category (LCZ3) (STEWART; OKE, 2012). This assumption may be conservative, as denser urban areas are likely to experience even more intense UHI effects (LÓPEZ-GUERRERO et al., 2022, 2024). Consequently, if urban overheating mitigation strategies, such as urban greening, are not implemented, the proposed guidelines are designed to provide a buffer against uncertainties in the future performance of urban buildings.

This investigation used the 90% acceptability limits of the ASHRAE Adaptive Comfort model as a thermal comfort indicator to address growth in living standards (LUBBOCK; VIVARES, 2022; WORLD BANK, 2024), while most articles rely on the 80% limits for indoor operative temperature (FLORES-LARSEN; FILIPPÍN; BAREA, 2019; NUNES; GIGLIO, 2022; TRIANA; LAMBERTS; SASSI, 2018). Studies emphasize a preference for natural ventilation in tropical climates, where residents often adjust clothing for comfort (ALVES; DUARTE; GONÇALVES, 2016; ALVES; GONÇALVES; DUARTE, 2021). However, rising purchasing power in Global South countries drives an 80% projected growth in conditioned spaces, highlighting a critical gap in the energy discourse (IEA, 2018, 2022).

From the machine learning perspective, the models developed to predict degree-hours and energy demand for the evaluated cities demonstrated performance comparable to the literature (CRUZ et al., 2024a), achieving R^2 values exceeding 80% for both algorithms (XGBoost and ANN). Furthermore, this study applied transfer learning to enhance computational efficiency, a technique still underutilized in the building performance field but proven effective (KO; PARK, 2021a, 2021b). However, transfer learning has limitations when applied to multiple building types. For instance, (YAN; JI; YAN, 2022b) found its predictive performance declines when design parameters or performance goals vary significantly. In this study, although identical input parameters, variations in output results across architectural designs slightly reduced the effectiveness of transfer learning. However, datasets with similar performance values generally enhanced its efficacy. Consequently, despite the slight reduction in effectiveness, transfer learning proved to be an efficient and viable strategy. Finally, combining machine learning with optimization algorithms effectively identified strategies for energy efficiency and thermal comfort. While rare in the literature (HOSNA et al., 2022;

KO; PARK, 2021b), this approach should be more widely adopted, as it reduces simulation requirements and efficiently evaluates technologies, materials, and solutions (LAGUNAS et al., 2023; PAN; YANG, 2010).

4.5 Conclusion

This study proposed a procedure for developing construction guidelines to support climate-resilient building design in the Global South's residential sector. More specifically, this study applied this proposed simulation-based procedure into five cities (Rio de Janeiro, Sao Paulo, Santiago, Bogota, and Lima) across four Latin American countries (Brazil, Chile, Colombia and Peru), selected based on their status as major urban centers in emerging economies, high housing deficit indices, and diverse climates.

In the first step, this study compares future climate projections and generates future urban weather files by integrating IPCC emissions scenarios with urban heat island (UHI) effects. The results indicated that the A2 scenario from the Special Report on Emissions Scenarios (SRES) and the Shared Socioeconomic Pathways SSP5-8.5 provide similar climate projections for both 2050 and 2080, with a percentage deviation of no more than 10%. As expected, future urban weather predictions showed a significant increase in the analyzed parameters by 2080 when compared to historical data. On average, the dry-bulb temperature is projected to rise by up to 5°C, relative humidity by 2%, and global horizontal radiation by up to 6 Wh/m².

Subsequently, Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) were applied and compared as surrogate models leveraging transfer learning techniques to efficiently explore three architectural designs. Overall, XGBoost and ANN demonstrated comparable performance in degree-hours and energy demand models across all cities, achieving higher R^2 and lower MAE and MAPE values. Transfer learning also proved beneficial in this study, with a general trend emerging: performance results were similar between the source domain (detached house) and target domain 1 (low-rise apartment), with a slight performance decline observed in target domain 2 (simplified model). Despite identical input parameters, the simplified model's distinct performance metrics limit its effectiveness for transfer learning, whereas the similarity between the detached house and low-rise apartment enhances transfer learning efficacy.

The proposed procedure, comprising three key steps—contextualization, investigation, and definition—integrated optimization loops, cluster analysis, heatmaps, and frequency analysis to establish design thresholds for transparent and opaque building components. During the contextualization step, while the Pareto front for the detached house and low-rise apartment datasets exhibited overlapping performance ranges, the simplified model often showed significant deviations. In the investigation step, the silhouette score identified two as the optimal number of clusters across all cities, with overlapping cluster behavior being a common trend. Analysis of heatmap distributions indicated that the most frequent configurations in these clusters were highly similar. To simplify the analysis and ensure consistency, the study focused on investigating the entire dataset during the frequency analysis. The resulting design thresholds targeted three key building components: walls, roofs, and windows. Variations in these thresholds were observed across cities due to differing climatic contexts. Nevertheless, certain configurations consistently emerged as favorable, including low solar absorptance for walls and roofs, high-performance glazing, small windows, and shaded openings. Low thermal transmittance and thermal capacity for roofs were recommended for all cities except Bogota, while these properties were suggested for walls only in Sao Paulo, Santiago, and Lima. Lastly, these findings underscore the simulation-based procedure's ability to deliver valuable insights, supporting Latin American policymakers in developing construction guidelines for climate-resilient building design in the Global South's residential sector.

4.5.1 Directions for future research

This paper addressed an important research topic, though several gaps remain to be explored in future investigations: 1) Cost Analysis: Life-cycle cost (LCC) analysis was not included. Future studies should evaluate the costs of the proposed strategies to better understand their feasibility. 2) Environmental performance: The integration of Life-cycle assessments (LCA) into the optimization process is necessary to address environmental performance and advance decarbonization efforts in the built environment. 3) Urban Typologies: This research incorporated urban heat island effects using only the LCZ3 classification. Future studies should examine other urban typologies, particularly denser areas such as LCZ1 and LCZ2, for broader analysis. 4) Ventilation Modes: Only natural and mechanical ventilation were considered. Mixed-mode approaches should be explored to assess their potential in the context of climate change. 5) Building Typologies: This study focused exclusively on residential buildings. Extending the methodology to other typologies, such as commercial buildings, is essential for a more comprehensive understanding. 6) Shading devices: This study focused on overhangs and side fins, whereas others have explored balconies. Future research should investigate a wider range of shading strategies to better understand their potential in the context of climate change. 7) Transfer learning: This study used the model with an intermediate level of complexity as the source domain. Future studies should explore all possible source domain combinations, including the simplest model, to boost the efficiency of transfer learning in this research field.

5. Chapter 5: How feasible is climate-resilient building design is within the Global South context? Insights from Latin American residential sector

Abstract: Developing climate-resilient building design is inherently complex, requiring a careful balance between adaptation and mitigation challenges. Within this discussion, this investigation explores the climate-resilient building design feasibility in five Latin American cities. This study generates hypothetical future urban weather files by integrating IPCC emissions scenarios with urban heat island (UHI) effects. Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) are considered and compared as surrogate models, leveraging transfer learning to efficiently capture climate-driven thermal-energy performance shifts. The Shapley Additive Explanation (SHAP) method is used to evaluate how climate change influences the importance of input variables on the output variable. These surrogate models are then integrated with the Non-Dominated Sorting Genetic Algorithm III (NSGA-III) to optimize the envelope system based on thermal performance, carbon emissions, and costs. Lastly, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) performs the trade-off analysis, employing different weighting factors for each metric to assess the impact of varying preferences. The results showed future urban weather conditions trending towards higher dry-bulb temperature, relative humidity, and global horizontal radiation. Both XGBoost and ANN demonstrated a comparable performance, with the future urban context significantly influencing the importance of variables in thermal performance. Additionally, the transfer learning technique proved beneficial. Despite climatic variations, the optimal configurations under the Equal Weights context remained consistent across cities. While advanced construction systems could enhance adaptation to future climates, their feasibility is constrained by cost and carbon emissions. Finally, this study concluded that climate resilience in Latin America is best accomplished through architectural passive design. Optimizing solar orientation—along with moderately sized windows, light-colored envelopes, and insulated roof—offers a cost-effective, sustainable, and equitable solution to protect vulnerable communities in the Global South.

Keywords: Global South, Latin America, Climate Change, Life Cycle Assessment, Life Cycle Cost, Building Performance Simulation, Machine Learning, Optimization.

5.1 Introduction

More than one billion people globally face housing shortages, with the majority residing in the Global South (GS). The GS refers to nations commonly known as 'developing countries,' including those in Latin America, Africa, Asia (excluding Israel, Japan, and South Korea), and Oceania (excluding Australia and New Zealand) (DADOS; CONNELL, 2012). These regions face challenges like rapid urban growth, population increases, and economic inequality. In addition, the Intergovernmental Panel on Climate Change (IPCC) underscores that global warming is having the greatest impact on vulnerable GS communities (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). At least 1 billion people face cooling access risks, while over 2 billion are likely to rely on inefficient cooling devices, leading to a significant rise in energy consumption and associated carbon emissions (IEA, 2018, 2022). Addressing these interconnected challenges requires urgent and integrated solutions that prioritize sustainable development, equitable access to resources, and climate resilience, ensuring that the most vulnerable populations are not left behind (CRUZ et al., 2024b).

Latin America (see **Figure 30**) is particularly notable in the GS context due to its recent economic and social progress, driven by growth in industries like manufacturing, services, and technology, supported by foreign investments and trade agreements (LUBBOCK; VIVARES, 2022; WORLD BANK, 2024). However, the region still faces a significant housing deficit, affecting millions and leading to the growth of informal settlements, such as slums and favelas (OECD, 2015). Latin America's construction methods share common features shaped by historical, climatic, and economic factors. Affordable raw materials, such as limestone and clay, have facilitated the widespread use of concrete and masonry in self-built housing, effectively addressing urgent housing needs (VIGEVANI; RAMANZINI JUNIOR, 2022). The housing crisis goes beyond a lack of shelter, as it also includes poor living conditions and exposure to environmental risks, which have worsened due to climate change (INTER-AMERICAN DEVELOPMENT BANK, 2022; MARÍN-RESTREPO et al., 2023). Therefore, solving the housing deficit in Latin America requires a broad approach that considers social needs when promoting climate-resilient building designs (UN, 2022, 2023a).

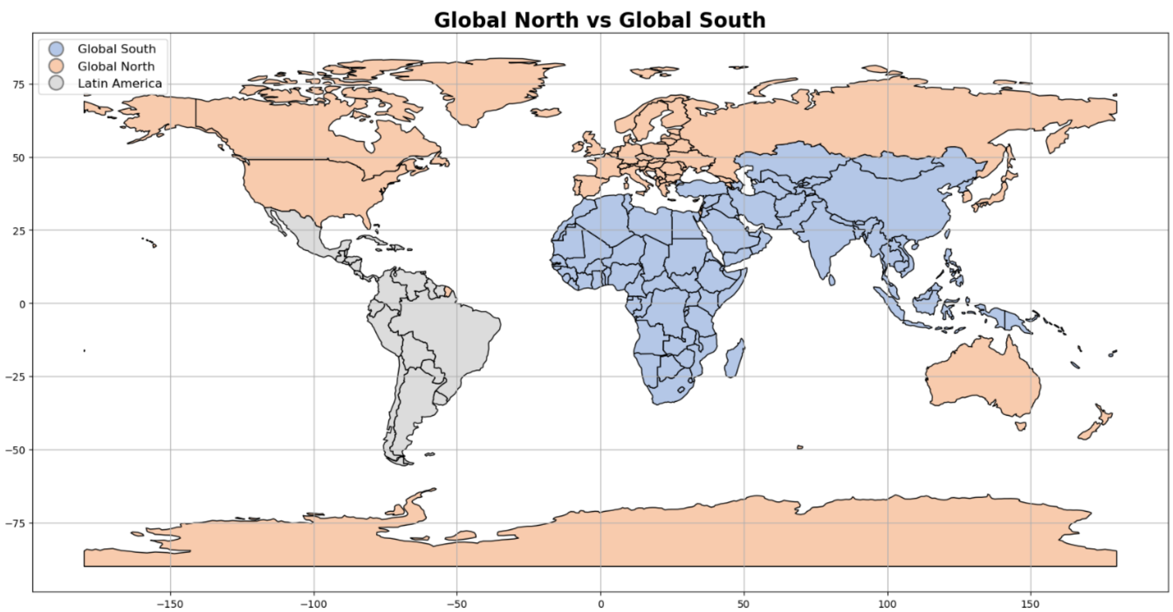


Figure 30. Latin America within Global South context.

The concept of resilience has changed over time (ATTIA et al., 2021; HOMAEI; HAMDY, 2021; KESIK; O'BRIEN; OZKAN, 2022; MILLER et al., 2021), but when it comes to buildings, resilience is shaped by four main factors: vulnerability, adaptability, mitigation, and resistance (IPCC, 1990, 1995, 2001, 2007, 2014, 2023). Vulnerability refers to how easily a building can be harmed, damaged, or disrupted by external forces. Adaptability is the ability to adjust to current or future climate conditions and their effects on people. Mitigation focuses on reducing greenhouse gas (GHG) emissions or increasing their absorption and storage. Resistance is a building's capacity to withstand external forces without major damage or loss of functionality. Therefore, climate-resilient building design starts with assessing vulnerability, which can guide the creation of adaptation and mitigation strategies to improve resistance to future weather conditions (ATTIA et al., 2021; HOMAEI; HAMDY, 2021; KESIK; O'BRIEN; OZKAN, 2022; MILLER et al., 2021).

Building performance simulation (BPS) tools are increasingly utilized to assess resilience, particularly in analyzing overheating risks posed by climate change (CRAWLEY; LAWRIE, 2019). Simulation studies play a critical role in advancing research by addressing the limitations of traditional experiments, such as scale and geographic constraints. Rather than relying on historical climate data, researchers advocate for updating weather files to incorporate projected climate patterns (COLE; EVINS; EAMES, 2024; MACHARD et al., 2020). The IPCC's Assessment Reports (AR) offer emissions scenarios that model future climates under varying GHG levels. These include: 1) the Special Report on Emissions Scenarios (SRES) from AR3 (IPCC, 2001) and AR4 (IPCC, 2007), 2) the Representative Concentration Pathways (RCP) from AR5 (IPCC, 2014), and 3) the Shared Socioeconomic Pathways (SSP) from AR6 (IPCC, 2023). Leveraging these scenarios, BPS tools facilitate detailed assessments of building performance in diverse future climates, aiding in the development of effective resilience strategies (COLE; EVINS; EAMES, 2024; CRAWLEY; LAWRIE, 2019; ESCANDÓN et al., 2023; MACHARD et al., 2020; RODRIGUES; FERNANDES; CARVALHO, 2023).

5.1.1 Literature review

Despite significant uncertainty about the prevailing climate pathway, all IPCC scenarios consistently project a trend toward a warmer future climate. Hugo (2023) used SRES scenarios to evaluate informal settlements in Pretoria, South Africa, predicting up to a 40% increase in heat stress exposure due to climate change. Xiong et al. (2023) applied SSP scenarios to assess residential buildings in Harbin, Beijing, Chongqing, Guangzhou, and Kunming (China), estimating that cooling energy demand could rise by 20% by 2060. Verichev; Zamorano; Carpio, (2020) analyzed residential buildings in Chile using RCP scenarios, finding that heating energy consumption may decrease by up to 16%. Callejas et al. (2021) projected a 64% increase in energy consumption for residential buildings in Cuiabá, Brazil, by 2050, based on SRES scenarios. Likewise, studies utilizing SRES projections in locations like Mexico (BORBON-ALMADA et al., 2020) and Ghana (DODOO; AYARKWA, 2019) projected energy demand increases of up to 50% by 2080.

Moreover, weather files are often derived from remote stations far from urban areas, failing to capture local conditions influenced by urban heat island (UHI) effects (VERICHEV et al., 2021; VERICHEV; ZAMORANO; CARPIO, 2020). Alternatives include using data from nearby urban stations or employing tools like the Urban Weather Generator (UWG) to model UHI impacts (KAMAL et al., 2023a). For instance, Palme et al. (2017) reported thermal load increases ranging from 15% to 200% in residential buildings across Guayaquil (Ecuador), Lima (Peru), and Antofagasta and Valparaíso (Chile) due to UHI effects. Litardo et al. (2020) found cooling demands rose up to 70% in Duran, Ecuador. Liu et al. (2017) and Ma; Yu (2024) observed energy consumption increases up to 11% in residential buildings in Singapore and Hong Kong, respectively. Similar results can be found in Maceio, Brazil (LIMA; SCALCO; LAMBERTS, 2019) and Delhi, India (KUMARI et al., 2020). As modern buildings are designed to last at least 50 years (ANDERSEN; NEGENDAHL, 2023), it is essential to consider diverse future climate scenarios and the UHI effects to gain valuable insights and guide the development of climate-resilient building designs.

BPS tools are often combined with automation software to enhance assessments through methods like parametric analysis, sensitivity analysis, and optimization. Parametric analysis explores combinations of design variables, while sensitivity analysis identifies those with the greatest and least impact on performance (FLORES-LARSEN; FILIPPÍN; BAREA, 2019; GAMERO-SALINAS et al., 2021). Optimization employs advanced techniques to efficiently explore the design space, enabling strategic solutions to complex problems by identifying the best-performing configurations (GONÇALVES et al., 2024; KRELLING et al., 2024). Although optimization is a powerful technique, it can become computationally expensive when each iteration relies on BPS tools to run energy simulations. A viable alternative is optimization using surrogate models, also referred to as statistical models, meta-models, or response surface approximations (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019). These models are trained on pre-existing data to understand the relationships between input and output variables. Once well trained, they replicate the behavior of the original model, enabling quick and accurate predictions for new input scenarios (AMASYALI; EL-GOHARY, 2018; SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017).

Zou et al. (2021a) optimized the design of a classroom in Guangzhou, China, using RCP projections. They combined an Artificial Neural Network (ANN) with the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), finding that optimal solutions under future weather conditions tend to lower the SHGC and enhance the thermal insulation of the building envelope. Li et al., (2023b) conducted an optimization study on a residential building in Huangshan, China, using RCP projections. They assessed various machine learning models (AdaBoost, Extra Trees, and XGBoost) to estimate heating, cooling, and costs, and integrated these models with NSGA-II for optimization. The optimal solution suggested an increase in roof insulation thickness. Yan; Ji; Yan(2022b) applied NSGA-II to optimize the design of two residential buildings in Singapore using SSP projections. Their findings revealed the importance of enhancing envelope insulation to address future warming scenarios. They combined the XGBoost algorithm with transfer learning to predict the performance of two distinct building types. Transfer learning enables a machine learning model to be retrained on new datasets while retaining core insights learned from the initial data (HOSNA et al., 2022; KO; PARK, 2021b). Essentially, it is a technique where knowledge acquired from one task is leveraged to improve performance on a related task, by reusing pre-trained models or learned features (LAGUNAS et al., 2023; PAN; YANG, 2010).

Optimization often involves addressing multiple, often conflicting objectives, highlighting the complexity of building design. A commonly employed approach to manage such conflicts is the Pareto front, which produces a set of optimal solutions highlighting the trade-offs between objectives. This approach offers decision-makers the flexibility to select the most suitable solution based on their priorities. For instance, Wang; Lu; Feng (2020) investigated retrofit strategies for a residential building in Tianjin, China, selecting the optimal solution based on the shortest payback period. Gonçalves et al. (2024) examined construction systems Brazilian social housing located in Belém, evaluating the optimal solutions using cost-benefit ratios. The cost-benefit solution achieved 95% of thermal autonomy hours and a notable 31% reduction in investment costs. On the other hand, several studies apply multi-criteria decision-making (MCDM) techniques to select preferred solution. For instance, Saryazdi et al. (2022) optimized a typical residential building in Kuwait and used the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method. The TOPSIS-suggested solution achieved reductions in energy consumption, discomfort hours, and carbon emissions of 39%, 63%, and 40%, respectively. Similarly, Song et al. (2023) proposed a life cycle retrofit for a rural building in Turpan, China. The TOPSIS-suggested solution enhanced building performance, achieving reductions of 61%, 53%, and 14% in global warming potential, life cycle costs, and discomfort hours, respectively. Chen; Tsay; Ni, (2022); Chen; Tsay; Zhang, (2023) highlighted that differing value ranges of objectives can skew the selection process, with targets showing significant changes dominating outcomes. To address this, the authors incorporated refined standard deviation/normalization formulas into the Utopia Solution (US) method, mitigating these effects. Their results showed reductions in carbon emissions, discomfort hours, and global cost by up to 50%, 40%, and 20%, respectively.

5.1.2 Novelty and main contribution

Although Latin America offers fertile ground for collaborative efforts to tackle climate change in the building sector—owing to the housing deficit (INTER-AMERICAN DEVELOPMENT BANK, 2022; VIGEVANI; RAMANZINI JUNIOR, 2022), common construction practices (UN, 2022, 2023a), shared socioeconomic conditions (MARÍN-RESTREPO et al., 2023; OECD, 2015), and regional agreements (LUBBOCK; VIVARES, 2022; WORLD BANK, 2024) —no studies propose a macro-level geopolitical perspective analysis. Furthermore, studies utilizing future urban weather files predominantly focus on adaptation strategies, often neglecting mitigation analysis (CRUZ et al., 2024b). Insufficient mitigation efforts increase future adaptation costs, while effective adaptation can reduce mitigation requirements (HAMIN; GURRAN, 2009). Synergies emerge when combining multiple measures enhance overall outcomes, though trade-offs may occur if one measure undermines the other (XU et al., 2019). For instance, the higher construction costs for passive designs and the potential for increased carbon emissions from energy-intensive materials (HAMIN; GURRAN, 2009; XU et al., 2019). In other words, designing climate-resilient buildings is inherently complex, requiring the balancing of multiple, often conflicting objectives to address both adaptation and mitigation challenges. Key considerations include the optimization of thermal performance, energy efficiency, environmental impacts, and costs, where trade-offs must ensure solutions that are sustainable and equitable. As a consequence, a pivotal question emerges: How feasible is climate-resilient building design within the Global South context?

Within this discussion, this investigation explores the climate-resilient building design feasibility in five Latin American cities. This study generates hypothetical future urban weather files by integrating IPCC emissions scenarios with urban heat island (UHI) effects. Extreme Gradient Boosting (XGBoost) and Artificial Neural Networks (ANN) are considered and compared as surrogate models, leveraging transfer learning to efficiently capture climate-driven thermal-energy performance shifts. The Shapley Additive Explanation (SHAP) method is used to evaluate how climate change influences the importance of input variables on the output variable. These surrogate models are then integrated with the Non-Dominated Sorting Genetic Algorithm III (NSGA-III) to optimize the envelope system based on thermal performance, carbon emissions, and costs. Lastly, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) performs the trade-off analysis, employing different weighting factors for each metric to assess the impact of varying preferences. Consequently, this research introduces two key novel contributions: 1) a macro-level geopolitical perspective that fosters international collaboration, and 2) a simulation-based investigation that integrates machine learning with optimization and multi-criteria decision-making (MCDM) techniques to explore the feasibility of climate-resilient building design in the GS context.

Finally, to provide a clear structure, the remaining sections of this paper are organized as follows: Section 5.2 outlines the research method conducted, explaining all the steps related to future urban weather predictions, surrogate modeling, optimization and decision-making process. Section 5.3 illustrates the prediction findings, modeling evaluations, optimization outcomes and decision-making results. Section 5.4 discusses and compares the results with prior studies. Finally, Section 5.5 presents the conclusions and directions for future research in the field.

5.2 Method

Table 31 outlines the research methodology for this study, breaking it down into distinct steps. Each step highlights the objectives, approaches, design variables, and metrics considered.

Table 31. Research method.

Step	Description	Goal	Approach	Design variables	Metrics
1	Future urban weather prediction	Predict future weather conditions in the urban environment	• Morphing method. • UHI modeling.	• Location. • Emission scenarios. • Urban context.	• Dry-bulb temperature. • Relative humidity. • Global horizontal radiation.
2	Surrogate modeling	Develop a machine learning model to predict thermal-energy performance indicator	• XGBoost. • ANN. • Transfer learning. • Shapley Additive Explanation.	• Weather data. • Envelope properties.	• Thermal load • SHAP. • R^2, MAE, and MAPE;
3	Optimization	To improve thermal performance, carbon emissions, and costs	• NSGA-III algorithm.		• Thermal load. • Carbon emissions. • Cost.
4	Decision-making procedure	Identify the optimal solution for varying preferences	• TOPSIS method • Radar plot	Weighting factors	

The initial phase focused on projecting hypothetical future urban weather patterns for the chosen cities by combining IPCC emissions scenarios with the UHI effect into historical weather data. The SSP scenarios from the latest IPCC AR are considered and the UWG is used to incorporate UHI effects. During this stage, the primary indicators for assessing future urban weather conditions include dry-bulb temperature (DBT), relative humidity (RH), and global horizontal radiation (GHR).

The second step involved developing machine learning models to predict the thermal-energy performance of two residential buildings. The architectural designs included a detached house and a low-rise apartment, with Thermal Load (TL) used as a key thermal-energy performance metric. XGBoost and ANN are considered and compared as surrogate models, leveraging transfer learning techniques to efficiently capture thermal-energy performance shifts driven by climate change. This approach reduces the resource intensity and time demands of training standalone models. In addition, the SHAP method is used to evaluate how climate change may influence the importance of input variables on the output, serving as a form of sensitivity analysis.

In the third step, surrogate models are integrated with NSGA-III to optimize thermal performance, carbon emissions, and costs simultaneously. Various envelope systems are analyzed to determine their influence on thermal, carbon, and cost performances. More specifically, the design variables include orientation; types of walls, roofs, ceilings, and glazing; window size; and absorptance values for walls and roofs. Carbon emissions are estimated using the Ecoinvent database, while cost calculations are based on various relevant databases. The fourth and final step emphasizes the decision-making process to identify the optimal solution within the Pareto front for a given preference context. The TOPSIS method is applied to perform the trade-off analysis, using different weighting factors for each metric to assess the impact of varying preferences. To facilitate result visualization and interpretation, radar plots are employed.

5.2.1 Future urban weather predictions

This study employed hypothetical future urban weather projections for five cities in four Latin American countries—Brazil, Chile, Colombia, and Peru—selected for their status as major urban hubs in emerging economies, significant housing deficits, and diverse climatic conditions. Historical climate data are represented by Typical Meteorological Year (TMY) files (CLIMATE.ONEBUILDING.ORG). Key climate parameters, such as DBT, RH, and GHR, are detailed in **Table 32** and **Figure 31** for the analyzed locations.

Table 32. Weather data for the evaluated cities.

City	Country	Koppen-Geiger	DBT (°C)			RH (%)	GHR (Wh/m²)
			Average	Max	Min	Average	Average
Rio de Janeiro	Brazil	Aw	24	38	13	82	209
Sao Paulo	Brazil	Cfa	19	33	7.5	82	213
Santiago	Chile	Csb	15	33	-6	71	204
Bogota	Colombia	Cfb	13	24	0	80	184
Lima	Peru	BWh	19	30	11	81	178

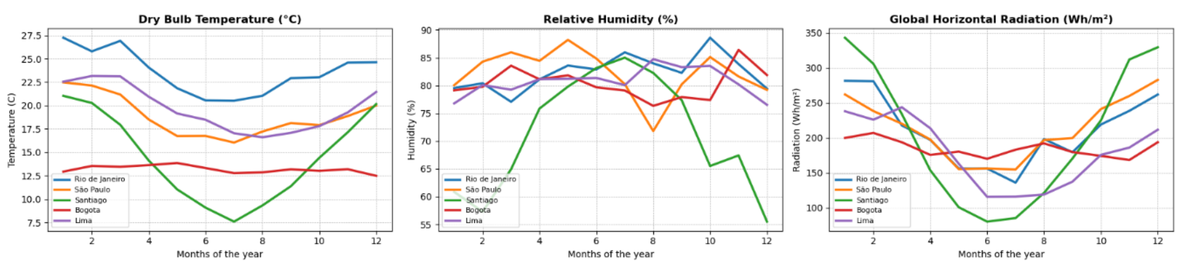


Figure 31. Weather data for the evaluated cities, featuring monthly averages of DBT, RH, and GHR.

Future climate projections rely on Global Climate Models (GCMs), which simulate Earth system interactions and are validated against historical data before using IPCC emissions scenarios (CAMPAGNA; FIORITO, 2022; EYRING et al., 2016). Due to their coarse resolution and biases, GCM outputs require downscaling for BPS tools (RODRIGUES; FERNANDES; CARVALHO, 2023). Downscaling can be statistical—via stochastic or imposed offset techniques—or dynamical (COLE; EVINS; EAMES, 2024). Regional Climate Models (RCMs) use dynamic downscaling to refine GCM data, improving mesoscale weather simulations (BRACHT et al., 2024; CAMPAGNA; FIORITO, 2022). While stochastic and dynamical methods are computationally intensive, the statistical imposed offset technique (morphing method) offers an efficient alternative (CAMPAGNA; FIORITO, 2022; ESCANDÓN et al., 2023; MACHARD et al., 2020). Therefore, to address uncertainties in future projections, this study considered the Future Weather Generator tool that applies the morphing method to generate future weather files (RODRIGUES; FERNANDES; CARVALHO, 2023). The tool is based on CMIP6, offers all Shared Socioeconomic Pathways (SSP) scenarios for 2050 and 2080.

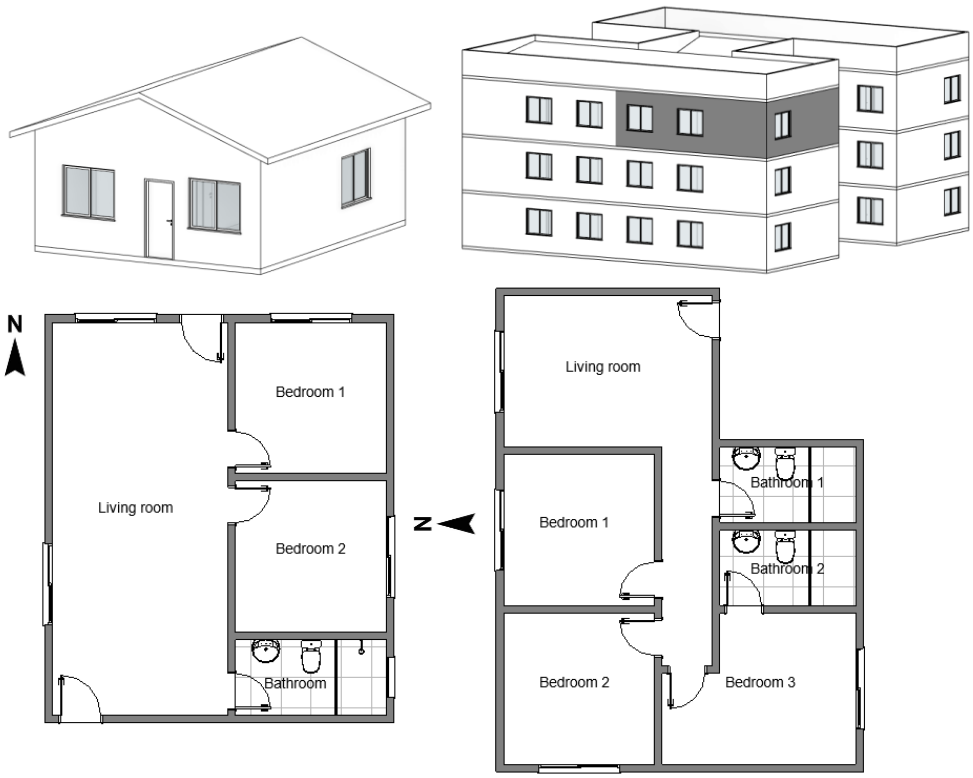
Furthermore, this study utilized the open-access UWG tool to incorporate UHI effects into weather data. The UWG relies on inputs such as microclimate conditions, urban morphology, vegetation, and building attributes (BUENO et al., 2014; MAO et al., 2017; SALVATI et al., 2019). These inputs were tailored to reflect the typical low- and medium-rise residential urban layouts in Latin American cities. Two main criteria guided the definition of the urban parameters. First, the urban configuration is classified using the Local Climate Zone (LCZ) system (STEWART; OKE, 2012). The compact mid-rise class (LCZ2) was combined with the open mid-rise class (LCZ5) to define LCZ2$_5$, representing low-rise apartment context. Similarly, the compact low-rise class (LCZ3) was combined with the open low-rise class (LCZ6) to define $LCZ3_6$, representing detached house context. This classification was based on two key considerations: Latin American cities are characterized by heterogeneous urban fabrics (LITARDO et al., 2020; LÓPEZ-GUERRERO et al., 2024; PALME et al., 2017); and the LCZ subcategories with favorable urban conditions helps mitigate the overestimation of UHI effects on buildings (LÓPEZ-GUERRERO et al., 2024; SALVATI et al., 2019). Drawing insights from previous studies (DA SILVA; LIMA; SAITO, 2023; FERNÁNDEZ; KOPLOW-VILLAVICENCIO; MONTOYA-TANGARIFE, 2023; LIMA; SCALCO; LAMBERTS, 2019; VÁSQUEZ et al., 2019), the primary urban parameters were standardized across all cities evaluated to ensure consistency and comparability. These parameters included green coverage (GC) of 0.25, average building high (ABH) of 12m and 5m, site coverage ratio (SCR) of 0.5, façade-to-site ratio (FSR) of 0.85 and 0.75, and anthropogenic heat from traffic (AHT) of 25 W/m^2 for $LCZ2_5$ and $LCZ3_6$, respectively. Finally, by combining future climate projections with UHI effect, a hypothetical future urban weather files were generated to assess how climate change may influence climate-resilient building design.

5.2.2 Surrogate modeling

Developing a surrogate model using simulation data involves several steps (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019). The process begins with defining the building design problem by identifying the inputs (design variables) and outputs (objective functions). Following this, a high-fidelity baseline simulation is performed, varying the design variables to generate a comprehensive dataset. This dataset undergoes preprocessing and is divided into training and testing subsets, often utilizing cross-validation techniques to ensure robustness (WANG; SRINIVASAN, 2017). Next, an appropriate machine learning algorithm is chosen to train the surrogate model, capturing the relationship between inputs and outputs. The model's accuracy is validated by comparing its predictions with the test set, using evaluation metrics to assess performance (SUN; HAGHIGHAT; FUNG, 2020). If the results are unsatisfactory, the model is refined through techniques such as hyperparameter tuning, retraining, or augmenting the dataset (AMASYALI; EL-GOHARY, 2018). Once validated, the surrogate model is ready for application in tasks like optimization or real-time predictions (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019). This enables rapid and efficient approximations of the original simulation model, significantly reducing computational time and effort. This study employed surrogate modeling to predict the TL (thermal-energy performance metric) of two architectural buildings under two climate scenarios: historical and future urban weather conditions.

5.2.2.1 Architectural designs

This study evaluated two representative architectural designs: a detached house (DH) and a low-rise apartment (LRA). Both models feature a ceiling height of 3 meters, with floor areas of 56 m² and 62 m², respectively (See **Figure 32** for 3D views and floorplans). While detached houses comprise the majority of the residential building stock, urban areas are increasingly defined by vertical developments (ARUL BABU; SRIVASTAVA; RAI, 2024; GUARDA et al., 2020; LI et al., 2023b; LIU et al., 2020b; NUNES; GIGLIO, 2022; TRIANA; LAMBERTS; SASSI, 2018). Consequently, analyzing diverse architectural designs is essential to assess the broader applicability of the findings across various building types (CRUZ et al., 2024b).



b) Detached house b) Low-rise apartment

Figure 32. 3D views and floor plans for: (a) Detached house, and (b) Low-rise apartment.

To enhance the reliability of simulation results and minimize discrepancies with field measurements—especially during the design phase before the building is constructed—it is essential to employ robust strategies. In the absence of calibration opportunities, accuracy can be improved by utilizing validated software, precise input data, and baseline comparisons. These steps help identify potential errors in input data or modeling assumptions (CRUZ; BASTOS, 2024). In this study, the detached house model was calibrated using data from a previously published study (LÓPEZ-GUERRERO et al., 2024; LOPEZ-GUERRERO et al., 2024), and similar configuration properties were applied to ensure the accuracy of the low-rise apartment model. All models were developed using EnergyPlus, a validated simulation tool, with key inputs aligned to building regulation standards and calibrated results (BRAZIL, 2023). For example, the thermal zones accounted for occupancy of two to four people with a metabolic rate of 108 W/person, a lighting power density of 6 W/m², and a constant equipment load of 1.5 W/m² (BRAZIL, 2023).

In detached houses, ground temperature significantly influences thermal performance due to direct contact with the ground. In contrast, this heat exchange is less relevant in apartments, as the residential unit may not be in direct contact with the ground. Therefore, for the detached house model, ground soil temperature was determined using the EnergyPlus Slab Program, while for the low-rise apartment model, the ground was configured under adiabatic conditions. Furthermore, since occupant behavior is a critical factor that can cause inaccuracies in thermal-energy performance assessments. In this study, the occupancy schedule was defined as occupants being home at all times, illustrating a work-from-home scenario. This approach was chosen to represent a worst-case scenario for occupancy-generated heat, with a higher tendency for overheating risks. Section 2.3.1 explains how EnergyPlus was used to calculate the TL metric, which represents the amount of heat that must be added or removed to maintain thermal comfort conditions.

5.2.2.1.1 Design variables

While the study incorporated the most common construction systems used in the residential sector, it also explored emerging technologies available in the market, as many of these new systems offer superior thermal and carbon performance. **Table 33** describes the thermal properties for all wall, roof, ceiling and glazing types considered in this study. Specifically, Insulated Concrete Forms (ICF), Structural Concrete Insulated Panels (SCIP), Steel Frame, and Wood Frame systems were considered as potential options for walls. ICF and SCIP walls feature expanded polystyrene (EPS) blocks/panels that serve as permanent formwork for reinforced concrete. Both durable construction configurations provide excellent thermal and sound insulation, enhanced energy efficiency, and simplified construction processes (BHATTI, 2016; MANTESI et al., 2019). Steel and wood frame systems consist of steel or wooden studs and beams, typically insulated and sheathed with materials such as rock wool, oriented strand board (OSB), or cement/plaster board. These systems offer advantages such as improved thermal performance and ease of construction (AMER et al., 2020). Wood framing is renewable and provides good insulation, while steel framing is more resistant to moisture and pests (CHO et al., 2019). Finally, the complete list of design variables, along with their respective value ranges, is further detailed in **Table 34**.

Table 33. Thermal properties of the construction systems examined in this research.

Component	Index	Construction system	Description (Layers)	Thickness (m)	Specific gravity (kg/m³)	Thermal conductivity (W/mK)	Specific heat (kJ/kgK)
Wall	W1	Traditional masonry	Coating mortar	0.02	1950	1.15	1.00
			Ceramic blocks (horizontally perforated)	0.09	459	0.47	0.93
			Coating mortar	0.02	1950	1.15	1.00
			Construction system's properties: U-value = 2.77 W/(m²K) and TC = 117 kJ/(m²K)				
	W2	Concrete block	Coating mortar	0.02	1950	1.15	1.00
			Concrete blocks (vertically perforated)	0.14	840	1.01	1.00
			Coating mortar	0.02	1950	1.15	1.00
			Construction system's properties: U-value = 2.73 W/(m²K) and TC = 195 kJ/(m²K)				
	W3	Concrete wall	Cast-in-place concrete wall	0.10	2300	1.75	1.00
			Construction system's properties: U-value = 4.40 W/(m²K) and TC = 230 kJ/(m²K)				
	W4	Insulated Concrete Forms	Coating mortar	0.02	1950	1.15	1.00
			EPS board	0.05	2300	1.75	1.00
			Concrete	0.10	2300	1.75	1.00
			EPS board	0.05	2300	1.75	1.00
			Coating mortar	0.02	1950	1.15	1.00
			Construction system's properties: U-value = 0.40 W/(m2K) and TC = 325 kJ/(m²K)				
	W5	Structural Concrete Insulated Panels	Coating mortar	0.02	1950	1.15	1.00
			Concrete	0.05	2300	1.75	1.00
			EPS board	0.05	2300	1.75	1.00
			Concrete	0.05	2300	1.75	1.00
			Coating mortar	0.02	1950	1.15	1.00
			Construction system's properties: U-value = 0.7 W/(m²K) and TC = 320 kJ/(m²K)				

	W6/7	Wood/Steel frame	Cement board	0.01	2300	1.75	1.00
			OSB	0.02	1500	1.15	1.00
			Rock wool	0.05	20	0.045	0.75
			Air gap	-	-	-	-
			OSB	0.02	1500	1.15	1.00
			Cement board	0.01	2300	1.75	1.00
			Construction system’s properties: U-value = 0.6 W/(m^2K) and TC = 116 kJ/(m^2K)				
Roof	R1	Fiber cement tiles		0.006	1700	0.65	0.84
	R2	Clay tile		0.01	1500	1.15	1.00
	R3	Thermoacoustic metal tile	Metal tiles	0.01	7800	55	0.46
			EPS board	0.10	2300	1.75	1.00
			Metal tiles	0.01	7800	55	0.46
	R4	Metal tiles		0.01	7800	55	0.46
Ceiling	C1	Plaster panel		0.01	900	0.35	0.87
	C2	Wooden lining		0.01	650	0.15	2.30
	C3	Polyvinyl chloride (PVC) board		0.01	273	0.2	0.96
	C4	Concrete		0.10	2300	1.75	1.00
	C5	EPS board		0.03	35	0.04	1.42
Glazing	C1	Simple glazing		U-value = 5.87 W/(m^2K) and SHCG = 0.87			
	C2	Double pane glazing (low-e)		U-value = 2.1W/(m^2K) and SHCG = 0.62			
	C3	Triple pane glazing (low-e)		U-value = 1.2W/(m^2K) and SHCG = 0.45			

Table 34. Description of design variables, including their units and ranges considered in the study.

Category	ID	Description	Unit	Range
Envelope	DV1	Orientation	(°)	{0, 45, 90, 135, 180, 225, 270, 315}
	DV2	Wall type	Dimensionless	{1, 2, 3, 4, 5, 6, 7} – See Table 3
	DV3	Roof type	Dimensionless	{1, 2, 3, 4} – See Table 3
	DV4	Ceiling type	Dimensionless	{1, 2, 3, 4, 5} – See Table 3
	DV5	Glazing type	Dimensionless	{1, 2, 3} – See Table 3
	DV6	WWR	%	{20, 30, 40, 50, 60}
	DV7	Absorptance value - Wall	Dimensionless	{0.2, 0.3, 0.4, 0.50, 0.6, 0.7, 0.80}
	DV8	Absorptance value - Roof	Dimensionless	{0.2, 0.3, 0.4, 0.50, 0.6, 0.7, 0.80}

5.2.2.2 Dataset and analysis

The dataset creation step selects design points to maximize information gain while minimizing sampling time. While Latin Hypercube Sampling (LHS) is popular (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019), Sobol's method is superior for generating low-discrepancy quasi-random sequences, offering uniform input space coverage. This advantage reduces clustering, achieves faster convergence with fewer samples, and ensures scalability and reproducibility, making Sobol ideal for complex, high-dimensional models (CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023).

This study examined two distinct building types (detached house and low-rise apartment) within two climate contexts: historical and future urban weather. Consequently, four datasets were required for each evaluated city. The combinations of all design variables listed in Table 5.4 resulted in 10^6 possible scenarios per dataset. However, generating such extensive datasets is resource-intensive and time-consuming. To optimize the balance between simulation time and data requirements for transfer learning, different sample sizes were used for each weather context (YAN; JI; YAN, 2022b). Specifically, 1,000 samples were generated for the historical weather context and 500 for the future urban weather context. This approach was based on the hypothesis that the historical weather dataset serves as an effective source domain for transfer learning, capturing the relationship between input and output variables, while the smaller future urban weather dataset adequately reflects shifts in TL driven by climate change.

In parallel, to better validate this hypothesis, the Shapley Additive Explanation (SHAP) method was employed to evaluate the contributions of input variables to output variables when considering different weather contexts. The SHAP method, rooted in cooperative game theory, quantifies the contribution of each input feature to a model's predictions, offering both global and local interpretability, accounting for feature interactions, and providing intuitive visualizations, making it a robust and versatile tool (LUNDBERG; LEE, 2017). Acting as a form of sensitivity analysis, this approach examines how climate change may influence the relative importance of input variables, providing valuable insights into potential shifts in the drivers of thermal-energy performance metric.

Subsequently, each dataset was pre-processed to prevent features with larger values from disproportionately influencing predictions. To ensure all features had equal weight, z-score normalization was applied (see Equation 5.1), which scales each feature to the same range, where μ is the mean of all the *x* values and σ is their standard deviation.

$$z = \frac{x - \mu}{\sigma} \tag{5.1}$$

To robustly assess the regression model's performance, cross-validation was employed instead of a simple train-test split. This technique partitions the dataset into multiple folds, ensuring each data point is used for both training and validation. By averaging results across these folds, cross-validation provides a reliable estimate of the model's generalizability, mitigating overfitting and underfitting risks (SUN; HAGHIGHAT; FUNG, 2020; WANG; SRINIVASAN, 2017).

5.2.2.3 Transfer learning technique

Transfer learning was adopted to predict thermal-energy outcome for two distinct buildings under different weather conditions, addressing the inefficiency of training separate models for each scenario. This approach utilizes a pre-trained model that extracts general features from a large dataset, which are subsequently adapted or fine-tuned for a smaller dataset. Transfer learning is particularly effective when tasks share similarities, allowing the model to apply knowledge from the source task to the target task efficiently (KO; PARK, 2021b).

The process begins with a source task (T_s) and a target task (T_t), each associated with their respective datasets (D_s and D_t). In supervised learning, a task T comprises two key elements: the label space (*Y*) and a predictive function *f(x)* that maps an input *x* to an output *y*. The aim is to use knowledge from the source task to enhance performance on the target task. The model trained on the source task $f_s(x)$ extracts valuable features *h(x)* from the source data, which are then transferred and adapted to build a new target-specific model $f_t(x)$. This target model integrates the feature extractor with a new task-specific component (*g(.)* as shown in Equation 5.2). Fine-tuning involves adjusting the pre-trained model's parameters ϑ_s to suit the target task by minimizing a loss function (*L*, as defined in Equation 5.3). During fine-tuning, only a subset of parameters (ϑ_t) is updated, preserving the general knowledge encoded in ϑs. The goal is to reduce the loss on the target dataset (D_t) using he sample-wise loss function *l(.)* (LAGUNAS et al., 2023; PAN; YANG, 2010).

$$f_t(x) = g\big(h(x)\big) \tag{5.2}$$

$$L(f_t(x_t), y_t) = \frac{1}{N_t}\sum_{j=1}^{N_t} l(f_t(x_t^j), y_t^j) \tag{5.3}$$

The transfer learning process involves two primary steps: (1) training the model on the source domain and (2) refining it for the target domain (KO; PARK, 2021b). In this study, the models trained using the historical weather served as the source domain, while the models trained using the future urban weather file are used as target domains. As mentioned, this approach was based on the hypothesis that the historical weather dataset serves as an effective source domain, capturing the relationship between input and output variables, while the future urban weather dataset adequately reflects shifts in TL driven by climate change. Therefore, by using this approach, the model is retrained with a smaller dataset, allowing it to efficiently refine its knowledge and adapt to the effects of climate change.

Two machine learning algorithms, XGBoost and ANN, were evaluated for transfer learning. XGBoost, a powerful gradient boosting algorithm, constructs decision trees sequentially, with each tree correcting the errors of the previous ones. By optimizing a custom loss function and incorporating regularization, it achieves high accuracy while mitigating overfitting (CHEN; GUESTRIN, 2016). In transfer learning, XGBoost applies ensemble learning to bridge errors between domains. On the other hand, transfer learning is often associated with deep learning models, so ANN was tested as well. An ANN consists of an input layer, one or more hidden layers, and an output layer, with interconnected neurons that process data through activation functions (HASTIE; FRIEDMAN; TIBSHIRANI, 2001). By freezing early layers to retain general features and fine-tuning later layers, ANN efficiently adapts to new tasks while maintaining foundational knowledge (HOSNA et al., 2022).

Hyperparameter tuning plays a critical role in the performance of surrogate models. Optimization methods like grid search, random search, Bayesian optimization, and evolutionary algorithms are commonly used (CRUZ et al., 2024a). This study adopted random search for its simplicity, scalability, and efficiency in high-dimensional parameter spaces, outperforming grid search while avoiding the complexity of Bayesian and evolutionary techniques. For XGBoost, the tuned hyperparameters included the number of trees, maximum depth, and learning rate (CHEN; GUESTRIN, 2016), while for ANN, they included the number of hidden layers, neurons per layer, activation functions, and learning rate (HASTIE; FRIEDMAN; TIBSHIRANI, 2001). The implementation utilized Python libraries such as TensorFlow, Scikit-learn, and XGBoost.

5.2.2.4 Performance evaluation of machine learning models

The evaluation of machine learning models focused on testing their accuracy with unseen data by comparing predictions to actual results. Performance is commonly measured using metrics such as the coefficient of determination (R^2), root mean square error (RMSE), mean square error (MSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) (CRUZ et al., 2024a; WESTERMANN; EVINS, 2019). R^2 quantifies the variance explained by the model, with values near 1 indicating a good fit. MAE measures average absolute errors in the target's units, while MAPE expresses errors as percentages, enabling comparison across datasets with different scales. Together, these metrics assess goodness-of-fit, absolute accuracy, and relative accuracy, providing a comprehensive evaluation of predictive performance. These metrics were calculated using Equation 5.4 to 5.6, where n is the total number of the test target samples; y_i' is the actual value; y_i is the arithmetic mean of y; and y_i'' is the predicted value of the model.

$$R^2 = 1 - \frac{\sum_i^n (y_i - y_i')^2}{\sum_i^n \left(y_i - y_i''\right)^2} \tag{5.4}$$

$$MAE = \frac{1}{n}\sum_i^n |y_i - y_i'| \tag{5.5}$$

$$MAPE = \frac{1}{n}\sum_{i}^{n}\left|\frac{y_i - y_i'}{y_i}\right| \tag{5.6}$$

5.2.3 Optimization

The goal of this study was to evaluate the feasibility of climate-resilient design within the GS context, with a particular focus on Latin America. To achieve this, various building envelope systems were examined to understand their impact on thermal performance, carbon emissions, and costs. Algorithms such as the Strength Pareto Evolutionary Algorithm 2 (SPEA2) and Multi-Objective Particle Swarm Optimization (MOPSO) are widely applied in the building performance field (EVINS, 2013; MACHAIRAS; TSANGRASSOULIS; AXARLI, 2014). However, NSGA-II, a population-based evolutionary algorithm known for its robustness and ability to solve complex non-linear problems, remains a preferred choice (DEB et al., 2002). Recognizing the underutilization of emerging algorithms, this study adopted NSGA-III to address this gap.

NSGA-III is a multi-objective optimization algorithm designed to handle problems with more than two objectives. It extends NSGA-II by introducing reference points to guide the search process and ensure diversity in the solution set. The algorithm begins with an initial population, evaluates fitness based on Pareto dominance, and applies selection, crossover, and mutation to evolve solutions. Its key advantage lies in its ability to maintain a well-distributed set of solutions along the Pareto front, making it suitable for high-dimensional problems. Additionally, its reference-point-based approach improves scalability and convergence compared to earlier algorithms. Finally, the Python library Pymoo was used to implement NSGA-III with Das-Dennis reference directions, mixed-variable sampling and mating, duplicate elimination, and 300 generations.

5.2.3.1 Thermal performance

When the building envelope is unable to sustain thermal comfort, dependence on HVAC systems becomes essential. In Latin America, however, the adoption of HVAC systems is often constrained by socio-economic and cultural factors, including limited financial resources (INTER-AMERICAN DEVELOPMENT BANK, 2022; LUBBOCK; VIVARES, 2022; OECD, 2015; VIGEVANI; RAMANZINI JUNIOR, 2022; WORLD BANK, 2024). Although natural ventilation is traditionally favored, increasing living standards and growing expectations for indoor comfort are driving higher demand for HVAC systems (IEA, 2018, 2022). Balancing mechanical and natural ventilation poses design challenges (MENDES et al., 2024b); for instance, enhancing thermal insulation can improve energy efficiency but may also raise the risk of overheating during summer months if effective passive or adaptive cooling strategies are not employed (CRUZ; BASTOS, 2024; CRUZ; CUNHA, 2022; CRUZ; DE CARVALHO; DA CUNHA, 2020).

Therefore, this study combined the Airflow Network object with the Ideal Loads Air System object in EnergyPlus to calculate the TL metric (MENDES et al., 2024b). The Airflow Network object simulates infiltration driven by wind-induced pressure differences while windows and doors remain closed. Meanwhile, the Ideal Loads Air System object represents an ideal HVAC system, without incorporating efficiency coefficients, and operates only during occupied hours according to a thermostat schedule. This approach enables more accurate load estimation, supporting the optimization of thermal performance and energy efficiency in building designs (MENDES et al., 2024a). Thus, the performance metric used was the TL for combined cooling and heating, as defined in Equation 5.7. TL_{total} represents the amount of heat, expressed in kWh/m², that must be added ($TL_{heating}$) to or removed ($TL_{cooling}$) from all zones per square meter (A_{total} that refers to the total floor area of the building) to maintain thermal comfort based on a setpoint of 20°C for heating and 25°C for cooling. Consequently, lower TL_{total} values indicate better thermal performance and are the desired outcome.

$$TL_{total} = \frac{\sum TL_{cooling} + \sum TL_{heating}}{A_{total}} \tag{5.7}$$

5.2.3.2 Carbon performance

Carbon emissions for the envelope design were estimated using the Life Cycle Assessment (LCA) methodology. According to ISO 14040:2006, a systematic LCA involves four main steps: (1) defining goals and scope, (2) analyzing the Life Cycle Inventory (LCI), (3) conducting the Life Cycle Impact Assessment (LCIA), and (4) interpreting the results (ISO, 2006). The goal of the carbon assessment in this study was to quantify $kgCO_2$-eq associated with the production and construction of the envelope setup for each architectural model. The scope of assessment focused on the production phase of the life cycle, covering climate change impacts from raw material extraction to fabrication, as well as the transportation of materials to the construction site (A1–A4), according to EN 15804:2019 (CEN).

For the LCI, this study utilized the Ecoinvent database v.3.8 since different countries are evaluated. Ecoinvent has a broader range of material data and ensures consistency and comparability across all study locations (ECOINVENT, 2025). The total carbon emissions for each element and the overall construction solution were calculated using Equations 5.8 and 5.9. In these equations, CE_w, CE_r, CE_c and CE_g represent the carbon emissions for walls, roofs, ceilings, and glazing, respectively. CE_i denotes the carbon emissions of the i^{th} component of an element, AV_i is the built area or volume of the element, n is the number of components considered for each element, and CE is the total carbon emission for the considered elements. In the LCIA, EN 15804:2019 method is used. The results, expressed in kilograms of CO_2 equivalent ($kgCO_2$-eq), account for GHG such as CO_2, Nitrogen dioxide (NO_2), Methane (CH_4) and other GHGs. **Figure 33** presents the total carbon emissions for each building element in the two architectural designs considered in this study. The takeoff of these elements was derived from a Building Information Modeling (BIM) model using Autodesk Revit. Appendix A provides the surface areas of each envelope system for both architectural models and lists the materials comprising the construction systems explored in this study, along with their respective carbon emission values and units.

$$CE_{w,r,c,g} = \sum_{i=1}^{n} CE_i \times AV_i \tag{5.8}$$

$$CE = CE_w + CE_r + CE_c + CE_g \tag{5.9}$$

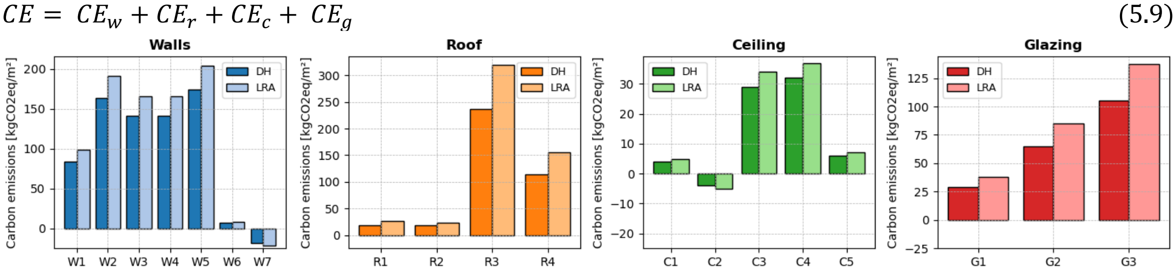


Figure 33. Carbon emissions for each envelope system.

5.2.3.3 Cost performance

To calculate the associated costs for each architectural model, an inventory of all materials used in the envelope systems was created using various databases that provide estimated prices for construction inputs. The National Survey/Database System for Construction Costs and Indices were utilized (CAIXA, (2025); DANE (2025), ; INE (2025); INEI, (2025)). The costs of elements not found in these databases were obtained through local market quotations and labor costs were excluded from the analysis. Variations in purchase values were observed depending on the building's location; therefore, **Figure 34** illustrates the range of purchase values for each envelope system considered in this study, identified by their IDs (see Table 33). The official currencies of Brazil, Chile, Colombia, and Peru are the Brazilian Real (BRL), Chilean Peso (CLP), Colombian Peso (COP), and Peruvian Sol (PEN), respectively. For the cost analysis, all costs were converted to BRL to ensure consistency and facilitate a comprehensive evaluation. The total cost for each element and the overall construction cost were calculated using Equations 5.10 and 5.11. In these equations, TC_w, TC_r, TC_c and TC_g represent the costs for walls, roofs, ceilings, and glazing, respectively; C_i is the cost of the i^{th} component of an element, A_i is the built area of the element, n is the number of components considered for each element, and TC is the total construction cost for the considered elements.

$$TC_{w,r,c,g} = \sum_{i=1}^{n} C_i \times A_i \tag{5.10}$$

$$TC = TC_w + TC_r + TC_c + TC_g \tag{5.11}$$

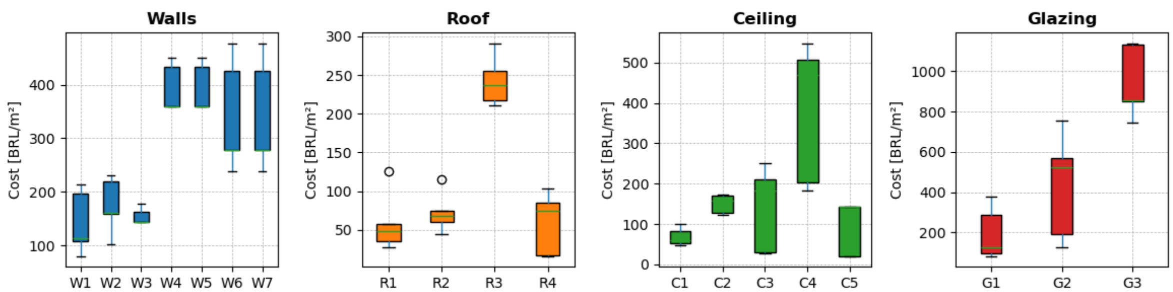


Figure 34. Range of purchase value for each envelope construction system.

5.2.4 Decision-making process

Selecting a solution from the Pareto front requires decision-making strategies (HWANG; YOON, 1981; YANG; CHEN; HUNG, 2007). Common approaches include: (1) Subjective Selection, based on human judgment; (2) Weighted Sum, which assigns weights to objectives for single-objective optimization; (3) Constrained Selection, where thresholds define acceptable solutions; and (4) MCDM methods, which systematically identify optimal solutions (CRUZ et al., 2024a). MCDM is preferred for its structured, objective, and adaptable approach to balancing multiple criteria (SARYAZDI et al., 2022; SONG et al., 2023).

In this study, the final step emphasized the decision-making process to identify the optimal solution within the Pareto front for various preference contexts. TOPSIS method was selected due to its flexibility in weighting criteria, robustness in complex scenarios, and clear, interpretable rankings make it widely applicable and practical. TOPSIS evaluates alternatives based on their proximity to the ideal solution and distance from the worst solution, considering both positive and negative values (SHIH; SHYUR; LEE, 2007). However, previous studies emphasize the importance of normalizing results, as varying ranges among objectives can disproportionately influence the final selection (CHEN; TSAY; NI, 2022; CHEN; TSAY; ZHANG, 2023).

The trade-off analysis applied different weighting factors for each metric to evaluate how varying performance preferences shape the definition of an optimal solution within a given context.

Specifically, this approach examined the feasibility of climate-resilient design in the GS, ensuring that trade-offs yield solutions that are both sustainable and equitable. **Table 35** outlines the preference contexts considered in this study, along with their descriptions. To enhance result visualization and interpretation, radar plots are utilized at this stage.

Table 35. Preference contexts considered in this study, along with their criteria descriptions.

Index	Preference context	Criteria description	Weighting factors
1	Thermal load	The best solution in terms of TL metric.	[TL = 1, CE = 0, TC =0]
3	Carbon emissions	The best solution in terms of CE metric.	[TL = 0, CE = 1, TC =0]
4	Total Cost	The best solution in terms of TC metric.	[TL = 0, CE = 0, TC =1]
5	Equal weights	The best solution in terms of TL, CE, and TC metrics	[TL = 1/3, CE = 1/3, TC =1/3]

5.3 Results

5.3.1 Future urban weather predictions results

This study utilizes hypothetical future urban weather predictions for five cities across four Latin American countries to assess how may influence climate-resilient building design in urban centers. In the first step, the study explored the future projections. Although the Future Weather Generator tool provides projections for 2050 and 2080, this study focuses exclusively on 2080. The selected scenarios—SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5—were used to assess the impact of future climate conditions. **Figure 35** presents the monthly average values of DBT, RH, and GHR for each city, providing a comparative overview of the projected climate conditions for all SSP scenarios across all evaluated cities.

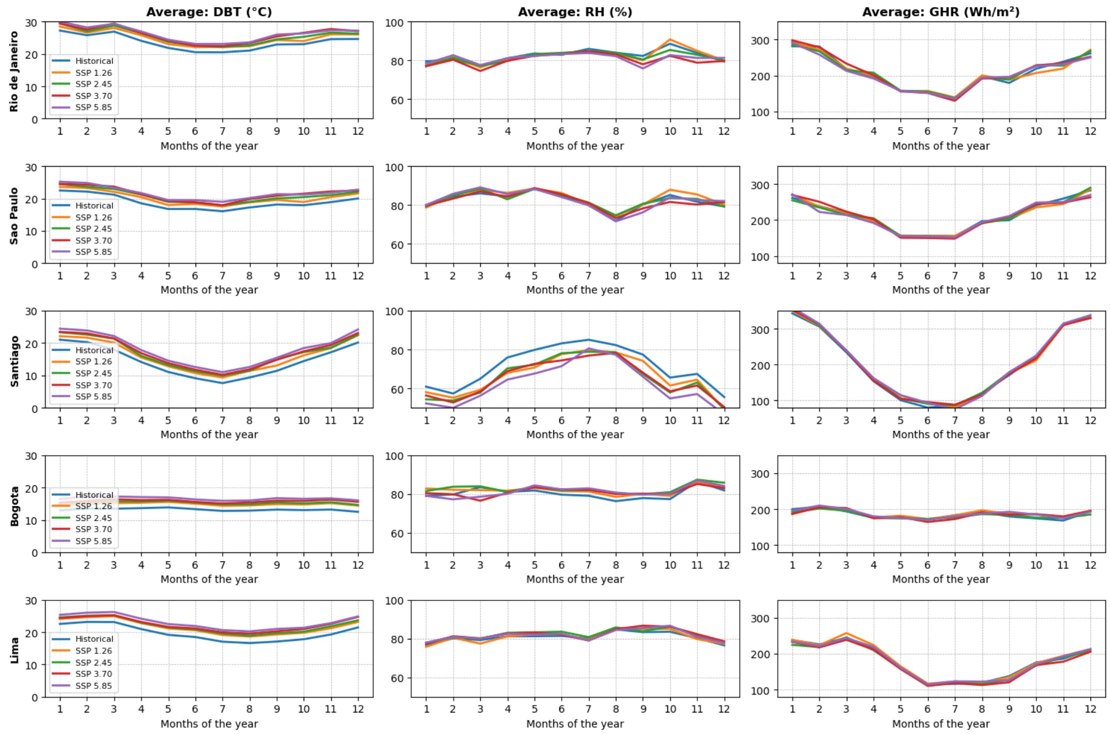


Figure 35. Comparison of average monthly values for dry-bulb temperature, relative humidity, and global horizontal radiation in the year 2080 under different SSP projections.

Figure 35 illustrates a significant increase in the parameters analyzed by 2080 when comparing historical data and future projections. The DBT is projected to increase, depending on the SSP scenario, by 1.3°C to 2.71°C in Rio de Janeiro, 1.3°C to 2.85°C in Sao Paulo, 1.7°C to 3.63°C in Santiago, 1.7°C to 3.4°C in Bogota, and 1.9°C to 3.36°C in Lima. RH is expected to rise by 0.30% to 1.39% in Rio de Janeiro, 0.15% to 1.2% in Sao Paulo, 4.9% to 9.2% in Santiago, 0.8% to 2.4% in Bogota, and 0.6% to 1.4% in Lima. Similarly, GHR is projected to increase by 0.9 Wh/m^2 to 2.3 Wh/m^2 in Rio de Janeiro, 0.6 Wh/m^2 to 2.0 Wh/m^2 in Sao Paulo, 2.3 Wh/m^2 to 5.3 Wh/m^2 in Santiago, 0.3 Wh/m^2 to 2.5 Wh/m^2 in Bogota, and 0.4 Wh/m^2 to 2.2 Wh/m^2 in Lima.

Furthermore, in the second step, the $LCZ2_5$ and $LCZ3_6$ were applied using the UWG tool to incorporate UHI effects into the weather data, representing the urban contexts of a low-rise apartment and detached house, respectively. The urban configurations were uniformly applied to ensure consistency and comparability across all evaluated cities. To simplify the analysis, this study concentrated solely on the year 2080 within the SSP5-8.5 scenario, as it reflects the most extreme projection for future climate conditions. **Figure 36** presents the distribution of DBT and **Table 36** summarizes the average DBT for the historical, future, and future + urban $LCZ2_5$, and future + urban $LCZ3_6$ contexts for all analyzed cities.

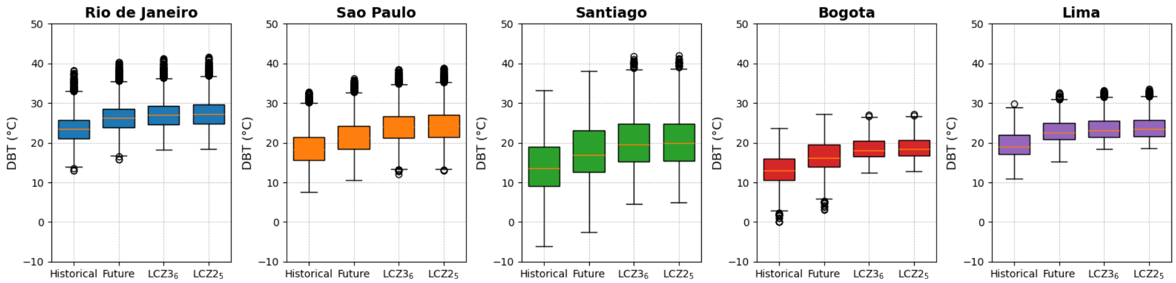


Figure 36. Comparison between the distribution of DBT values for historical, future, future urban LCZ2_5, and future urban LCZ3_6 predicted.

Table 36. Average in DBT for the year 2080 for different future and urban projections.

City	Average DBT			
	Historical	Future (SSP5-8.5)	Future + Urban (LCZ2_5)	Future + Urban (LCZ3_6)
Rio de Janeiro	23.6°C	26.3°C	27.1°C	27.4°C
Sao Paulo	18.9°C	21.6°C	24.1°C	24.4°C
Santiago	14.4°C	18.0°C	20.4°C	20.6°C
Bogota	13.2°C	16.6°C	18.5°C	18.8°C
Lima	19.7°C	23.0°C	23.7°C	23.9°C

As expected, historical weather files, based on data from rural meteorological stations or sourced from distant stations, exhibited the lowest average DBT values compared to those derived from future projections and UHI models. Overall, UHI modeling produced highly comparable results for the LCZ2_5 and LCZ3_6 contexts. Consequently, for the cities of Rio de Janeiro, Sao Paulo, Santiago, Bogota, and Lima, future urban projections suggest increases in average DBT up to 3.8°C, 5.5°C, 6.2°C, 5.6°C, and 4.2°C, respectively. The average DBT difference between historical and future climates is around 3°C across all cities. However, this difference increased significantly with the inclusion of the UHI effect, with deviations rising to as much as 6°C. This highlights the combined impact of climate change and urbanization on local temperature patterns. These findings underscore the importance of developing urban-specific climate models to effectively predict temperature fluctuations and inform strategies for climate-resilient building design.

5.3.2 Surrogate modeling results

In this study, datasets for each architectural design and weather context were generated using Sobol's method. Different sample sizes were assigned to each weather context to optimize the balance between simulation time and data requirements for transfer learning. Subsequently, XGBoost and ANN were considered and compared as surrogate models, leveraging transfer learning techniques to efficiently capture thermal-energy performance shifts driven by climate change. To prevent overfitting, cross-validation (10-fold) was applied, and the models were evaluated using R^2, MAE, and MAPE. In addition, the SHAP method was used to evaluate how climate change may influence the importance of input variables on the output. The following sections present the results, detailing dataset analysis, the performance evaluation of the machine learning models, and the sensitivity analysis results.

5.3.2.1 Analysis of dataset

Figure 37 presents the TL results from the simulated dataset for each city analyzed under historical and future urban weather conditions. The graphs summarize the distribution of the TL metric across the detached house and low-rise apartment, respectively.

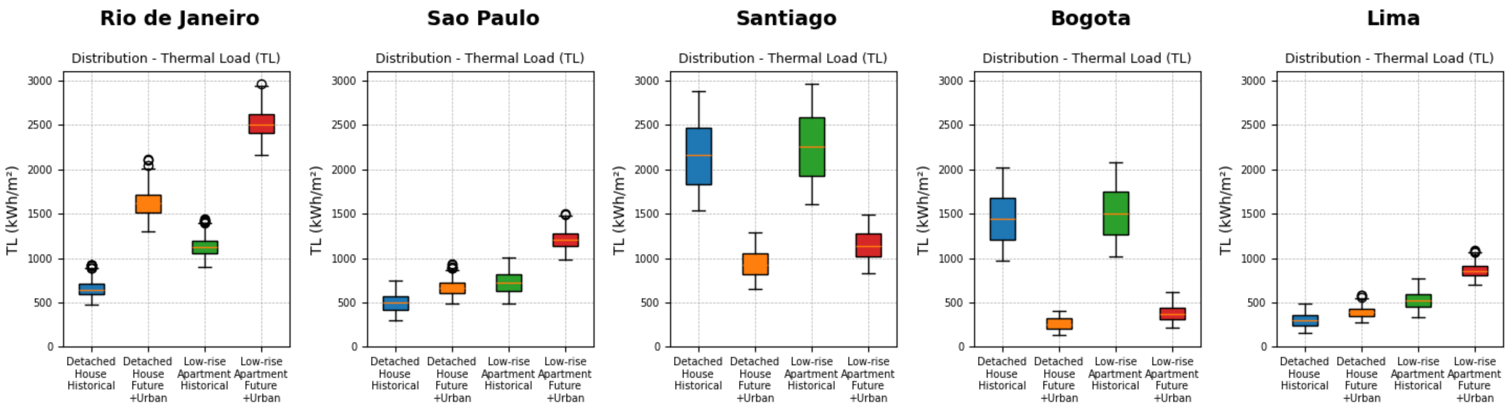


Figure 37. Distribution of thermal load values for each dataset generated.

Figure 37 presents the distribution of TL metric for each city, highlighting variations in the climate contexts considered in this study. In addition, the distinct performance between the detached house and the low-rise apartment is attributed to ground contact, which affects heat exchange within the built environment. Under historical weather conditions, Santiago and Bogota exhibited the poorest performance, while Rio de Janeiro, Sao Paulo, and Lima achieved the best results for both architectural designs. In future urban weather scenarios, Sao Paulo and Lima continued to demonstrate the best performance, whereas Rio de Janeiro experienced the most significant decline. Meanwhile, Santiago and Bogota showed improved results. These findings indicate that as temperatures rise in colder climates like Santiago, heating energy demand decreases, leading to more comfortable indoor temperatures, and consequently, lower TL metric values. Conversely, in warmer climates, the TL metric increases due to the rising demand for cooling. For Rio de Janeiro, the mean deviation of the TL metric between the historical and future urban weather contexts was 150% for the detached house and 123% for the low-rise apartment, with deviations between architectural models reaching up to 54%. In Sao Paulo, these deviations were 34% for the detached house and 67% for the low-rise apartment, while differences between architectural models reached 80%. For Santiago, the respective deviations were -57% and -50%, with architectural model variations up to 21%. In Bogota, deviations were -83% for the detached house and -75% for the low-rise apartment, with architectural model differences reaching 46%. Finally, for Lima, the TL metric deviation was 30% for the detached house and 63% for the low-rise apartment, while architectural model variations peaked at 117%.

5.3.2.2 Performance evaluation of machine learning models

In this study, XGBoost and ANN were evaluated in combination with transfer learning techniques. This investigation utilized random search to determine the optimal hyperparameter settings. **Table 37** presents the performance evaluation of each model across all cities, with the historical weather context used as the source domain and future urban weather context used as target domains, respectively.

Table 37. Machine learning model performance results across the source domain and target domain each city in this study.

City	Algorithm	Model	Source domain (Historical)			Target domain (Future)		
			R^2	MAE	MAPE	R^2	MAE	MAPE
Rio de Janeiro	XGBoost	Detached house	0.937	16	2	0.935	30	2
		Low-rise apartment	0.941	17	1	0.925	36	1
	ANN	Detached house	0.898	27	13	0.903	21	11
		Low-rise apartment	0.852	40	9	0.872	32	7
Sao Paulo	XGBoost	Detached house	0.985	9	2	0.910	20	3
		Low-rise apartment	0.981	12	2	0.934	21	2
	ANN	Detached house	0.930	21	25	0.810	30	15
		Low-rise apartment	0.914	27	18	0.832	34	9
Santiago	XGBoost	Detached house	0.998	12	1	0.978	17	2
		Low-rise apartment	0.998	12	1	0.980	18	2
	ANN	Detached house	0.985	40	22	0.960	25	19
		Low-rise apartment	0.963	42	22	0.960	27	17
Bogota	XGBoost	Detached house	0.998	10	1	0.967	9	4
		Low-rise apartment	0.998	10	1	0.934	17	5
	ANN	Detached house	0.986	29	25	0.869	22	33
		Low-rise apartment	0.977	37	23	0.871	26	27
Lima	XGBoost	Detached house	0.986	7	2	0.922	14	3
		Low-rise apartment	0.981	10	2	0.935	16	2
	ANN	Detached house	0.926	15	19	0.861	23	17
		Low-rise apartment	0.903	23	21	0.843	25	15

Table 5.7 highlights the similar performance of XGBoost and ANN in surrogate modeling. Particularly, XGBoost achieved slightly better results for R^2, MAE, and MAPE metrics across TL model in all cities. Overall, both algorithms consistently delivered R^2 values above 85%, MAE below 40 kWh/m^2, and MAPE below 30% for the output. The application of transfer learning, which fine-tunes a pre-trained model from a larger dataset to a smaller one, proved effective. The initial hypothesis was validated: the historical weather dataset served as an effective source domain, capturing the relationship between input and output variables, while the smaller future urban weather dataset adequately reflected shifts in thermal load driven by climate change. However, a consistent trend emerged across all cases—a slight decrease in performance metrics was observed when transitioning from the source domain to the target domain. Ultimately, XGBoost was chosen for the optimization phase because of its rapid training capabilities and ease of interpretation. In machine learning, an interpretable model enables humans to readily understand and explain their predictions or decisions. Although ANN delivered very similar results, it demands longer training periods and does not provide the same level of interpretability.

5.3.2.3 Sensitivity analysis

To validate the previous hypothesis mentioned, the SHAP method was used to evaluate the input contributions to output across XGBoost models under the historical and future urban weather contexts. This sensitivity analysis highlights how climate change may alter input variable importance, offering insights into shifts in thermal-energy performance drivers.

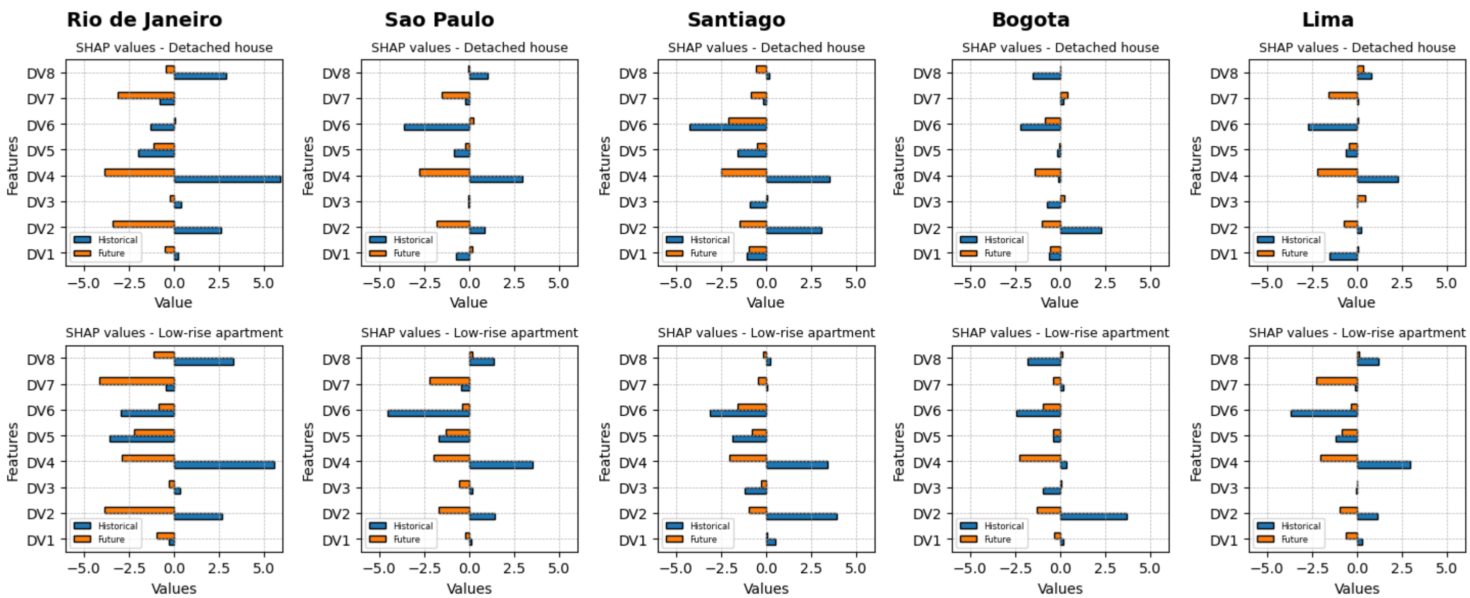


Figure 38. SHAP values for each design variable in the detached house and low-rise apartment, analyzed under historical and future urban weather contexts.

SHAP values are interpreted as the contribution of each input feature to the model's prediction, with positive values indicating a feature's role in increasing the prediction and negative values indicating its role in decreasing it. The hypothesis assumed that under the future urban climate file, the SHAP values would only vary in magnitude, maintaining the same ranking and priority of variables. However, in all cities, instances were observed where a variable's impact shifted from positive to negative or vice versa. This indicates that the climate change and the UHI effects can significantly alter the importance of variables in the thermal-energy performance of buildings. Furthermore, these findings underscore the effectiveness of transfer learning in capturing shifts in thermal-energy performance, as the relationship between input variables and the output adapts to different weather contexts.

5.3.3 Optimization results

This study aimed to assess climate-resilient design feasibility in the GS, focusing on Latin America. Various building envelope systems were analyzed for their effects on thermal performance, carbon emissions, and costs. The NSGA-III algorithm was applied for multi-objective optimization, handling more than two objectives. Figure 39 presents the Pareto front for each city under historical and future urban weather contexts, with architectural designs labeled. The CE metric is displayed on the x-axis, the TL metric on the y-axis, and the TC metric is represented by the size of the dots.

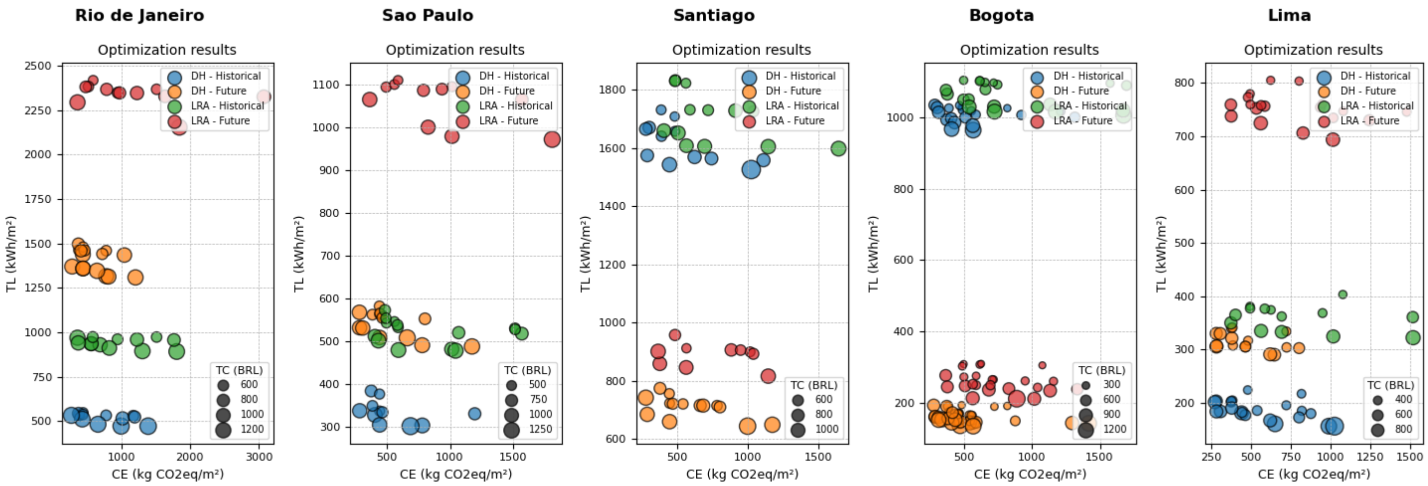


Figure 39. Pareto front results from each optimization categorized as outcomes for the detached house and low-rise apartment under historical and future urban weather contexts.

As illustrated in Figure 39, the Pareto front distributions highlighted the impact of climate variations across the evaluated cities. Pareto fronts for certain cases exhibited overlaps. For instance, in Sao Paulo and Lima, the Pareto front for detached houses under the future urban weather scenario coincided with the results for low-rise apartments under historical weather conditions. Similarly, in Santiago and Bogota, the Pareto front for detached houses under historical weather conditions overlapped with those for low-rise apartments under the same historical context. Finally, it is important to note that variations in the results are primarily driven by location and climate context, which directly affect the TC and TL metrics, while the CE metric remains constant across different locations.

5.3.4 Decision-making process results

The final step focused on the decision-making process to identify the optimal solution. The trade-off analysis used the TOPSIS method and applied different weighting factors for each metric to evaluate how varying performance preferences shape the definition of an optimal solution within a given context. Figure 40 illustrates the results for TL, CE, TC, and Equal weights preference contexts for both architectural models under future urban weather conditions. To streamline the assessment process and focus on the study's primary objective—resilience to future urban weather conditions—only the future urban context was presented and evaluated at this stage.

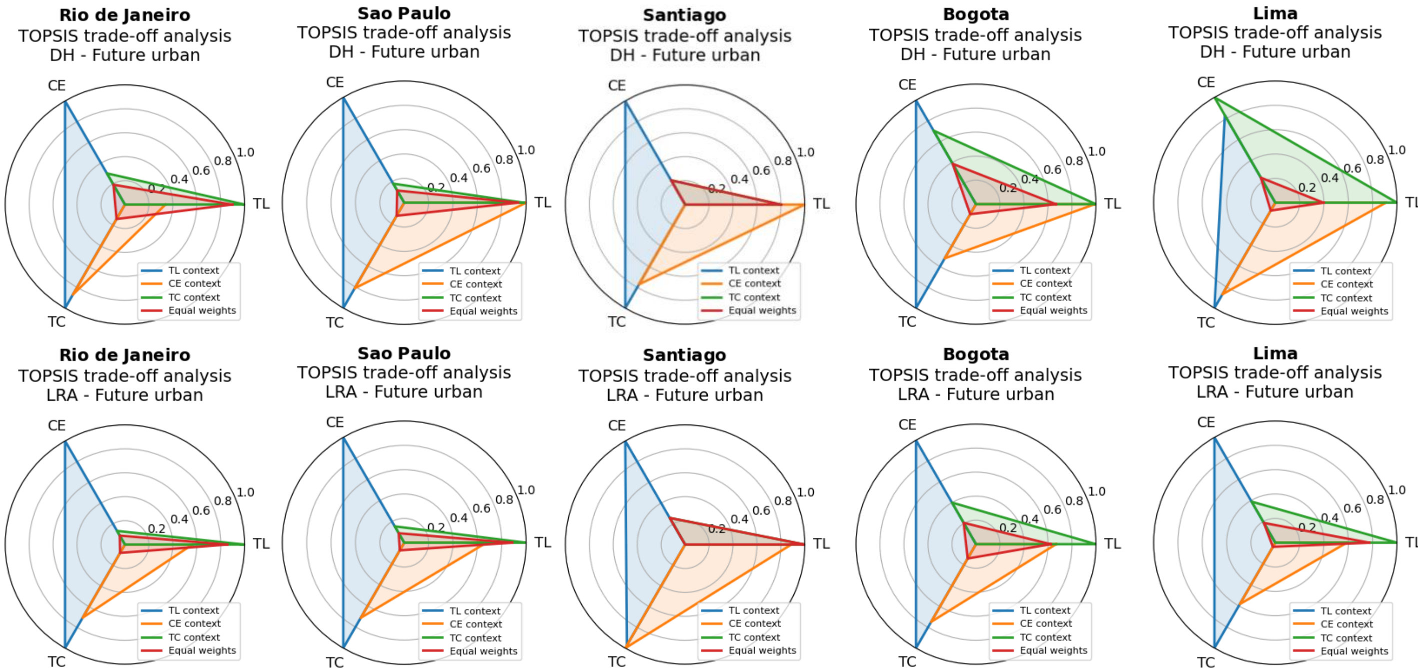


Figure 40. TOPSIS trade-off analysis for the detached house and low-rise apartment under future urban weather contexts.

Figure 40 highlights that for both architectural models, using the TOPSIS method to select the optimal option based on a single metric (i.e., TL, CE, or TC) causes significant scaling in the other metrics. Notably, the optimal solution for the TL metric resulted in a significant increase in the CE and TC metrics. This dynamic underscore the complexity of developing climate-resilient building designs, which require a comprehensive performance perspective. For instance, focusing solely on thermal performance may enhance adaptation but can lead to increased carbon emissions and total costs, undermining mitigation efforts and economic feasibility—and vice versa. Therefore, to evaluate the feasibility of climate-resilient building design, the Equal Weights context identifies solutions that prioritize all metrics equally.

For Rio de Janeiro, the TOPSIS solution under the Equal Weights context would increase the TL metric by 12% and 11%, the CE metric by 35% and 44%, and the TC metric by 17% and 16% for the detached house and low-rise apartment, respectively. For São Paulo, the TL metric would increase by 15% and 12%, the CE metric by 35% and 36%, and the TC metric by 18% and 13% for the detached house and low-rise apartment, respectively. In Santiago, the Equal Weights context would increase the TL metric by 12% and 11%, the CE metric by 61% and 55%, and the TC metric by 0% for both detached house and low-rise apartment, respectively. In Bogota, the Equal Weights context would increase the TL metric by 29% and 28%, the CE metric by 42% and 36%, and the TC metric by 36% and 35% for both detached house and low-rise apartment, respectively. In Lima, the Equal Weights context would increase the TL metric by 6% and 12%, the CE metric by 36% and 32%, and the TC metric by 8% and 7% for both detached house and low-rise apartment, respectively. Appendix A contains the complete list of optimal solutions for each context considered in each city. Finally, Table 38 illustrates the configurations of the optimal solutions selected through the TOPSIS method under the Equal Weights context.

Table 38. TOPSIS optimal solutions settings under the Equal Weights context for future urban weather contexts.

City	Model	Orientation	Wall type	Roof type	Ceiling type	Glazing type	WWR	Absorptance value - Wall	Absorptance value - Roof
Rio de Janeiro	Detached house	270	W1	R2	C5	G1	20	0.2	0.2
	Low-rise apartment	135	W1	R1	C5	G1	20	0.2	0.2
Sao Paulo	Detached house	90	W1	R2	C5	G1	20	0.2	0.3
	Low-rise apartment	90	W1	R2	C5	G1	20	0.2	0.3
Santiago	Detached house	270	W1	R2	C5	G1	20	0.2	0.3
	Low-rise apartment	135	W1	R1	C5	G1	20	0.2	0.2
Bogota	Detached house	45	W1	R2	C5	G1	20	0.3	0.3
	Low-rise apartment	90	W1	R1	C5	G1	20	0.2	0.2
Lima	Detached house	270	W1	R1	C5	G1	20	0.2	0.2
	Low-rise apartment	180	W1	R1	C5	G1	20	0.3	0.2

Table 5.8 indicates that optimal configurations remain consistent across cities despite their distinct climatic conditions. Constructive systems, such as traditional masonry, fiber cement or clay tiles with EPS boards for ceilings, and simple glazing, dominate the configuration settings. The primary difference lies in the variation of building orientation values, not only between cities but also among architectural models. Additionally, solutions derived from the TOPSIS method under the Equal Weight context revealed no differences among architectural models, such as wall, roof, ceiling, and glazing types remain largely uniform. Furthermore, the findings highlighted that future urban weather conditions necessitate small windows combined with low-absorptance values for the building envelope (walls and roofs) and insulated roof to enhance thermal performance. Lastly, while new and advanced construction systems available on the market could improve adaptation and mitigation to future urban climates, their feasibility is limited by cost and carbon emissions. The optimization results indicated that climate resilience is best accomplished through architectural passive design. A design that prioritizes solar orientation to enhance thermal performance, combined with moderately sized windows, light-colored walls and roofs, and insulated roof offers a cost-effective approach while promoting more sustainable and equitable solutions.

5.4 Discussion

Given the inherent uncertainty of climate change, this study distinguished itself from others (BORBON-ALMADA et al., 2020; CALLEJAS et al., 2021; DODOO; AYARKWA, 2019; HUGO, 2023; VERICHEV; ZAMORANO; CARPIO, 2020; XIONG et al., 2023) by incorporating the latest IPCC emissions scenario—SSP5-8.5—along with UHI effects to generate hypothetical future urban weather datasets. Furthermore, accounting for the diverse climatic conditions across multiple locations proved to be a highly effective strategy. As demonstrated in previous studies (BRACHT et al., 2024; RODRIGUES; FERNANDES, 2020; RODRIGUES; PARENTE; FERNANDES, 2024), this approach allows for a more comprehensive assessment of technical solutions, showcasing its adaptability and potential. Consequently, BPS tools play a crucial role in overcoming experimental constraints, particularly when addressing complex and uncertain challenges such as climate change (CRUZ et al., 2024b).

From a machine learning perspective, the models developed for predicting TL in the evaluated cities achieved performance levels comparable to those reported in the literature (CRUZ et al., 2024a), with R^2 values exceeding 85% for both XGBoost and ANN. Additionally, this study leveraged transfer learning to improve computational efficiency—a technique still underutilized in the building performance field (KO; PARK, 2021a, 2021b). While previous research has highlighted the limitations of transfer learning when applied to multiple building types—particularly as performance deteriorates with significant variations in design parameters or performance objectives (YAN; JI; YAN, 2022b) —this study demonstrated its viability and efficiency. Moreover, SHAP analysis revealed that climate change and UHI effects can substantially alter the influence of key variables on a building's thermal-energy performance. Despite these shifts, the transfer learning approach effectively adapted to different climatic conditions, capturing variations in thermal-energy performance. Lastly, integrating machine learning with optimization algorithms successfully identified energy-efficient strategies that enhance thermal comfort. Though rarely explored in the literature (HOSNA et al., 2022; KO; PARK, 2021b), this combined approach offers significant advantages by reducing simulation demands and facilitating the evaluation of technologies, materials, and design solutions more efficiently (LAGUNAS et al., 2023; PAN; YANG, 2010).

While multi-criteria decision-making techniques are ideal for selecting the optimal solution, many studies focus on analyzing the Pareto front settings (CRUZ et al., 2024a). Therefore, following previous studies, the TOPSIS method was chosen ensuring that trade-offs lead to solutions that are both sustainable and equitable. Although numerous studies highlight the thermal performance benefits of new construction systems such as ICF, SCIP, Steel and Wood Frame systems (AMER et al., 2020; BHATTI, 2016; CHO et al., 2019; MANTESI et al., 2019), their feasibility remains limited for vulnerable communities due to cost and carbon emission constraints. By evaluating thermal performance, carbon emissions, and costs, the TOPSIS analysis indicated that achieving climate resilience in Latin America is best accomplished through architectural passive design, a conclusion also reported in other studies (FLORES-LARSEN; FILIPPÍN; BAREA, 2019; GAMERO-SALINAS et al., 2021; GONÇALVES et al., 2024; KRELLING et al., 2024). The optimal solution typically combines conventional construction practices with passive design strategies, such as optimal solar orientation, moderate window sizing, and low-absorptance values for the building envelope (walls and roofs) and insulated roof. However, this presents a significant challenge because high-quality architectural design is often viewed as subjective and associated with high costs, making it less accessible to vulnerable communities. Although public policies can incentivize more affordable and efficient construction systems, quality of design remains a persistent issue. Governments frequently address the housing deficit by implementing standardized social housing prototypes (FLORES-LARSEN; FILIPPÍN; BAREA, 2019). Therefore, this one-size-fits-all approach should be replaced with locally adapted passive design solutions that can tackle future urban climate challenges in Latin America (ALVES; DUARTE; GONÇALVES, 2016; ALVES; GONÇALVES; DUARTE, 2021; FILIPPÍN et al., 2017; RODRIGUES et al., 2023; RODRIGUES; PARENTE; FERNANDES, 2024; ROUAULT et al., 2019; SILVERO et al., 2019; WANG et al., 2022; YU et al., 2023).

5.5 Conclusion

This study examined the feasibility of climate-resilient building design in the residential sector of the Global South. Specifically, a simulation-based analysis was conducted across five major urban centers—Rio de Janeiro, Sao Paulo, Santiago, Bogota, and Lima—spanning four Latin American countries (Brazil, Chile, Colombia, and Peru). These cities were selected based on their significance in emerging economies, high housing deficit indices, and diverse climatic conditions.

In the first step, this study generated hypothetical future urban weather files by integrating IPCC emissions scenarios with urban heat island effects. The results showed future urban weather conditions trending towards higher dry-bulb temperature, relative humidity, and global horizontal radiation. On average, the dry-bulb temperature difference between historical and future climates was approximately 3°C across all cities by 2080. However, this difference rose significantly with the inclusion of UHI effects, reaching deviations of up to 6°C. These results highlight the importance of developing urban-specific climate models to accurately predict temperature variations and support strategies for climate-resilient building design.

In the second step, XGBoost and ANN were compared as surrogate models, utilizing the transfer learning technique. In addition, the SHAP method was employed to analyze how climate change influences the importance of input variables on the output variable. The results showed that both algorithms consistently achieved R^2 values above 85%, MAE below 40 kWh/m², and MAPE below

30%. Additionally, SHAP value variations were observed across all cities, with some variables shifting in importance (positive to negative or vice versa), indicating that climate change and UHI effects can substantially alter the thermal-energy performance dynamics of buildings. These findings highlight the effectiveness of transfer learning in capturing and adapting to changes in thermal-energy performance under varying weather conditions.

In the third step, these surrogate models were then integrated with the NSGA-III to optimize the envelope system based on thermal performance, carbon emissions, and costs. Lastly, the TOPSIS method performed the trade-off analysis, employing different weighting factors for each metric to assess the impact of varying preferences. In general, selecting the optimal option based on a single metric led to significant increases in the other metrics. To assess the feasibility of climate-resilient building design, the Equal Weights context was applied to ensure all metrics were equally prioritized. The results for the detached house and low-rise apartment showed strong similarities. Overall, the TOPSIS Equal Weights context solution indicated potential increases of up to 12% in thermal load, 61% in carbon emissions, and 36% in total cost, depending on the city analyzed. Despite variations in climate, the optimal configurations remained consistent across cities. While new and advanced construction systems exist that could enhance adaptation and mitigation to future climates, their feasibility remains constrained by cost and carbon emissions. This study concluded that climate resilience is best accomplished through architectural passive design, as optimizing solar orientation—alongside moderately sized windows, light-colored envelope, and insulated roof—provides a cost-effective, sustainable, and equitable solution.

5.5.1 Directions for future research

This paper tackled a critical research topic, yet several areas warrant further exploration in future studies: 1) Cost Analysis: Expanding the cost assessment to encompass all building components, structural elements, and labor costs would provide a more robust understanding. 2) Environmental Performance: Future research should incorporate additional environmental performance metrics beyond carbon emissions to capture a broader perspective. 3) Operation Modes: Exploring various ventilation strategies, including natural, mechanical, and mixed-mode systems, could uncover their potential effectiveness in addressing climate change challenges. 4) Building Typologies: While this study focused solely on residential buildings, applying the methodology to other building types, such as commercial facilities, is crucial for a more comprehensive analysis. 5) Shading Devices: The role of shading devices was not considered in this study, and future investigations should assess their potential benefits within the climate change context.

6. Chapter 6: Conclusion

This document proposed a method for developing climate-resilient building design for the Global South through multi-objective optimization based on surrogate models. Specifically, this study focused on identifying promising resilience strategies for the built environment to simultaneously improve thermal, energy, carbon, and cost performances. The investigation placed particular emphasis on the residential building sector in Latin America, with a focus on five major cities: Rio de Janeiro, Sao Paulo, Santiago, Bogota, and Lima.

The research began with two Systematic Literature Reviews (SLRs) to assess state-of-the-art approaches, challenges, and opportunities in: 1) The potential of multi-objective optimization using surrogate models for sustainable building design; and 2) The use of building performance simulation tools for climate adaptation and mitigation using future weather files. Several research gaps were identified and prioritized. In the context of optimization and surrogate models, the findings underscore the need to incorporate a broader range of architectural designs to enhance result generalizability. Although transfer learning techniques have shown promise in building performance simulation, their application remains limited. Further exploration of sensitivity analyses and robust studies addressing uncertainties related to climate change is warranted. Additionally, integrating a multi-criteria decision-making method to select optimal solutions from the Pareto front and applying multi-objective optimization across various climate contexts is necessary. Regarding building performance and climate resilience, further research should assess the impact of occupant behavior and preferences, examine urban heat island effects combined with future weather projections across IPCC emission scenarios, and advocate for updated policies to address escalating climate risks. Incorporating optimization approaches into future studies can improve building design, while analyzing diverse and complex building typologies across different locations would better represent architectural variety. Additionally, Life Cycle Assessments (LCA) and Life Cycle Cost Analyses (LCCA) are essential for evaluating the environmental impact, decarbonization potential, and payback periods of adaptation strategies.

Based on the identified research gaps, this study makes two key contributions focused on the Global South, particularly in five major Latin American cities—Rio de Janeiro, Sao Paulo, Santiago, Bogota, and Lima—selected for their emerging economies, housing deficits, and diverse climates. First, the study develops a simulation-based procedure that integrates machine learning with optimization techniques to establish construction guidelines for climate-resilient building design. Second, it conducts a simulation-based investigation combining machine learning, optimization, and multi-criteria decision-making techniques to demonstrate the feasibility of climate-resilient buildings.

For both investigations, the results indicate that future urban weather conditions will trend toward higher dry-bulb temperatures, relative humidity, and global horizontal radiation. In the first investigation, XGBoost and ANN models exhibited comparable performance in predicting degree-hours and energy demand across all cities. Moreover, design thresholds for climate-resilient building design were established for three key components—walls, roofs, and windows—with favorable configurations consistently emerging, such as low solar absorptance, small and shaded windows, and roofs with low thermal transmittance and thermal capacity. In the second investigation, XGBoost and ANN again demonstrated similar performance. Although the future urban context significantly influenced the importance of design variables, transfer learning effectively captured climate-driven shifts in thermal-energy performance. While advanced construction systems might further enhance adaptation, their cost and carbon implications constrain feasibility, resulting in consistent optimal configurations across cities.

In summary, the first investigation offered a procedure that can provide valuable insights for Latin American policymakers in developing climate-resilient construction guidelines, particularly in the residential sector. The second investigation concluded that architectural passive design—

optimizing solar orientation, employing moderately sized windows, using light-colored envelopes, and installing insulated roofs—presents a cost-effective, sustainable, and equitable solution for enhancing climate resilience in the Global South.

6.1 Future studies

This thesis document addressed a vital research area, yet several aspects call for further investigation. For instance, broadening the cost analysis to cover all building elements, structural components, and labor expenses would offer a more comprehensive financial overview. Additionally, future work should incorporate a wider range of environmental performance indicators—not just carbon emissions—to provide a more holistic assessment. Exploring different operational strategies, including natural, mechanical, and hybrid ventilation systems, could also reveal their potential in mitigating climate challenges. Finally, while the current study concentrated on residential buildings, extending the methodology to other building typologies, such as commercial structures, is essential for a more thorough evaluation.

7. Appendix A. Material takeoff for architectural designs and carbon emission indexes.

Table 1 details the surface areas (in square meters) of each envelope system for both the detached house and low-rise apartment. Table 2 lists the materials comprising the construction systems explored in this study, along with their respective carbon emission values and units. Finally, Table 3 contains the complete list of optimal solutions for each context considered in each city.

Table 1. Surface areas of each envelope system.

Take-off in square meters (m^2)			
Index	Envelope system	Detached house	Low-rise apartment
1	Wall	120	160
2	Roof	78	120
3	Ceiling	56	62
4	Glazing: 20% WWR	9	9
5	Glazing: 30% WWR	14	14
6	Glazing: 40% WWR	19	19
7	Glazing: 50% WWR	23	23
8	Glazing: 60% WWR	28	28

Table 2. List of materials used with their respective carbon emission values.

Carbon emission indexes			
Index	List of material	$kgCO_2$-eq	Unit
1	Coating mortar	412.7	m³
2	Ceramic blocks	0.15	kg
3	Concrete blocks	0.11	kg
4	Concrete	254.7	m³
5	EPS board	4.8	kg
6	Cement board	1.2	kg
7	OSB board	-662	m³
8	Rock wool	1.3	kg
9	Fiber cement tiles	0.83	kg
10	Clay tiles	0.89	unit
11	Metal tiles	3.03	kg
12	Plaster panel	0.33	kg
13	Wooden lining	-5,4	m²
14	PVC board	3.1	kg
15	Simple glazing	29	m²
16	Double panel glazing	65	m²
17	Triple panel glazing	105	m²

Table 3. List of optimal solutions for each context considered in each city.

City	Context	Model	Orientation	Wall type	Roof type	Ceiling type	Glazing type	WWR	Absorptance value - Wall	Absorptance value - Roof
Rio de Janeiro	TL	DH	270	W5	R1	C5	G3	20	0.3	0.2
	CE		270	W7	R1	C5	G1	20	0.2	0.2
	TC		225	W3	R1	C5	G1	20	0.2	0.2
	Equal Weights		270	W1	R2	C5	G1	20	0.2	0.2
	TL	LRA	0	W5	R1	C5	G3	20	0.3	0.5
	CE		0	W7	R2	C2	G1	20	0.3	0.2
	TC		135	W3	R1	C5	G1	20	0.2	0.2
	Equal Weights		135	W1	R1	C5	G1	20	0.2	0.2
Sao Paulo	TL	DH	315	W4	R3	C5	G3	20	0.2	0.5
	CE		180	W7	R1	C1	G1	20	0.2	0.2
	TC		90	W3	R1	C5	G1	20	0.2	0.3

City	Context	Model	Orientation	Wall type	Roof type	Ceiling type	Glazing type	WWR	Absorptance value - Wall	Absorptance value - Roof
	Equal Weights		90	W1	R2	C5	G1	20	0.2	0.3
	TL	LRA	45	W4	R3	C5	G2	20	0.2	0.7
	CE		0	W7	R2	C2	G1	20	0.2	0.2
	TC		90	W3	R1	C3	G1	20	0.2	0.2
	Equal Weights		90	W1	R2	C5	G1	20	0.2	0.2
Santiago	TL	DH	225	W4	R2	C5	G3	20	0.2	0.2
	CE		225	W7	R1	C5	G1	20	0.3	0.2
	TC		270	W1	R4	C1	G1	20	0.2	0.2
	Equal Weights		270	W1	R2	C5	G1	20	0.2	0.2
	TL	LRA	135	W4	R3	C5	G2	20	0.3	0.7
	CE		135	W7	R4	C2	G1	20	0.2	0.2
	TC		135	W1	R4	C1	G1	20	0.3	0.2
	Equal Weights		135	W1	R2	C5	G1	20	0.2	0.2
Bogota	TL	DH	180	W4	R4	C4	G1	20	0.6	0.8
	CE		0	W 7	R2	C2	G1	20	0.8	0.2
	TC		0	W1	R4	C1	G1	20	0.7	0.4
	Equal Weights		45	W 1	R1	C5	G1	20	0.7	0.4
	TL	LRA	0	W4	R1	C5	G2	20	0.8	0.5
	CE		0	W7	R2	C2	G1	20	0.8	0.2
	TC		90	W1	R4	C1	G1	20	0.3	0.5
	Equal Weights		90	W1	R1	C5	G1	20	0.3	0.5
Lima	TL	DH	270	W6	R1	C5	G2	20	0.2	0.2
	CE		0	W7	R1	C1	G1	20	0.2	0.2
	TC		270	W1	R1	C1	G2	20	0.2	0.2
	Equal Weights		270	W1	R1	C5	G1	20	0.2	0.2
	TL	LRA	180	W4	R2	C5	G2	20	0.5	0.3
	CE		180	W7	R1	C1	G1	20	0.3	0.2
	TC		180	W1	R4	C1	G1	20	0.2	0.2
	Equal Weights		180	W1	R1	C5	G1	20	0.3	0.2

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