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Passive Cooling Strategies for Low-Energy Rural Self-Construction in Cold Regions of China

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Abstract

Rural self-constructed homes in China's cold-temperate regions often exhibit poor energy performance due to limited budgets and substandard construction, leading to a high reliance on active systems and low climate resilience. This study assesses four passive cooling strategies, nighttime natural ventilation (NNV), envelope retrofitting (ER), window shading (WS), and window-to-wall ratio adjustment (WWR), under 2040–2080 representative future climate conditions using energy simulation, multi-objective optimization, sensitivity analysis, and life-cycle cost assessment. Combined measures (COM) cut annual cooling demand by ~43% and representative peak cooling loads by ~50%. NNV alone delivers ~37% cooling reduction with rapid payback, while ER primarily mitigates heating demand. WS provides moderate cooling but slightly increases winter energy use, and WWR has minimal impact. Economic and sensitivity analyses indicate that COM and NNV are robust and cost-effective, making them the most suitable strategies for low-energy, climate-resilient retrofits in cold-climate rural residences. Since statistically extreme heat events are not explicitly modeled, the findings reflect relative performance under representative climatic conditions rather than guaranteed resilience under extreme heatwaves.

Keywords: future climate adaptation; passive cooling design strategies; low-energy self-construction; multi-objective optimization; cold temperate climate; China

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1. Introduction

Climate change is one of the world's most significant challenges in the twenty-first century [1]. To address this, the 26th United Nations Climate Change Conference aims to maintain the Paris Agreement's goal of limiting the increase in global temperature to 1.5 °C and to gradually reduce coal use [2]. The built environment accounts for over 40% of global greenhouse gas (GHG) emissions [3], the majority of cooling and heating demand. Extreme weather events, heatwaves, droughts, and blizzards are expected to exacerbate indoor thermal discomfort, increasing cooling demand and overall energy use [4–8]. These impacts are particularly pronounced in China's cold regions, where buildings traditionally optimized for winter heating increasingly experience summer overheating under climate change [9].

Rising temperatures are expected to alter indoor thermal comfort and drive higher cooling energy demand in buildings [10], as maintaining indoor thermal comfort is energy-intensive [11–13]. The International Energy Agency (IEA) projects that, with rising temperatures, air-conditioning use in rural China will increase substantially to maintain indoor thermal comfort, with the number of units per 100 households expected to reach 208 by 2050 [13]. China has set an ambitious goal of achieving carbon neutrality by 2060 [14], which necessitates substantial reductions in energy consumption and the implementation of decarbonization measures across its existing building stock.

In China's cold regions, long-standing design priorities have centered on winter heating, with minimal attention to summer performance [15]. Rising outdoor temperatures and more frequent heatwaves exacerbate indoor thermal discomfort, increase health risks, and drive higher energy consumption to maintain acceptable indoor conditions [16,17]. Rural residential buildings account for 18% of national building energy use [18], with half of this energy used for improving indoor thermal comfort [19], and about 70% requiring energy-efficiency retrofits [18]. However, most of these houses are poorly designed and lack adequate insulation, resulting in significant heat loss in winter and excessive heat gain in summer [8]. Furthermore, studies [20–25] have shown that most rural households rely on self-construction and active energy systems. This reliance is energy- and money-intensive but fails to ensure adequate indoor thermal conditions.

Enhancing energy efficiency, limiting cooling demand, and reducing reliance on air conditioning are critical for climate-resilient buildings [26]. Passive cooling strategies, including nighttime natural ventilation, window shading, thermal mass optimization, and reflective or insulating materials, have been shown to substantially reduce building energy consumption, lower peak loads, decrease carbon emissions, and improve indoor thermal comfort [27–31]. Globally, cooling demand is projected to rise while heating demand declines, with mid-century projections under RCP4.5 indicating median cooling energy increases of ~18% (10–25%) and under RCP8.5 of ~25% (15–40%) [28]. Despite these trends, regional evidence remains limited, particularly in cold-climate cities such as Xi'an, where passive design research has traditionally focused on minimizing winter heating.

Future climate scenarios pose challenges for buildings in cold regions; however, many studies have demonstrated that passive cooling retrofits can help reduce energy use and GHG emissions while addressing these challenges [29]. In low-income, self-construction rural buildings, passive strategies offer a sustainable and cost-effective solution to rising temperatures [30]. In Xi'an, for instance, shading and ventilation can reduce cooling loads by 15–25% and peak indoor temperatures by up to 2.5 °C [31], and reflective façades and optimized thermal mass in Europe, lowering overheating hours by 40–60% and cooling demand by up to 35% [32]. These findings highlight the potential of targeted passive retrofits to enhance thermal comfort and energy efficiency across diverse climates.

Although previous studies have examined building energy demand under climate change, the implications for future cooling demand in cold-climate Chinese cities, particularly self-construction rural houses in Xi'an, remain largely unexplored. While indoor thermal comfort is a relevant consideration, this study primarily focuses on the low-energy potential of passive cooling strategies, and comfort metrics such as overheating hours or degree-hours are not explicitly evaluated. Building on this context, the present study evaluates the effectiveness of four passive cooling strategies—nighttime natural ventilation (NNV), envelope retrofitting (ER), window shading (WS), and window-to-wall ratio adjustment (WWR)—and their combinations under 2040–2080 climate scenarios. Specifically, we address three research questions:

1. How will cooling demand in self-construction rural houses in Xi'an change under future climate scenarios?

2. How effective are four passive cooling strategies and their combinations in reducing cooling load?
3. Which strategies are most robust across the building life-cycle and climate scenarios, making them suitable for low-energy, climate-resilient retrofits?

2. Materials and Methods

In this study, we develop an integrated framework to evaluate passive cooling strategies for self-construction housing retrofits in Xi'an, China, under current and projected future climate conditions. The framework (Figure 1) combines three complementary evaluation methods: (1) economic assessment using life-cycle cost analysis (LCCA) to estimate long-term financial implications, including initial construction costs, passive technology investments, and operational energy expenses; (2) multi-objective optimization to quantify and balance annual cooling and heating demands, peak cooling load, and economic return, with normalized and weighted composite scores for each strategy; and (3) sensitivity analysis to evaluate the robustness of strategy performance under ±10% variations in the weighting of cooling energy.

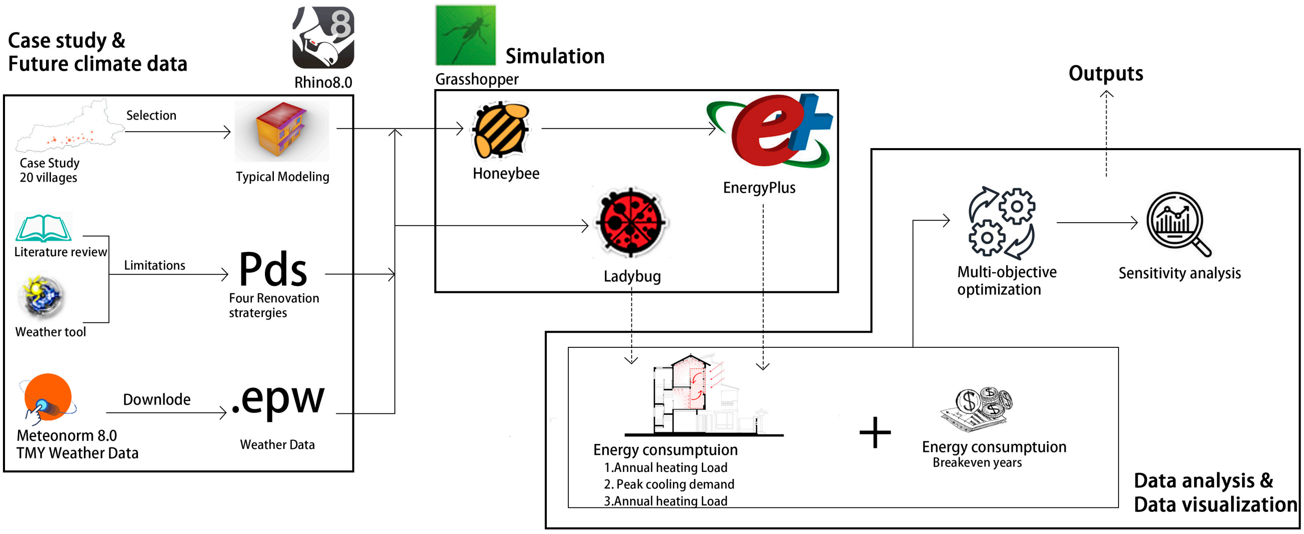

Figure 1. Methodology.

2.1. Case Study Location

Xi'an's rural areas are estimated to contain approximately 300,000–450,000 self-constructed [33]. However, those self-constructed in China's cold-temperate regions generally exhibit poor energy performance and uncomfortable indoor conditions due to limited budgets and substandard construction [34]. To characterize typical rural self-construction housing in Xi'an, a stratified random survey was conducted across 20 villages. Villages were first classified by natural environment, economic activity, and settlement patterns, and a sample was randomly selected from each category. On-site measurements documented building geometry, construction period, structural system, envelope materials, orientation, and internal layouts for 287 households. Most dwellings, built between the 1980s and 2000s, were highly similar in size, materials, and envelopes, with only minor variations in internal layouts. A representative housing reflecting the most common characteristics was selected as the case study (Figure 2). The study focuses on passive cooling retrofits in the main living areas, living rooms, bedrooms, kitchens, and auxiliary rooms, as these are the spaces most frequently used by residents, within the cold-temperate Köppen climate zone [35].

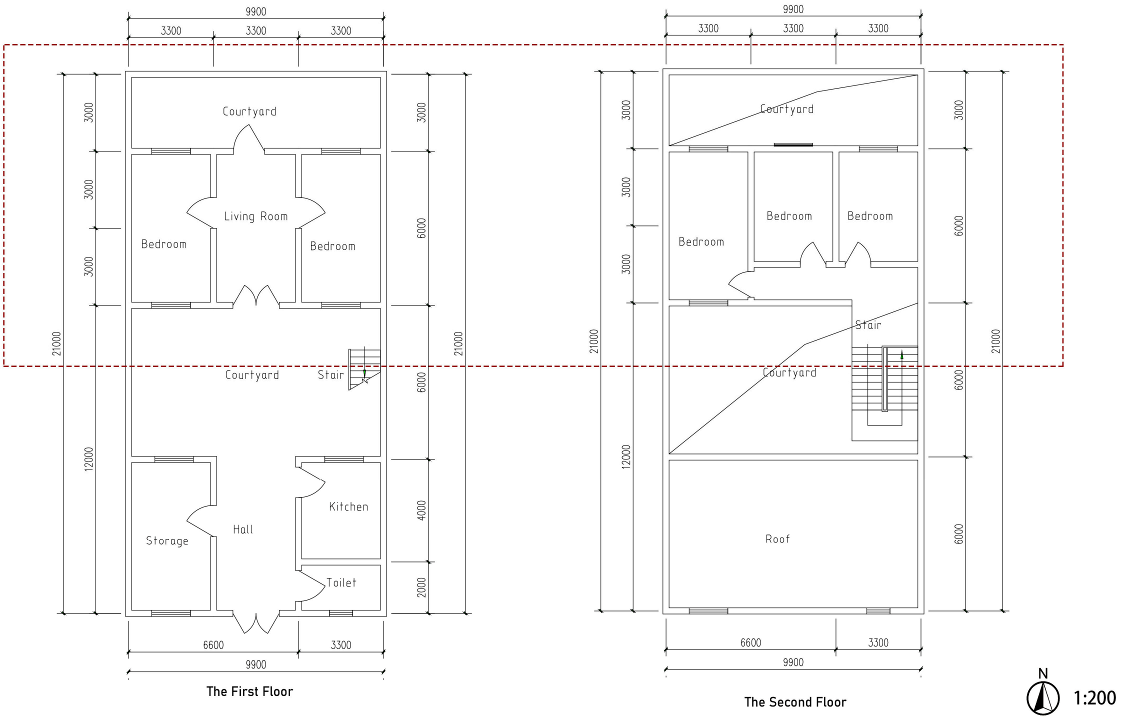

Figure 2. Typical housing layout. The red-dotted areas indicate the main living spaces selected for passive cooling retrofit analysis. All dimensions are millimeters (mm).

In addition, based on a survey of the envelope construction of self-construction residential buildings in Xi'an, the current envelope constructions of walls, floors, roofs, windows and doors (Table A1). The thermal performance of these components was evaluated using the steady-state heat conduction equation for a single-layer, homogeneous, flat wall. Using Equation (1), the thermal resistances (R) and U-values of the envelope components were calculated, providing a quantitative assessment of their heat transfer characteristics.

$$q = \frac{\theta_i - \theta_e}{\frac{d}{\lambda}} (W/m^2) \quad (1)$$

Here, θ_i is the inside temperature of the wall (°C);
θ_e is the outside temperature of the wall (°C);
λ is the thermal conductivity of the wall material (W/m·K);
d is the thickness of a single solid material (m);
q is the heat flux through the wall (W/m^2).

The exterior walls, composed of 370 mm rammed earth brick with 10 mm white lime mortar, have a total thermal resistance of approximately R ≈ 0.50 m^2·K/W (U ≈ 2.0 W/(m^2·K)). Internal walls consist of 240 mm rammed earth brick sandwiched between 10 mm lime mortar layers on each side, yielding R ≈ 0.423 m^2·K/W (U ≈ 2.37 W/(m^2·K)). The ground floor, made of a 400 mm rammed earth slab with 10 mm cement mortar, has R ≈ 0.538 m^2·K/W (U ≈ 1.86 W/(m^2·K)), while the roof—comprising 160 mm rubble concrete, 10 mm cement mortar, and 4 mm felt—has R ≈ 0.352 m^2·K/W (U ≈ 2.84 W/(m^2·K)). Standard glass windows and solid wood doors display R ≈ 0.176 m^2·K/W (U ≈ 5.7 W/(m^2·K)) and R ≈ 0.287 m^2·K/W (U ≈ 3.48 W/(m^2·K)), respectively. All values include standard interior and exterior surface resistances.

2.2. Passive Cooling Design Strategies Analysis

Future climate scenarios pose challenges for buildings in cold regions; however, many studies have demonstrated that passive cooling retrofits can help reduce energy use and greenhouse gas emissions while addressing these challenges [29]. In low-income, self-constructed rural buildings, passive strategies offer a sustainable and cost-effective solution to rising temperatures [30]. References [36–38] show that China and Europe consistently identify four key measures, shading, natural ventilation, thermal mass optimization, and reflective/insulating materials, as highly effective, with shading and ventilation reducing cooling loads by 15–25% and peak indoor temperatures by up to 2.5 °C in Xi'an [31], and reflective façades and optimized thermal mass in Europe, lowering overheating hours by 40–60% and cooling demand by up to 35% [32]. In addition, a climate-specific screening was conducted for Xi'an using typical meteorological data analyzed through EnergyPlus and the Weather Tool (Figure 3A). The results reveal pronounced seasonal differences in strategy performance. Natural ventilation is highly effective, delivering substantial benefits for thermal regulation and humidity control in summer and autumn. In contrast, passive solar heating and direct evaporative cooling show limited effectiveness under local climatic conditions, while indirect evaporative cooling demonstrates potential during warm seasons (Figure 3B).

(**A**)

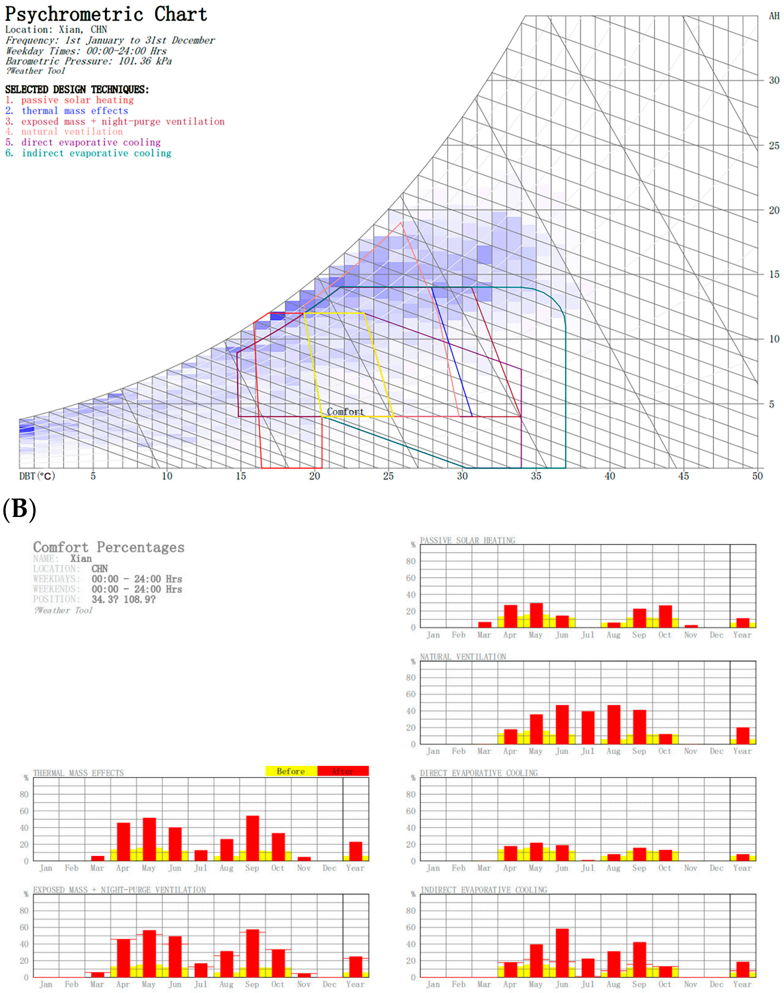

Figure 3. (**A**) Effective range of various passive strategies in the Xi'an region throughout the year (from the Weather tool). (**B**) The improvement of the comfort percentage by each passive strategy (from the Weather tool).

Based on the preceding analysis of passive cooling design strategies and simulations using the Weather Tool software v3.0, four passive cooling retrofit strategies were selected according to the following criteria: (1) the strategy can be implemented during building operation, (2) it is purely passive rather than active, and (3) it is economically feasible, taking into account the financial conditions of rural residents. Accordingly, the four selected strategies are: natural ventilation at night, modification of the building envelope, window shading, and adjustment of the window-to-wall ratio.

2.2.1. Night-Time Natural Ventilation

Natural ventilation, as a passive cooling strategy, can markedly enhance indoor thermal comfort and air quality [39], particularly during summer and transitional seasons [40], by promoting air movement. Beyond lowering reliance on mechanical cooling, it offers practical applicability and cost-effectiveness in both multi-story and rural residential buildings [41]. In this study, night-time natural ventilation (NNV) was implemented during the summer months (June–August) with a 50% window-openable-area ratio, operating from 22:00 to 07:00 whenever indoor temperature exceeded outdoor temperature by 1 °C, consistent with the 0.5–2 °C range recommended by ASHRAE 55 [42], for night-time natural ventilation. Table 1 summarizes the key control assumptions for NNV, including window-openable fraction, ventilation period, temperature threshold, and implementation method.

To isolate the maximum cooling potential achievable through ventilation-driven heat dissipation under favorable conditions, NNV was modeled using fixed window-opening schedules and full occupant compliance. This idealized representation does not explicitly account for practical constraints such as security concerns, outdoor noise, insects, occupant preferences, weather variability, or limited wind availability, all of which may restrict window opening and effective airflow in real-world operation. Consequently, the cooling reductions attributed to NNV in this study should be interpreted as upper-bound estimates of achievable performance, rather than direct predictions of realized energy savings or comfort outcomes in occupied dwellings. Future work will incorporate dynamic occupancy modeling and empirically informed behavioral scenarios to more accurately capture real-world ventilation effectiveness.

Table 1. Nighttime Natural Ventilation (NNV) Control Assumptions (Base Case).

Parameter	Base Case	Justification
Openable window fraction	50%	Typical rural residential window operability [43]
Ventilation period	22:00–07:00	Nighttime operation, avoids daytime heat gain [44,45]
Temperature threshold	Tin > Tout + 1 °C	ASHRAE 55 recommended range [42]
Compliance	100%	Ideal assumption to simplify the simulation
Implementation/Mode	EnergyPlus airflow network with temperature-driven window opening	Explicit modeling method [46]
Notes/Assumptions	NNV applied only during the summer months (June–August)	Nighttime operation prioritizes accumulated heat removal [45,47,48]

2.2.2. Building Envelope Modification

The building's external envelope interface is the first and most important defense against adverse outdoor climate conditions [49]. As a key determinant of the heat transfer coefficient, the thickness of envelope materials strongly influences thermal insulation performance [50]. According to the Design Standard for Energy Efficiency of Civil Buildings in Shaanxi Province (DBJ 51/T 221-2016 [51]) [52] and the Assessment Standard for Green Building (GB/T 50378-2019) [53], the experimental parameters were established (Table A2). The external wall assembly, comprising cement mortar, Expanded Polystyrene (EPS) insulation, mortar and hollow brick, achieves a total thermal resistance of approximately 2.01 m^2·K/W. Internal walls composed of cement mortar and hollow brick provide an R-value of 0.76 $m^2 \cdot K/W$. Windows with double glazing and an air cavity yield an R-value of 1.21 $m^2 \cdot K/W$. The ground structure (soil, concrete, and wood) reaches 2.04 $m^2 \cdot K/W$, while the roof system (ceramic tiles, timber beams, asphalt felt, rubble concrete, and cement mortar) exhibits 0.58 $m^2 \cdot K/W$. Thermal resistance values were derived from standard material properties using simplified steady-state calculations. For the ground and window systems, idealized assumptions were adopted, which may slightly overestimate thermal resistance but remain acceptable for comparative simulation analysis.

2.2.3. Window Shading

Reducing solar irradiance on building envelopes is an effective strategy to mitigate high surface temperatures and indoor overheating in summer [54,55]. In this study, exterior shading devices were parametrically modeled in Honeybee (Rhino 8.0 +Grasshopper) for south-facing windows measuring 1.5 m × 1.8 m. The shading system consisted of five repeated louvers, each 0.5 m deep and tilted at 0.4 rad, designed to block high summer sun angles while preserving daylight access. Window units were defined as double-glass with a 30 mm air cavity, achieving a U-value of 0.72 $W/m^2 \cdot K$ and an SHGC of 0.78 (Detailed values and layer specifications are summarized in Table A2). These parameters are consistent with ranges reported in previous studies on fixed external shading devices, in which shading depth is typically 20–50% of the window height and louvre angles are optimized to block summer sun while maintaining daylight access [56]. Their effectiveness was verified through parametric simulations applied to all relevant transparent surfaces.

2.2.4. Window-to-Wall Ratio

The window-to-wall ratio (WWR), defined as the ratio of window area to the corresponding facade area, directly influences solar heat gain and indoor thermal performance [57]. Excessive WWR on the south facade increases solar radiation in winter but may lead to cold air infiltration at night and higher cooling demand in summer [58]. According to the Design Standard for Energy Saving of Residential Buildings (DB61/T 5033-2022 [59]) [60] and (GB/T 50378-2019) [53], the WWR of residential buildings in Xi'an is strictly regulated. In the experimental case of self-constructed housing in Baolong Village, the south-facing WWR is designed to achieve approximately 40% winter solar heat gain while preventing summer overheating. North-facing windows, with a WWR of 30%, are minimized to reduce winter heat loss, while east–west facades are window-free. Overall, window design adheres to both regulatory requirements and principles of climatic adaptation, ensuring adequate daylighting and ventilation while promoting passive cooling.

2.2.5. Combined Passive Cooling Strategies (COM)

To evaluate the holistic energy-saving potential and synergetic effects of the aforementioned strategies, an integrated simulation framework was developed [61]. Instead of a simple linear superposition of individual results, a 'Composite Scenario' was created, in which the optimal configurations for nighttime natural ventilation (Section 2.2.1), envelope insulation (Section 2.2.2), external shading (Section 2.2.3), and window-to-wall ratios (Section 2.2.4) were implemented simultaneously in EnergyPlus. This approach leverages the software's simultaneous heat-balance algorithms to capture the coupled thermal interactions among strategies [62]. Specifically, the model accounts for the interplay between reduced solar heat gain (from shading and WWR optimization) and enhanced heat dissipation (via nighttime natural ventilation and envelope thermal mass). While this simulation captures these interactive effects, it is still based on model assumptions rather than real-world measurements. Nevertheless, this methodology provides a more realistic benchmark for evaluating the combined performance of passive cooling retrofits in rural residential buildings [63,64].

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2.3. Historical and Future Climate Data

Global climate change, driven by increasing carbon emissions from buildings, is expected to have profound impacts on built environments [65]. Future climate conditions are commonly assessed using standardized GHG concentration scenarios, namely Representative Concentration Pathways (RCPs), as defined by the IPCC [66–68]. For Xi'an, hourly climate data in EPW format were generated using Meteonorm 8.0 to produce Typical Meteorological Years (TMYs) for RCP4.5 and RCP8.5, representing medium- and high-emission futures; RCP2.6 was excluded due to the improbability of achieving immediate stringent mitigation [66,69]. These TMYs for 2050 and 2080 were used to simulate changes in building cooling demand and evaluate passive design strategies. While suitable for assessing annual performance and representative peak loads, it should be noted that TMYs do not capture statistically extreme events such as prolonged heatwaves or compound climate extremes [70,71].

Based on the TMY 2020 and TMYs for 2050 and 2080, following RCP 4.5 and RCP 8.5, a summary of the average monthly temperatures of the different climate scenarios is provided (Figure 4). Under future climate scenarios, the region's annual mean temperature shows a clear warming trend. Under RCP4.5, it increases from 14.1 °C in 2020 to 16.4 °C in 2080 (+2.3 °C). Moreover, at the same time, the high-emission pathway (RCP8.5) is consistently warmer than RCP4.5, with differences of 0.4 °C by 2050 and 1.6 °C by 2080. These changes indicate progressively milder winters and hotter summers, which may exacerbate imbalances between heating and cooling demands and increase the frequency of extreme heat events.

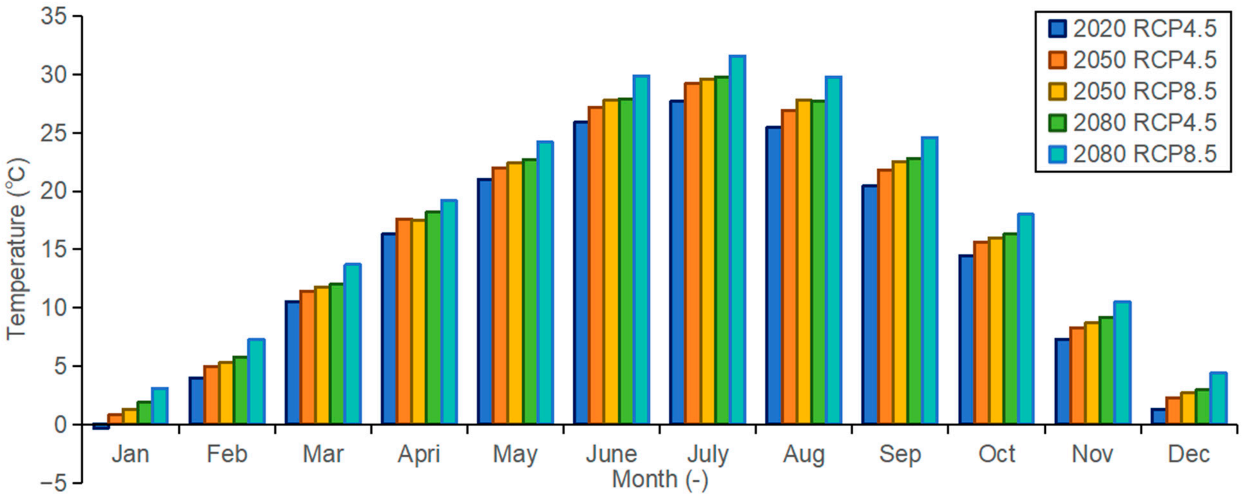


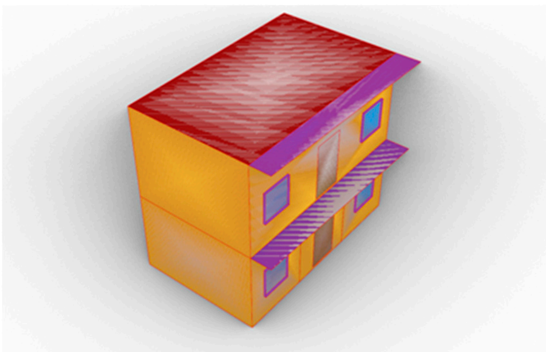
Figure 4. Average monthly temperature of the different future climate scenarios.

This study evaluates passive cooling performance under representative future climate conditions rather than statistically extreme heat events. Future climate conditions in this study are represented using Typical Meteorological Year (TMY) datasets for RCP4.5 and RCP8.5. TMY files are designed to characterize statistically representative climatic conditions and are suitable for assessing annual energy demand and representative peak loads associated with long-term mean climate change. However, they do not explicitly reproduce low-probability extreme heat events such as prolonged heatwaves, compound hot–humid episodes, or persistent hot nights. Accordingly, the term climate robustness in this study refers to the consistency of strategy performance and ranking across multiple future climate pathways and time horizons, rather than demonstrated resilience to extreme heat events.

2.4. Simulation Setup

In the first stage of the environmental assessment, the spatial representation of the case study was developed in Rhino/Grasshopper. At the same time, the thermal envelope properties, operational schedules, solar shading, occupancy patterns, internal equipment loads, and heating and cooling setpoints were assigned using the Ladybug and Honeybee plugins. All simulations were performed in EnergyPlus v23.1 via Honeybee 1.82, using the default timestep of 10 min (six per hour) to capture short-term thermal and airflow variations. Historical weather data and projected future climate scenarios from Meteonorm were used as boundary conditions to reflect current and anticipated climatic conditions. The purpose of these simulations was to evaluate the performance of the four passive cooling strategies proposed in this study.

The simulation strategy adopted in this study was structured around a baseline model, which served as the principal reference (Figure 5A). The reference model was established based on surveys of rural residences in the Xi'an region (Figure 5B), reflecting the most prevalent characteristics of local housing in terms of spatial layout, number of stories, and envelope construction (Table A1). Building on this, five additional scenarios were developed in which individual passive cooling measures were tested in isolation—namely, improvements to the building envelope, solar shading, natural ventilation, and adjustments to the window-to-wall ratio. At the same time, a comprehensive scenario integrated optimal configurations of all four measures to systematically evaluate their synergistic impact on overall energy performance. In total, six simulation sets (Table 2), including the baseline, were generated and compared. This framework provided a basis for evaluating passive cooling design strategies to alleviate future cooling demand in Xi'an under projected climate conditions.



(**A**)

(**B**)

Figure 5. (**A**) Energy model of the case study building. (**B**) Image of the building.

Table 2. Description of cases.

Scenarios	Description	Abbreviation
1	Base Case	BASE
2	Night-Time Natural Ventilation	NNV
3	Envelope Renovation	ER
4	Window-Shading Renovation	WS
5	Window-to-Wall Ratio	WWR
6	Combination of cases 1–5	COM

Since the effectiveness of natural ventilation is closely linked to occupant behavior and internal heat sources [72], occupancy and internal heat gains were explicitly considered in the simulation (Table 3). The case study residence was assumed to accommodate 2 occupants, in line with the average household size in contemporary rural China [73].

The occupancy schedule was set to 30% on weekdays (Monday–Friday) and 70% on weekends (Saturday–Sunday) [74], reflecting typical residential behavior and enabling a realistic representation of internal heat gains in the simulation. Each occupant contributed an internal heat gain of 80 [75,76], accounting for both sensible and latent heat. HVAC setpoints were selected based on thermal comfort requirements and residential energy simulation practice, with heating initiated below 18 °C and cooling above 26 °C in line with typical residential thermostat guidelines [42]. These parameters were treated as static assumptions to simplify the simulation, acknowledging that actual occupant behavior, occupancy patterns, and internal heat gains can vary in practice. In addition, cooling and heating loads were simulated using the Ideal Loads module in EnergyPlus, which assumes an ideal HVAC system capable of meeting setpoints without limitations. Therefore, the reported loads represent thermal demand rather than actual energy consumption, which depends on the system's efficiency and operating conditions.

Table 3. Occupancy and other parameters of the cases.

Description	Parameter	Unit
Occupancy	2	people
Occupancy schedule	Workday: 30%, Weekend: 70%	%
Occupancy load	80	W/person
Heating setpoint	18	°C
Cooling setpoint	26	°C

In addition, the baseline model was established based on these input assumptions to represent typical rural residential buildings in Xi'an, reflecting common spatial layouts, number of stories, and envelope constructions (Table A1). Infiltration was modeled using a fixed rate of 0.5 ACH with the EnergyPlus Simple Infiltration object, representing typical rural building leakage, consistent with typical natural infiltration assumptions used in residential simulation studies and low-energy building standards [77]. Due to the lack of monitored data, the model was not calibrated. To evaluate its plausibility, simulated annual heating and cooling intensities (kWh/m^2·yr) were compared with values reported for similar rural buildings in Xi'an and with the recommended ranges in the Chinese Green Building Standards [78–82]. As summarized in Table 4, the simulated baseline values fall within these ranges, supporting their suitability for comparative analysis. Uncertainty bounds of ±10% were applied to account for potential variability. Accordingly, all energy savings and payback estimates are interpreted as relative comparisons, rather than absolute predictions.

Table 4. Baseline Model Plausibility Benchmark.

Metric	Simulated Baseline (in 2020)	Literature/Standard Range	Notes/Uncertainty
Heating intensity	65.57 kWh/m^2·yr	50–80 kWh/m^2·yr	±10% uncertainty
Cooling intensity	26.41 kWh/m^2·yr	15–30 kWh/m^2·yr	±10% uncertainty

2.5. Life-Cycle Cost Analysis

Life-cycle costs of different building design strategies were assessed by considering both construction and operational expenditures, enabling a comprehensive comparison of their economic performance over the building lifetime [83]. Construction costs were estimated based on material and labor expenditures, with labor assumed to be 20–40% of material costs [84], reflecting typical construction practice in China. Operational savings from reduced heating and cooling energy consumption, along with lower maintenance costs due to reduced reliance on active systems, were incorporated into a discounted cash flow analysis to express future savings in present value terms. The breakeven year is reached when cumulative discounted operational savings equal the additional construction investment, as shown in Equation (2):

$$\sum_{t=1}^{T}\left(\frac{S_t}{(1+r)^t}\right) = C_{\text{construction}} \tag{2}$$

Here, S_t is the annual savings from energy and maintenance reductions (Yuan/year);
r is the discount rate;
$C_{\text{construction}}$ is the total construction cost (Yuan);
T is the breakeven year (Year).

This analysis was conducted over 30 years, with operational energy savings estimated from simulated heating and cooling loads and electricity costs calculated using Xi'an's rural tariff (0.5 RMB/kWh). All passive strategies, envelope retrofitting (ER), window-to-wall ratio adjustments (WWR), nighttime natural ventilation (NNV), and window shading (WS), as well as conventional building systems, were included in the LCC analysis (Table A3). Sensitivity analyses were not conducted; variations in the discount rate, energy prices, or initial costs may affect the results. In addition, to account for uncertainties in key economic parameters, a simple sensitivity analysis was conducted on retrofit costs. Construction costs were varied by ±20% to evaluate their impact on the breakeven year. Rural electricity prices were not varied due to their low absolute value and minimal influence on the results [85]. The discount rate was fixed at 5%, following typical practice in building life-cycle cost studies [86,87].

The life-cycle cost analysis adopts fixed values for the electricity price and discount rate to enable consistent comparison across retrofit strategies. These parameters are subject to long-term uncertainty related to energy market fluctuations, policy interventions, and macroeconomic conditions. Consequently, the resulting payback periods should be interpreted as scenario-dependent indicators for relative comparison rather than precise economic forecasts. Payback periods exceeding the assumed analysis horizon or typical building service life are considered economically non-viable under conventional investment criteria.

2.6. Multi-Objective Optimization and Sensitivity Analysis

2.6.1. Multi-Objective Optimization

A multi-objective optimization framework was employed to evaluate passive retrofit strategies based on four indicators: annual cooling demand, annual heating demand, peak cooling load, and breakeven year [88]. To ensure comparability across metrics with different units and scales, all indicators were min-max normalized to a 0–1 range, with 1 denoting optimal performance [88]. The algorithm is expressed as shown in Equation (3):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

Here, x' is the normalized value, ranging from 0 to 1;
x is the original value;
x_{max} x_{min} are the dataset's minimum and maximum values, respectively.

The weights for the multi-objective aggregation were assigned to reflect the relative importance of each performance criterion. For each passive retrofit strategy (NNV, ER, WS, WWR, and COM), the key performance indicators—including annual cooling and heating demands, peak cooling load, and breakeven year—were first normalized and then combined using a weighted aggregation approach, with baseline weights of 0.45, 0.35, 0.10, and 0.10, respectively [88–90]. Annual cooling demand was given the highest weight

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(0.45) as the principal objective of passive retrofit strategies, consistent with prior studies emphasizing energy reduction in buildings. Annual heating demand was assigned a secondary weight (0.35) due to its importance for year-round energy performance and comfort. Peak cooling load and breakeven years were allocated lower weights (0.10 each), reflecting their supporting role in evaluating system sizing and economic feasibility without disproportionately influencing the overall strategy ranking. By structuring the analysis in this way, trade-offs between thermal performance and financial outcomes could be systematically examined, providing a solid quantitative basis for identifying the most effective passive retrofit strategies.

2.6.2. Sensitivity Analysis

A sensitivity analysis was conducted to examine the robustness of the multi-objective optimization results with respect to variations in the weighting of the annual cooling energy demand [91]. The study focused on quantifying how changes in the relative importance of cooling performance influence the overall ranking of passive retrofit strategies. Specifically, the weight of annual cooling demand was varied by ±10%, while the remaining weights were proportionally adjusted to maintain a total sum of 1.0. This ±10% weight variation is a commonly adopted range in multi-objective building optimization studies, providing an indication of how overall strategy rankings respond to changes in weighting assumptions, without implying specific stakeholder preferences [92,93]. All indicator weights were altered simultaneously, and the resulting variations in the composite performance scores for each strategy (NNV, ER, WS, WWR, and COM) were computed to highlight the relative influence of cooling-energy weighting on overall performance. Minor deviations indicate greater sensitivity to stakeholder-defined priorities [94,95].

The weighting scheme applied in the multi-objective optimization reflects a normative prioritization of performance criteria aligned with the primary objective of the study, namely the reduction in cooling-related energy demand under future climate conditions. As with all multi-criteria decision-making approaches, the selection of weights is inherently subjective and cannot represent the full diversity of stakeholder preferences, which may vary between households, designers, and policymakers. Accordingly, the optimization results are not intended to define a universally optimal solution, but rather to identify strategies that perform well under a cooling-focused decision logic commonly adopted in climate mitigation and retrofit studies.

3. Results

3.1. Energy Performance of Passive Strategies

3.1.1. Annual Cooling Load

Annual cooling demand exhibits a pronounced upward trajectory from 2020 to 2050 and further to 2080, with the most marked increase under the high-emission scenario (RCP8.5), where demand consistently exceeds that of RCP4.5. Among individual passive strategies, nighttime natural ventilation (NNV) proves the most effective, delivering a ap consistently 37% reduction in cooling energy across all scenarios. The reported cooling reductions for NNV should therefore be interpreted as best-case estimates under idealized operating conditions, as the model assumes fixed window opening and full occupant compliance. Window shading (WS) contributes moderately, achieving 15.3% savings in 2020, declining to 9.5% by 2080 under RCP4.5, indicating diminished effectiveness under future warming. Adjustments to the window-to-wall ratio (WWR) result in marginal reductions (0.8–3%). In contrast, envelope retrofits (ER) show minor increases under mild scenarios but achieve net decreases of about 4% under the extreme RCP8.5 scenario in 2080. The integrated strategy, combining all measures (COM), achieves the largest reduction, lowering annual cooling demand by 37.95–42.90% relative to the baseline (Figure 6A,B). These results highlight the critical importance of synergistic application of multiple strategies to maximize cooling energy savings under projected climate scenarios.

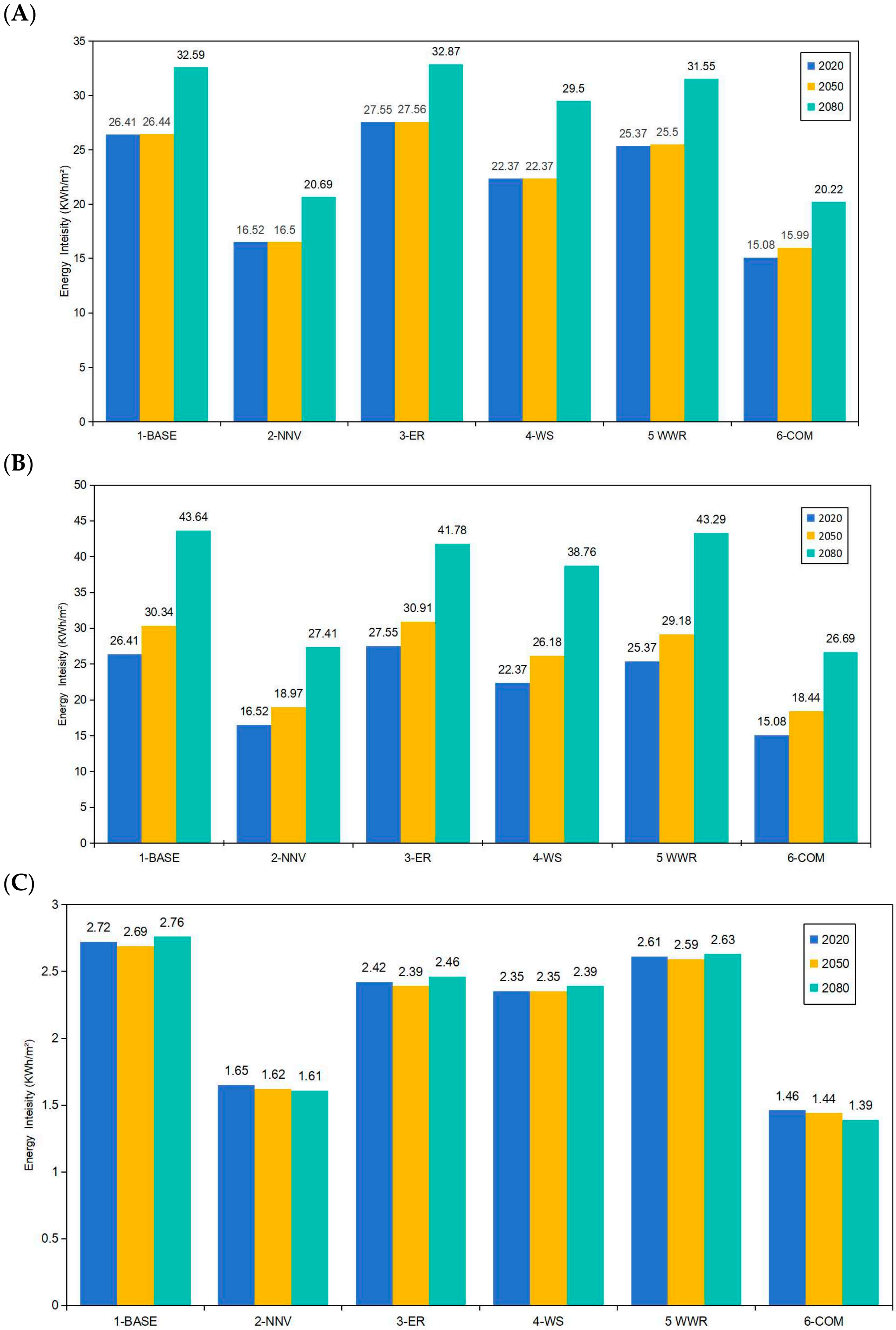

Figure 6. (**A**) Total annual cooling demand [kWh/m^2] for all cases, for the RCP4.5 future climate scenarios, in 2020, 2050 and 2080; (**B**) Total annual cooling demand [kWh/m^2] for all cases, for the RCP8.5 future climate scenarios, in 2020, 2050 and 2080; (**C**) Total peak cooling demand [kW] for all cases, for the RCP4.5 future climate scenarios, in 2020, 2050 and 2080.

3.1.2. Peak Cooling Demand

Analysis of peak cooling loads for the warmest day of the year (21 July) shows that all passive strategies contribute to significant peak mitigation. 21 July was selected as the hottest day of the year in Xi'an based on historical meteorological data from 2010 to 2024, representing the extreme peak summer temperature for peak cooling load analysis. COM reduces peak demand by 46–50%, whereas NNV alone accounts for 39–42% of that reduction. WS consistently lowers peak loads by approximately 13%, ER contributes roughly 10%, and WWR adjustments yield minor effects (~4%) (Figure 6C). Overall, these results demonstrate that targeted passive interventions can effectively flatten peak loads, thereby reducing the operational stress on cooling systems under design-day peak summer conditions. This approach follows the standard design-day methodology commonly used in building energy simulations to estimate peak load [96,97].

3.1.3. Annual Heating Load

In cold climates, energy-saving measures aimed at reducing cooling demand can sometimes increase heating requirements [26]. Simulations under RCP4.5 for 2020, 2050, and 2080 show that WS notably increases annual heating demand, from 8.95% in 2020 to 7.20% in 2080 (Figure 7). In contrast, NNV, WWR, and COM remain effective in reducing heating energy, though less pronounced than for cooling. ER, while minimally affecting cooling, substantially reduces heating consumption (~37%) across all periods. The combined passive approach achieves meaningful heating reductions of 22.58% in 2020 and 21.02% in 2080.

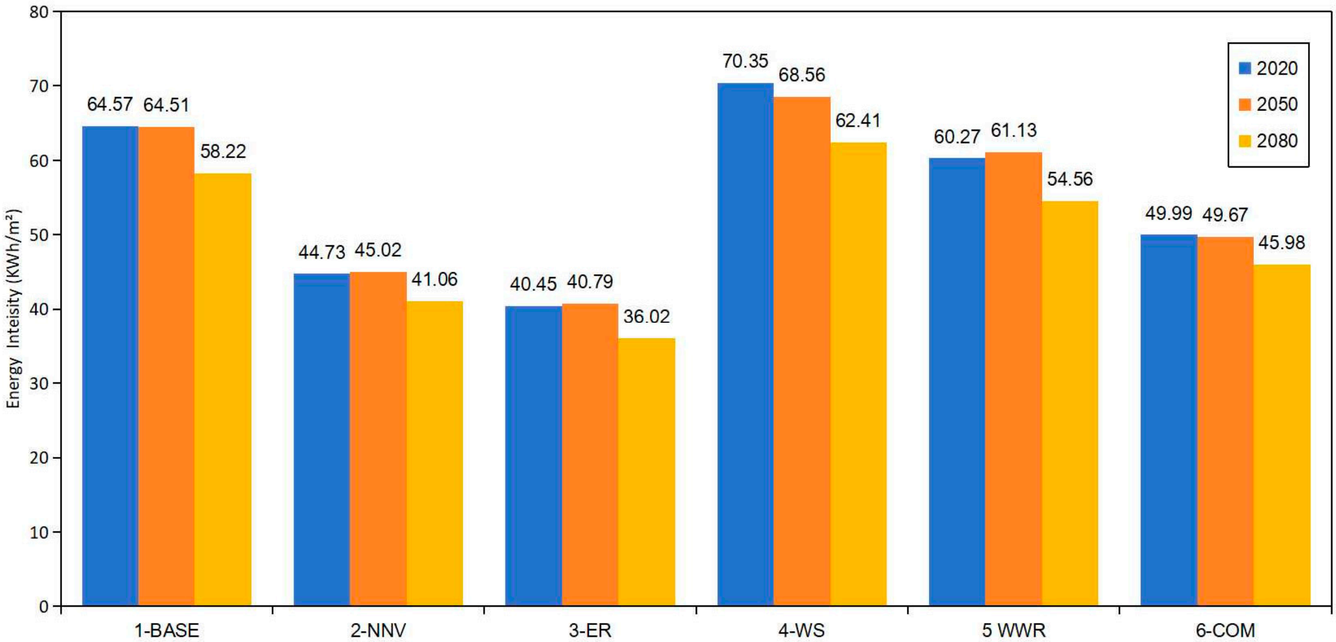

Figure 7. Total annual heating demand [kWh/m^2] for all cases, for the RCP4.5 future climate scenarios, in 2020, 2050 and 2080.

Considering both heating and cooling, COM consistently delivers the highest overall energy savings, with 37–43% reductions in annual cooling demand and 46–49% reductions in peak loads from 2020 to 2080. NNV emerges as the most effective single measure, offering robust reductions in both annual and peak cooling. WS provides moderate cooling savings but increases heating requirements; ER primarily enhances heating efficiency with limited cooling benefit, and WWR offers minor improvements across both metrics.

These results underscore the need to combine multiple strategies to achieve optimal, year-round energy performance in self-construction rural housing.

3.2. Economic Performance

Life-cycle cost (LCC) analysis was conducted over a 30-year horizon, incorporating ±20% variation in implementation costs for five passive strategies. NNV achieves the fastest payback, ranging from 5 to 16 years across scenarios, with the shortest payback occurring in 2080 under the high-emission RCP8.5 scenario, reflecting its moderate upfront cost and substantial operational energy savings. ER and WS exhibit intermediate payback periods of 20–41 years, while WWR shows the longest payback, exceeding 200 years in low-energy scenarios, indicating limited feasibility as a standalone measure. COM demonstrates stronger economic performance, reaching breakeven within 8–28 years depending on the scenario, particularly under high-emission projections. Sensitivity analysis shows that NNV and COM are relatively robust to cost fluctuations, whereas ER, WS, and WWR are more sensitive. For subsequent multi-objective evaluation, the median payback of each strategy is adopted as a representative value, providing a stable, consistent input that accounts for both cost uncertainty and climate variability (Table 5).

Payback periods extending beyond the 30-year analysis horizon indicate that these strategies are unlikely to be economically justified based on energy savings alone and are therefore reported primarily for comparative purposes. Specifically, some individual passives retrofit measures, particularly WWR adjustments, exhibit excessively long payback periods when implemented in isolation, limiting their standalone economic feasibility. In contrast, the comprehensive combination of all strategies (COM strategy) achieves substantially shorter payback periods while maintaining more balanced thermal performance. This demonstrates the economic realism of retrofits, showing that fully integrated packages can provide technically effective and economically justifiable outcomes over the building's lifetime.

Table 5. Breakeven years (unit: year).

Scenarios	2-NNV	3-ER	4-WS	5 WWR	6-Com
2020 RCP4.5	11.2–15.3	30.2–36.6	45.5–68.3	204–307	17.2–25.9
2050 RCP4.5	11.5–15.7	32.4–39.0	45.2–67.8	226–339	17.7–26.6
2050 RCP8.5	11.6–16.1	22.6–27.8	59.5–89.3	246–308	18.2–27.5
2080 RCP4.5	6.1–7.5	29.1–35.6	22.1–33.1	91–138	7.8–11.8
2080 RCP8.5	5.3–6.5	34.0–40.8	23.6–39.9	380–456	7.0–9.2

3.3. Multi-Objective and Sensitivity Analysis

3.3.1. Multi-Objective Optimization Results

Across the three climate scenarios (2020, 2050, and 2080), the combined strategy (COM) consistently achieves the highest weighted scores, reaching 0.884 in both 2020 and 2050 and remaining high at 0.864 in 2080. This performance is driven by its maximum cooling and peak cooling reduction across all periods, alongside stable breakeven outcomes. NNV shows the second-best performance across all scenarios, with weighted scores of 0.881, 0.910, and 0.898, respectively, reflecting strong cooling performance and overall stability, despite a gradual decline in heating performance under warmer future conditions. ER exhibits consistently optimal heating performance but provides no cooling benefit, resulting in moderate weighted scores ranging from 0.443 to 0.460. WS delivers modest cooling benefits in 2020 and 2050, followed by a notable decline by 2080, while WWR contributes marginally across all indicators and maintains the lowest overall scores

(Figure 8A–C). Overall, the results indicate that the combined strategy outperforms individual measures by offering the most balanced performance across all evaluated metrics under both current and future climate scenarios.

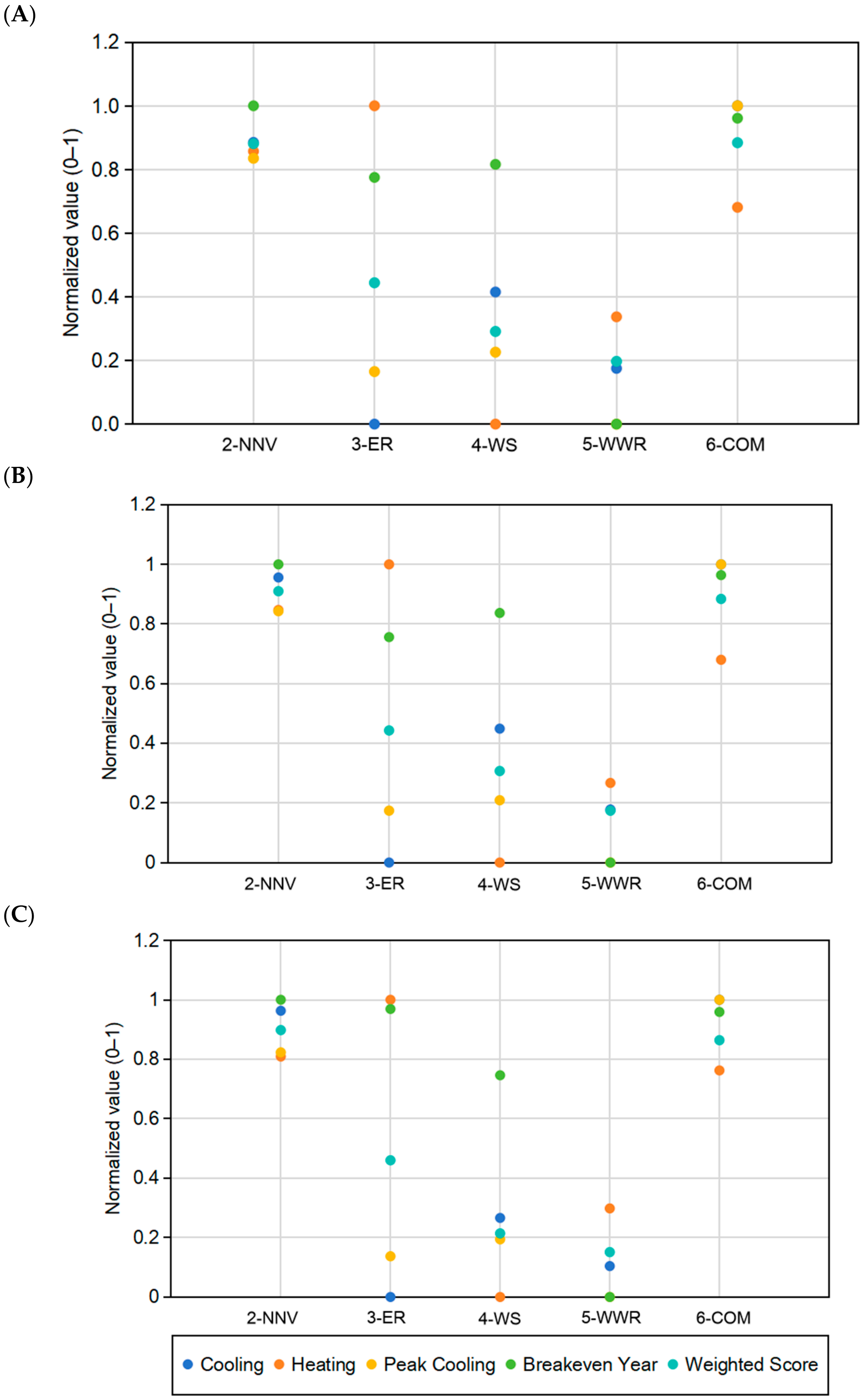

Figure 8. Comparative Multi-objective Weighted Analysis of Five Design Strategies under (**A**) 2020 RCP4.5 Scenario; (**B**) 2050 RCP4.5 Scenario; (**C**) 2080 RCP4.5 Scenario.

3.3.2. Sensitivity Analysis Results

Sensitivity analysis reveals distinct response patterns among the evaluated strategies across the three-time horizons (Figure 9A–C). NNV demonstrates consistently low sensitivity across all scenarios, with relatively small, balanced variations in 2020, 2050, and 2080, indicating stable performance under changing climatic conditions. WS shows increasing sensitivity over time, with larger variations in 2050 and a more asymmetric response by 2080, suggesting a growing influence of this strategy under future warming scenarios. ER exhibits the highest sensitivity in all periods, with pronounced positive and negative deviations, reflecting its strong but highly directional impact on thermal performance. COM and WWR display moderate sensitivity levels across all scenarios, remaining within a narrower response range than ER but exhibiting greater variability than NNV. Overall, the sensitivity results highlight clear differences in the magnitude and stability of strategy responses under current and future climates.

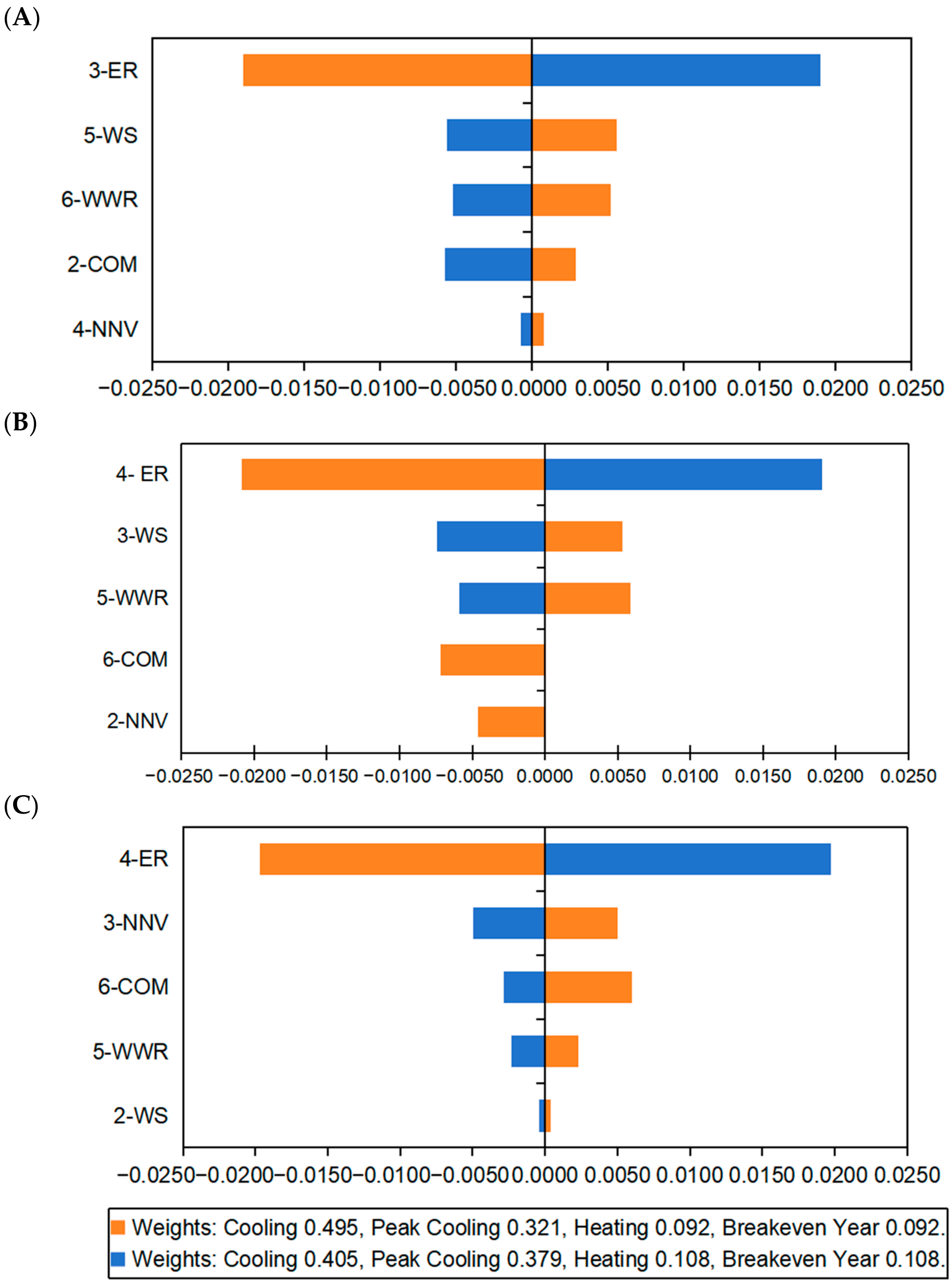

Figure 9. Comparative sensitivity analysis of five strategies in (**A**) 2020 RCP4.5 Scenario; (**B**) 2050 RCP4.5 Scenario; (**C**) 2080 RCP4.5 Scenario.

4. Discussion

This study demonstrates the potential of passive cooling strategies to reduce energy demand in rural self-constructed residences in cold-temperate regions of China under projected climate scenarios. Among the individual measures evaluated, nighttime natural ventilation (NNV) consistently emerges as a comparatively effective single strategy, achieving approximately 37% reductions in annual cooling demand. As NNV performance is highly sensitive to occupant behavior and environmental constraints, the simulated benefits likely overestimate realized cooling reductions in typical rural households. The integrated strategy (COM) delivers the highest overall performance, reducing annual cooling demand by up to 43% and representative peak cooling loads by nearly 50% under typical future climate conditions represented by TMY datasets. Seasonal trade-offs are evident, as certain cooling-oriented measures—particularly window shading (WS)—may increase winter heating demand, underscoring the importance of evaluating passive strategies within a year-round energy framework.

Multi-objective and sensitivity analyses indicate that COM and NNV maintain high weighted performance across the assessed future climate scenarios and are relatively insensitive to variations in weighting assumptions. In contrast, WS and window-to-wall ratio (WWR) adjustments exhibit greater sensitivity to climatic variability, suggesting that while individual measures can deliver targeted benefits, coordinated strategies offer more robust performance across scenarios.

Several limitations should be acknowledged. Indoor thermal comfort was not quantitatively assessed. While energy demand and peak load provide important performance indicators, reductions in these metrics generally correspond to lower indoor temperature excursions and mitigated overheating risk, offering indirect insight into occupant comfort. Metrics such as overheating hours (OH) or predicted mean vote (PMV) could provide additional quantitative evaluation under passive strategies. Future work should incorporate these comfort indicators to enable a more comprehensive assessment of the practical effectiveness of passive cooling strategies. Moreover, nighttime natural ventilation (NNV) was modeled under idealized conditions, assuming fixed window-opening schedules and full occupant compliance. Factors such as security concerns, noise, insects, and variable wind conditions were not considered. As a result, the cooling benefits of NNV are likely somewhat overestimated. Future work should incorporate comfort-based indicators and behavior-informed or probabilistic ventilation models to better capture real-world performance.

The combined (COM) strategy represents a single predefined configuration of passive measures, which limits the exploration of alternative or partial combinations that may yield different synergies or more cost-effective trade-offs. Envelope retrofits (ER) also exhibit asymmetric seasonal performance, providing substantial heating savings but comparatively limited cooling benefits. This suggests potential complementarities with cooling-oriented strategies that remain unexplored and merit further investigation. In addition, the analysis focuses on a single representative rural self-constructed dwelling in Xi'an. Regional differences in construction practices, material availability, climate conditions, and socio-economic contexts may therefore limit the generalizability of the findings.

While this study evaluates future cooling demand and representative peak loads under projected climate scenarios, it does not explicitly assess building performance under extreme heat events. Because TMY weather files exclude the persistence and intensity of rare heatwaves, the analysis cannot fully capture the conditions that often dominate cooling risk, occupant overheating, and system stress. As a result, claims of climate robustness should be understood as robustness to long-term climatic warming and scenario uncertainty, rather than proven resilience under extreme heat events. Nevertheless, evaluating strategy performance across multiple climate pathways (RCP4.5 and RCP8.5) and time horizons (2020–2080) provides valuable insight into whether passive retrofit strategies maintain their relative effectiveness as average climatic conditions shift. This form of robustness is particularly relevant for long-term retrofit planning, where decisions must remain valid under uncertain future climates, even if additional analysis is required to assess extreme-event resilience.

From an economic perspective, several strategies exhibit long payback periods that exceed typical building lifespans or household investment horizons. Such results highlight the limited economic attractiveness of certain passive measures when evaluated solely by energy cost savings under fixed electricity prices and discount rates. These findings should therefore not be interpreted as literal investment guidance but rather as an indication of relative economic performance. Broader benefits—such as improved thermal comfort, reduced heat stress exposure, and reduced reliance on mechanical cooling—may provide additional justification beyond simple payback metrics.

The multi-objective ranking results depend on the relative weighting assigned to cooling demand, heating demand, peak load, and economic performance. Although the applied weighting scheme reflects a plausible prioritization of passive cooling retrofits in rural housing, alternative stakeholder objectives—such as cost minimization or peak-load reduction—may yield different rankings of strategies. This highlights the importance of interpreting the optimization results as scenario-dependent rather than prescriptive.

Future research should address these limitations by systematically exploring alternative combinations of passive strategies, enhancing seasonal coordination between heating- and cooling-oriented measures, and incorporating dynamic, behavior-driven occupant models. The inclusion of comprehensive thermal comfort assessments—such as overheating hours, degree-hours, and adaptive comfort metrics—would enable a more nuanced evaluation of the trade-offs between energy savings and occupant well-being, thereby supporting the development of genuinely low-energy, climate-adaptive retrofit strategies for rural housing.

Despite these limitations, the integrated evaluation framework presented in this study provides a systematic approach to assessing passive strategies in terms of energy performance, representative peak-demand reduction, economic feasibility, and robustness across future climate scenarios. Prioritizing nighttime natural ventilation, in combination with complementary passive measures, emerges as the most effective and resilient pathway for low-energy retrofits in rural self-constructed housing under representative future climate conditions.

5. Conclusions

This study presents an integrated framework for evaluating passive cooling strategies in rural self-constructed residences in cold-temperate regions of China under projected representative climate scenarios for 2020, 2050, and 2080 (RCP4.5 and RCP8.5). The framework evaluates the energy, economic, and robustness performance of both individual and combined strategies, offering a novel and transferable pathway for low-energy, climate-resilient renovation of rural buildings. While this study focuses on a representative case in Xi'an, the approach can be extended to other cold-temperate regions, diverse building types, and longer-term simulations. Because future climates are represented using TMY-based weather files, the conclusions reflect comparative performance under representative conditions rather than resilience to statistically extreme heat events.

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Future research should incorporate occupant behavior and field monitoring to refine passive cooling strategies further and support broader, practical applications across regions and building types. Key findings include:

1. The integrated strategy (COM) performs strongly under the selected weighting scheme, while alternative priorities may favor different strategies. It reduced annual cooling demand by 38–43% while maintaining balanced heating demand, representative peak cooling loads, and life-cycle cost outcomes.
2. NNV demonstrates the highest theoretical cooling potential among the evaluated strategies, although its realized effectiveness depends strongly on occupant behavior and contextual constraints. It shows ~37% cooling savings and a rapid payback; ER enhances heating, WS provides moderate cooling, and WWR has minimal impact.
3. COM and NNV exhibit comparatively favorable economic performance under the assumed cost and discount-rate conditions, particularly when evaluated relative to other passive measures. Given the fixed assumptions regarding electricity prices and discount rates, the reported payback periods should be interpreted as comparative indicators rather than precise long-term economic predictions.
4. COM and NNV perform strongly under the selected weighting assumptions, offering favorable trade-offs between energy performance and cost-effectiveness for cooling-oriented retrofit objectives. WS and WWR exhibit higher sensitivity to changes in weighting assumptions. Because optimization relies on a predefined weighting scheme, the resulting rankings should be interpreted as indicative rather than universally optimal and may vary under alternative stakeholder priorities.
5. Effective retrofits require balancing cooling and heating objectives; prioritizing NNV as the foundation and selectively integrating complementary strategies optimizes year-round energy performance under representative future climate conditions.

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Abbreviations

The following abbreviations are used in this manuscript:

PDS	Passive Design Strategies
ER	Envelope Retrofitting
WS	Window Shading
WWR	Window-to-Wall Ratio
COM	Combination of Passive Strategies
RCP	Representative Concentration Pathway
GHG	Greenhouse Gas
IEA	International Energy Agency
LCC/LCCA	Life-Cycle Cost (Analysis)
TMY	Typical Meteorological Year
EPS	Expanded Polystyrene
HVAC	Heating, Ventilation, and Air Conditioning
EPW	EnergyPlus Weather file format
DBJ/GB	Chinese national or provincial standards for building design and green building assessment

Appendix A

Table A1. Typical envelope for Housing in the Xi'an Region.

Structure	Material	Thickness (mm)	Thermal Conductivity λ (W/m·K)	Layer R (m^2·K/W)
Exterior Wall	Rammed Earth Brick	0.37	1.16	0.319
	White Lime Mortar	0.01	0.93	0.011
Internal Wall	Rammed Earth Brick	0.24	1.16	0.207
	White Lime Mortar	0.015	0.431	0.046
Ground Floor	Rammed Earth Floor	0.4	1.16	0.345
	Cement Mortar	0.01	0.431	0.023
Roof	Rubble Concrete	0.4	1.16	0.345
	Cement Mortar	0.01	0.431	0.023
	Felt	0.004	0.6	0.007
Window	Standard Glass	0.006	1.046	0.006
Door	Solid Wood	0.04	0.343	0.117

Table A2. Material Parameters of the Enclosure Structure for Self-construction Housing in Baolong, Xi'an, China; data source: [52,53].

Structure	Material	Thickness (mm)	Thermal Conductivity λ (W/m·K)	Layer R (m^2·K/W)
Exterior Wall	Cement Mortar	10	0.431	0.0232
	EPS Insulation	30	0.035	0.8571
	Hollow Brick	370	0.335	1.1045
	Cement Mortar	10	0.431	0.0232
Internal Wall	Cement Mortar	10	0.431	0.0232
	Hollow Brick	240	0.335	0.7164
	Cement Mortar	10	0.431	0.0232
Ground Floor	Soil	1500	0.837	1.792
	Concrete	100	0.753	0.133
	Wood	25	0.209	0.119
Roof	Ceramic Tile	20	0.828	0.0242
	Timber Beam	50	0.15	0.3333
	Asphalt Felt	5	0.6	0.0083
	Rubble Concrete	200	1.05	0.1905
	Cement Mortar	10	0.431	0.0232
Window	Ordinary Glass	6	1.046	0.0057

	Air Layer	30	0.025	1.2
	Ordinary Glass	6	1.046	0.0057
Door	Solid Wood	0.04	0.343	0.117

Table A3. Economic break-even point between Basic Case and passive design strategies.

Passive Design Strategy/System	Material Cost (CNY/m²)	Labor Cost (CNY/m²)	Machinery Use Cost (CNY/m²)	Basic Construction Cost (CNY/m²)	Passive Technology Cost (CNY/m²)
ER	230	50	175	455	682.5
WWR	200	80	60	340	391
NNV	180	90	70	340	391
WS	50	20	30	100	115
COM	660	240	335	1235	1579.5
Cooling System Air Conditions (AC)	—	6	—	270	180
Heating System	—	1	—	130	90
Ventilation System Air Conditions/Fans	—	0.5	—	30	20
Insulation Material Recycling	—	70	80	100	200
Removal of Sunshade Components	—	150	50	150	1188
Demolition Cost	—	180	250	550	700
Other Costs	—	133	127	266	333

Note: Please note that cells marked with "—" indicate that the cost category is not applicable for the strategy or system and is treated as zero in the LCCA. The costs of the passive design strategies used in this study were obtained through market inquiries conducted in 2025, reflecting the additional expenses associated with implementing the respective energy-saving measures.

References

1. Bazazzadeh, H.; Pilechiha, P.; Nadolny, A.; Mahdavinejad, M.; Hashemi Safaei, S.S. The Impact Assessment of Climate Change on Building Energy Consumption in Poland. *Energies* **2021**, *14*, 4084.
2. The 26th COP26 Reached a "Compromise" Agreement at the Last Minute. The UN Secretary-General Called It an "Important Step, but Work Still Needs to Be Done". UN News. Available online: https://news.un.org/zh/story/2021/11/1094442 (accessed on 13 August 2023).
3. Brambilla, A.; Salvalai, G.; Imperadori, M.; Sesana, M.M. Nearly Zero Energy Building Renovation: From Energy Efficiency to Environmental Efficiency, a Pilot Case Study. *Energy Build.* **2018**, *166*, 271–283. https://doi.org/10.1016/j.enbuild.2018.02.002.
4. Bazazzadeh, H.; Nadolny, A.; Hashemi Safaei, S.S. Climate Change and Building Energy Consumption: A Review of the Impact of Weather Parameters Influenced by Climate Change on Household Heating and Cooling Demands of Buildings. *Eur. J. Sustain. Dev.* **2025**, *10*, 1–12. https://doi.org/10.14207/ejsd.2021.v10n2p1.
5. Luo, W.; Kramer, R.; de Kort, Y.; van Marken Lichtenbelt, W. Effectiveness of Personal Comfort Systems on Whole-Body Thermal Comfort—A Systematic Review on Which Body Segments to Target. *Energy Build.* **2022**, *256*, 111766. https://doi.org/10.1016/j.enbuild.2021.111766.
6. Salata, F.; Falasca, S.; Ciancio, V.; Curci, G.; de Wilde, P. Climate-Change Related Evolution of Future Building Cooling Energy Demand in a Mediterranean Country. *Energy Build.* **2023**, *290*, 113112. https://doi.org/10.1016/j.enbuild.2023.113112.
7. Yu, F.-W.; Ho, W.-T.; Wong, C.-F.J. Impact of Extreme Climates on Sustainable Cooling: A Case Study of a Subtropical Office Building. *Urban Clim.* **2025**, *63*, 102583. https://doi.org/10.1016/j.uclim.2025.102583.
8. Falchetta, G.; Cian, E.D.; Pavanello, F.; Wing, I.S. Inequalities in Global Residential Cooling Energy Use to 2050. *Nat. Commun.* **2024**, *15*, 7874. https://doi.org/10.1038/s41467-024-52028-8.
9. Wang, C.; Shao, Y.; Zhao, B.; Chen, Y.; Yu, J.; Guo, H. Study on the Influence of the Application of Phase Change Material on Residential Energy Consumption in Cold Regions of China. *Energies* **2024**, *17*, 1527.
10. Santamouris, M. Recent Progress on Urban Overheating and Heat Island Research. Integrated Assessment of the Energy, Environmental, Vulnerability and Health Impact. Synergies with the Global Climate Change. *Energy Build.* **2020**, *207*, 109482. https://doi.org/10.1016/j.enbuild.2019.109482.

11. Rabani, M.; Sønderland, S.; Rabani, M. Exploring Hybrid Ventilation in Cold Climates: Energy Efficiency, Thermal Comfort, and Future Climate Adaptation in a nZEB Case Study in Norway. *Front. Built Environ.* **2025**, *11*, 1606399. https://doi.org/10.3389/fbuil.2025.1606399.
12. Kajjoba, D.; Wesonga, R.; Lwanyaga, J.D.; Kasedde, H.; Olupot, P.W.; Kirabira, J.B. Assessment of Thermal Comfort and Its Potential for Energy Efficiency in Low-Income Tropical Buildings: A Review. *Sustain. Energy Res.* **2025**, *12*, 25. https://doi.org/10.1186/s40807-025-00169-9.
13. The Future of Cooling in China—Analysis—IEA. Available online: https://www.iea.org/reports/the-future-of-cooling-in-china (accessed on 24 August 2025).
14. UNFCCC. Fourth National Communication of the People's Republic of China under the United Nations Framework Convention on Climate Change. 2021. Available online: https://unfccc.int/sites/default/files/resource/China_NC4_English.pdf (accessed on 24 August 2025).
15. Bo, R.; Shao, Y.; Xu, Y.; Yu, Y.; Guo, H.; Chang, W.-S. Research on the Relationship between Thermal Insulation Thickness and Summer Overheating Risk: A Case Study in Severe Cold and Cold Regions of China. *Buildings* **2022**, *12*, 1032. https://doi.org/10.3390/buildings12071032.
16. Lin, Y.; Huang, T.; Yang, W.; Hu, X.; Li, C. A Review on the Impact of Outdoor Environment on Indoor Thermal Environment. *Buildings* **2023**, *13*, 2600. https://doi.org/10.3390/buildings13102600.
17. Heat and Health. Available online: https://www.who.int/news-room/fact-sheets/detail/climate-change-heat-and-health (accessed on 24 August 2025).
18. Building Energy Research Centre, Tsinghua University. Decarbonizing Rural Buildings and Rural Energy System: China Building Energy and Emission Yearbook. 2024. Available online: https://www.researchgate.net/publication/394731421_Decarbonizing_Rural_Buildings_and_Rural_Energy_System_China_Building_Energy_and_Emission_Yearbook_2024 (accessed on 24 August 2025).
19. Ni, S.; Zhu, N.; Hou, Y.; Zhang, Z. Research on Indoor Thermal Comfort and Energy Consumption of Zero Energy Wooden Structure Buildings in Severe Cold Zone. *J. Build. Eng.* **2023**, *67*, 105965. https://doi.org/10.1016/j.jobe.2023.105965.
20. Chen, C.; Wei, Y. Optimizing Energy Efficiency and Indoor Thermal Comfort in Rural Self-Built Housing: A Comparative Study of GA and EA Algorithms. *Case Stud. Therm. Eng.* **2025**, *73*, 106705. https://doi.org/10.1016/j.csite.2025.106705.
21. Rui, J.; Zhang, H.; Shi, C.; Pan, D.; Chen, Y.; Du, C. Survey on the Indoor Thermal Environment and Passive Design of Rural Residential Houses in the HSCW Zone of China. *Sustainability* **2019**, *11*, 6471. https://doi.org/10.3390/su11226471.
22. Yin, X.; Yu, J.; Dong, Q.; Jia, Y.; Sun, C. Energy Sustainability of Rural Residential Buildings with Bio-Based Building Fabric in Northeast China. *Energies* **2020**, *13*, 5806. https://doi.org/10.3390/en13215806.
23. Li, Y.; Zhou, T.; Wang, Z.; Li, W.; Zhou, L.; Cao, Y.; Shen, Q. Environment Improvement and Energy Saving in Chinese Rural Housing Based on the Field Study of Thermal Adaptability. *Energy Sustain. Dev.* **2022**, *71*, 315–329. https://doi.org/10.1016/j.esd.2022.10.006.
24. Zhang, A.; Li, B.; Wang, C. A Field Investigation on Summer Thermal Comfort of Occupants of Rural Houses in the North Area of Hot Summer and Warm Winter Zone, China. *Buildings* **2025**, *15*, 715.
25. Shao, T.; Zheng, W.; Jin, H. Analysis of the Indoor Thermal Environment and Passive Energy-Saving Optimization Design of Rural Dwellings in Zhalantun, Inner Mongolia, China. *Sustainability* **2020**, *12*, 1103.
26. Egerlid, H.; Wang, X.; Thuvander, L.; Maiullari, D. Carbon Efficiency of Passive Cooling Measures in Future Climate Scenarios: Renovating Multi-Family Residential Buildings in a Swedish Context. *Energy Build.* **2025**, *334*, 115502. https://doi.org/10.1016/j.enbuild.2025.115502.
27. Taleb, H.M. Using Passive Cooling Strategies to Improve Thermal Performance and Reduce Energy Consumption of Residential Buildings in U.A.E. Buildings. *Front. Archit. Res.* **2014**, *3*, 154–165. https://doi.org/10.1016/j.foar.2014.01.002.
28. Andrić, I.; Koc, M.; Al-Ghamdi, S.G. A Review of Climate Change Implications for Built Environment: Impacts, Mitigation Measures and Associated Challenges in Developed and Developing Countries. *J. Clean. Prod.* **2019**, *211*, 83–102. https://doi.org/10.1016/j.jclepro.2018.11.128.
29. Al Tamimi, N. Passive Design Strategies for Energy Efficient Buildings in the Arabian Desert. *Front. Built Environ.* **2025**, *7*, 805603. https://doi.org/10.3389/fbuil.2021.805603.
30. Culture, P. China Civil Affairs Statistical Yearbook. 2011. Available online: https://www.purpleculture.net/china-civil-affairs-statistical-yearbook-2011-p-11795/ (accessed on 4 November 2023).
31. Chang, H.; Hou, Y.; Lee, I.; Liu, T.; Acharya, T.D. Feasibility Study and Passive Design of Nearly Zero Energy Building on Rural Houses in Xi'an, China. *Buildings* **2022**, *12*, 341.

32. Banihashemi, F.; Maderspacher, J.; Brasche, J.; Lang, W. Effectiveness of Passive Climate Adaptation Measures in Residential Buildings in Germany. In Proceedings of the 33rd PLEA International Conference: Design to Thrive, Edinburgh, UK, 2–5 July 2017.
33. Shaanxi Statistical Yearbook. 2020. Available online: https://data.stats.gov.cn/english/ (accessed on 6 January 2026).
34. Main Statistical Bulletin of the Third National Agricultural Census of Shaanxi Province, People's Government of Shaanxi Province. Available online: https://www.shaanxi.gov.cn/zfxxgk/fdzdgknr/tjxx/tjgb_240/stjgb/202203/t20220301_2212371_wap.html (accessed on 1 September 2025).
35. Koppen Climate Classification|Definition, System, & Map|Britannica. Available online: https://www.britannica.com/science/Koppen-climate-classification (accessed on 25 August 2025).
36. Cao, P.; Wang, J.; Huang, D.; Cao, Z.; Li, D. Evaluation and Analysis of Passive Energy Saving Renovation Measures for Rural Residential Buildings in Cold Regions: A Case Study in Tongchuan, China. *Sustainability* **2025**, *17*, 540. https://doi.org/10.3390/su17020540.
37. Schiano-Phan, R. The Development of Passive Downdraught Evaporative Cooling Systems Using Porous Ceramic Evaporators and Their Application in Residential Buildings. Available online: https://www.researchgate.net/publication/267817111_The_Development_of_Passive_Downdraught_Evaporative_Cooling_Systems_Using_Porous_Ceramic_Evaporators_and_their_application_in_residential_buildings (accessed on 24 August 2025).
38. Garde, F.; Boyer, H.; Gatina, J.C. Elaboration of Global Quality Standards for Natural and Low Energy Cooling in French Tropical Island Buildings. *Build. Environ.* **1998**, *34*, 71–83.
39. Natural Ventilation|WBDG—Whole Building Design Guide. Available online: https://www.wbdg.org/resources/natural-ventilation (accessed on 25 August 2025).
40. Ali, R.A.; Megahed, N.A.; Shahda, M.M.; Hassan, A.M. Natural Ventilation as a Passive Cooling Strategy for Multi-Story Buildings: Analytic Vertical Skycourt Formations. *City Territ. Archit.* **2023**, *10*, 28. https://doi.org/10.1186/s40410-023-00212-6.
41. Yu, L.; Han, X.; Ju, S.; Tao, Y.; Xu, X. Optimization Design of Indoor Thermal Environment and Air Quality in Rural Residential Buildings in Northern China. *Buildings* **2025**, *15*, 2050. https://doi.org/10.3390/buildings15122050.
42. *ASHRAE 55-2020*; Thermal Environmental Conditions for Human Occupancy. ASHRAE: Peachtree Corners, GA, USA, 2020. Available online: https://www.scribd.com/document/695087734/ASHRAE-55-2020 (accessed on 1 September 2025).
43. Fong, M.-L.A.; Chan, W.-K. Natural Ventilation Technique of uNVeF in Urban Residential Unit Through a Case Study. *Urban Sci.* **2025**, *9*, 291. https://doi.org/10.3390/urbansci9080291.
44. Drury, P.; Watson, S.; Lomas, K.J. Summertime Overheating in UK Homes: Is There a Safe Haven? *Build. Cities* **2021**, *2*, 970–990. https://doi.org/10.5334/bc.152.
45. Xiang, H.; Li, J. Impact of Night Ventilation on Indoor Thermal Environment of Residential Buildings under the Dual Carbon Target: A Case Study of Xi'an. *Buildings* **2024**, *14*, 2459. https://doi.org/10.3390/buildings14082459.
46. Sarna, I.; Ferdyn-Grygierek, J. Natural Ventilation for Thermal Comfort: A Simulation-Based Comparison of Manual and Automated Window Control Strategies in Temperate Climate Housing. *Build. Environ.* **2025**, *285*, 113551. https://doi.org/10.1016/j.buildenv.2025.113551.
47. Solgi, E.; Hamedani, Z.; Fernando, R.; Skates, H.; Orji, N.E. A Literature Review of Night Ventilation Strategies in Buildings. *Energy Build.* **2018**, *173*, 337–352. https://doi.org/10.1016/j.enbuild.2018.05.052.
48. Wu, Z.; Zhang, Y.; Mai, J.; Wang, F.; Zhai, Y.; Zhang, Z. Adaptation-Based Indoor Environment Control with Night Natural Ventilation in Autumn in an Office Building in a Hot-Humid Area. *Build. Environ.* **2023**, *243*, 110702. https://doi.org/10.1016/j.buildenv.2023.110702.
49. Rudolphi, A. The Importance of Building Envelope: Understanding Its Role in Building Performance. Available online: https://perfval.com/importance-of-building-envelope/ (accessed on 25 April 2025).
50. Yuan, J. Impact of Insulation Type and Thickness on the Dynamic Thermal Characteristics of an External Wall Structure. *Sustainability* **2018**, *10*, 2835. https://doi.org/10.3390/su10082835.
51. *DBJ 51/T 221-2016*; Design Standard for Energy Efficiency of Civil Buildings. Shaanxi Provincial Department of Housing and Urban-Rural Development: Xi'an, China, 2016.
52. Design Standard for Energy Efficiency of Residential Buildings in Severe Cold and Cold Zones. Global Buildings Performance Network. Available online: https://library.gbpn.org/library/bc-detail-pages/china-severe-cold (accessed on 1 September 2025).
53. *GB/T 50378-2019*; Assessment Standard for Green Building (English Version). Code of China: Beijing, China, 2019. Available online: https://www.codeofchina.com/standard/GBT50378-2019.html (accessed on 1 September 2025).

54. Heisler, G.M. Trees Modify Metropolitan Climate and Noise. *Arboric. Urban For. AUF* **1977**, *3*, 201–207. https://doi.org/10.48044/jauf.1977.054.
55. Heidari, A.; Taghipour, M.; Yarmahmoodi, Z. The Effect of Fixed External Shading Devices on Daylighting and Thermal Comfort in Residential Building. *J. Daylighting* **2021**, *8*, 165–180. https://doi.org/10.15627/jd.2021.15.
56. Magri Elouadjeri, S.; Boussoualim, A.; Ait Haddou, H. Evaluating the Effect of External Horizontal Fixed Shading Devices' Geometry on Internal Air Temperature, Daylighting and Energy Demand in Hot Dry Climate. Case Study of Ghardaïa, Algeria. *Buildings* **2021**, *11*, 348. https://doi.org/10.3390/buildings11080348.
57. Sayadi, S.; Hayati, A.; Salmanzadeh, M. Optimization of Window-to-Wall Ratio for Buildings Located in Different Climates: An IDA-Indoor Climate and Energy Simulation Study. *Energies* **2025**, *14*, 1974. https://doi.org/10.3390/en14071974.
58. Lu, S.; Yang, D.; Huang, X.; Chen, T.; Wang, Z. Amended Calculation of Solar Heat Gain Coefficient Based on the Escape of Incident Solar Radiation. *Energies* **2024**, *17*, 5779. https://doi.org/10.3390/en17225779.
59. *DB61/T 5033-2022*; Design Standard for Energy Saving of Residential Buildings. Shaanxi Provincial Department of Housing and Urban-Rural Development. Xi'an, China, 2022.
60. *DB11/891-2020*; Energy Efficiency Design Standard for Residential Buildings. Beijing Municipal Commission of Planning and Natural Resources: Beijing, China, 2020. Available online: https://ghzrzyw.beijing.gov.cn/biaozhunguanli/bz/jzsj/202101/t20210106_2200771.html (accessed on 25 April 2025).
61. Crawley, D.B.; Lawrie, L.K.; Winkelmann, F.C.; Buhl, W.F.; Huang, Y.J.; Pedersen, C.O.; Strand, R.K.; Liesen, R.J.; Fisher, D.E.; Witte, M.J.; et al. EnergyPlus: Creating a New-Generation Building Energy Simulation Program. *Energy Build.* **2001**, *33*, 319–331. https://doi.org/10.1016/S0378-7788(00)00114-6.
62. Shaviv, E.; Yezioro, A.; Capeluto, I.G. Thermal Mass and Night Ventilation as Passive Cooling Design Strategy. *Renew. Energy* **2001**, *24*, 445–452. https://doi.org/10.1016/S0960-1481(01)00027-1.
63. Hou, J.; Zhang, T.; Liu, Z.; Zhang, L.; Fukuda, H. Application Evaluation of Passive Energy-Saving Strategies in Exterior Envelopes for Rural Traditional Dwellings in Northeast of Sichuan Hills, China. *Int. J. Low-Carbon Technol.* **2022**, *17*, 342–355. https://doi.org/10.1093/ijlct/ctac007.
64. Tian, C.; Ahmad, N.A.; Abd Rased, A.N.N.W.; Wang, S.; Tian, H. Establishing Energy-Efficient Retrofitting Strategies in Rural Housing in China: A Systematic Review. *Results Eng.* **2024**, *24*, 103653. https://doi.org/10.1016/j.rineng.2024.103653.
65. Greenhouse Gases' Effect on Climate—U.S. Energy Information Administration (EIA). Available online: https://www.eia.gov/energyexplained/energy-and-the-environment/greenhouse-gases-and-the-climate.php (accessed on 25 August 2025).
66. AR5 Synthesis Report: Climate Change 2014—IPCC. Available online: https://www.ipcc.ch/report/ar5/syr/ (accessed on 26 August 2025).
67. Van Vuuren, D.P.; Edmonds, J.; Kainuma, M.; Riahi, K.; Thomson, A.; Hibbard, K.; Hurtt, G.C.; Kram, T.; Krey, V.; Lamarque, J.-F.; et al. The Representative Concentration Pathways: An Overview. *Clim. Change* **2011**, *109*, 5. https://doi.org/10.1007/s10584-011-0148-z.
68. Understanding Shared Socio-Economic Pathways (SSPs)—ClimateData.Ca. Available online: https://climatedata.ca/resource/understanding-shared-socio-economic-pathways-ssps/ (accessed on 26 August 2025).
69. Meteonorm|Climate. Available online: https://meteonorm.com/climate/ (accessed on 1 September 2025).
70. La Fleur, L.; Moshfegh, B.; Rohdin, P. Measured and Predicted Energy Use and Indoor Climate before and after a Major Renovation of an Apartment Building in Sweden. *Energy Build.* **2017**, *146*, 98–110. https://doi.org/10.1016/j.enbuild.2017.04.042.
71. Malcheva, K.; Neykov, N.; Bocheva, L.; Stoycheva, A.; Neykova, N. Evaluation of the Spatio-Temporal Variation of Extreme Cold Events in Southeastern Europe Using an Intensity–Duration Model and Excess Cold Factor Severity Index. *Atmosphere* **2025**, *16*, 313. https://doi.org/10.3390/atmos16030313.
72. Schakib-Ekbatan, K.; Çakıcı, F.Z.; Schweiker, M.; Wagner, A. Does the Occupant Behavior Match the Energy Concept of the Building?—Analysis of a German Naturally Ventilated Office Building. *Build. Environ.* **2015**, *84*, 142–150. https://doi.org/10.1016/j.buildenv.2014.10.018.
73. The Seventh National Population Census of China. 2020. Available online: https://www.stats.gov.cn/zt_18555/zdtjgz/zgrkpc/dqcrkpc/ggl/202302/t20230215_1903998.html (accessed on 5 January 2026).
74. Ahmed, K.; Akhondzada, A.; Kurnitski, J.; Olesen, B. Occupancy Schedules for Energy Simulation in New prEN16798-1 and ISO/FDIS 17772-1 Standards. *Sustain. Cities Soc.* **2017**, *35*, 134–144. https://doi.org/10.1016/j.scs.2017.07.010.
75. Energy-models.com INTERNAL HEAT GAINS (IHG)|Energy-Models.Com. Available online: https://energy-models.com/internal-heat-gains-ihg (accessed on 5 January 2026).

76. Table 10 Sensible and Latent Gains from People. Available online: https://help.iesve.com/ve2021/table_10_sensible_and_latent_gains_from_people.htm (accessed on 5 January 2026).
77. Fu, X.; Qian, X.; Wang, L. Energy Efficiency for Airtightness and Exterior Wall Insulation of Passive Houses in Hot Summer and Cold Winter Zone of China. *Sustainability* **2017**, *9*, 1097. https://doi.org/10.3390/su9071097.
78. Geng, Y.; Dong, H.; Xue, B.; Fu, J. An Overview of Chinese Green Building Standards. *Sustain. Dev.* **2012**, *20*, 211–221. https://doi.org/10.1002/sd.1537.
79. Shan, M.; Wang, P.; Li, J.; Yue, G.; Yang, X. Energy and Environment in Chinese Rural Buildings: Situations, Challenges, and Intervention Strategies. *Build. Environ.* **2015**, *91*, 271–282. https://doi.org/10.1016/j.buildenv.2015.03.016.
80. Partner Country Series—Energy Use in the Chinese Building Sector—Analysis. Available online: https://www.iea.org/reports/partner-country-series-energy-use-in-the-chinese-building-sector (accessed on 5 January 2026).
81. Yue, W.; Pengjun, Z. Survey Research on Residential Building Energy Consumption in Urban and Rural Area of China. *Acta Sci. Nat. Univ. Pekin.* **2018**, *54*, 162. https://doi.org/10.13209/j.0479-8023.2017.159.
82. *GB/T 50824-2013*; Design Standard for Energy Efficiency of Rural Residential Building (English Version). Code of China: Beijing, China, 2013. Available online: https://www.codeofchina.com/standard/GBT50824-2013.html (accessed on 5 January 2026).
83. *ASTM E917-17e1*; Standard Practice for Measuring Life-Cycle Costs of Buildings and Building Systems. ASTM International: West Conshohocken, PA, USA, 2023. Available online: https://store.astm.org/e0917-17e01.html (accessed on 10 October 2025).
84. Uvarova, S.S.; Belyaeva, S.V.; Orlov, A.K.; Kankhva, V.S. Cost Forecasting for Building Materials under Conditions of Uncertainty: Methodology and Practice. *Buildings* **2023**, *13*, 2371. https://doi.org/10.3390/buildings13092371.
85. Nie, Y.; Zhang, G.; Zhong, L.; Su, B.; Xi, X. Urban–rural Disparities in Household Energy and Electricity Consumption under the Influence of Electricity Price Reform Policies. *Energy Policy* **2024**, *184*, 113868. https://doi.org/10.1016/j.enpol.2023.113868.
86. Biolek, V.; Hanák, T. LCC Estimation Model: A Construction Material Perspective. *Buildings* **2019**, *9*, 182. https://doi.org/10.3390/buildings9080182.
87. Petrović, B.; Zhang, X.; Eriksson, O.; Wallhagen, M. Life Cycle Cost Analysis of a Single-Family House in Sweden. *Buildings* **2021**, *11*, 215. https://doi.org/10.3390/buildings11050215.
88. Asadi, E.; da Silva, M.G.; Antunes, C.H.; Dias, L. A Multi-Objective Optimization Model for Building Retrofit Strategies Using TRNSYS Simulations, GenOpt and MATLAB. *Build. Environ.* **2012**, *56*, 370–378. https://doi.org/10.1016/j.buildenv.2012.04.005.
89. Pinzon Amorocho, J.A.; Hartmann, T. A Multi-Criteria Decision-Making Framework for Residential Building Renovation Using Pairwise Comparison and TOPSIS Methods. *J. Build. Eng.* **2022**, *53*, 104596. https://doi.org/10.1016/j.jobe.2022.104596.
90. Daniel, S.; Ghiaus, C. Multi-Criteria Decision Analysis for Energy Retrofit of Residential Buildings: Methodology and Feedback from Real Application. *Energies* **2023**, *16*, 902. https://doi.org/10.3390/en16020902.
91. Yu, S.; Eom, J.; Zhou, Y.; Evans, M.; Clarke, L. Scenarios of Building Energy Demand for China with a Detailed Regional Representation. *Energy* **2014**, *67*, 284–297. https://doi.org/10.1016/j.energy.2013.12.072.
92. Zhao, N.; Zhang, J.; Dong, Y.; Ding, C. Multi-Objective Optimization and Sensitivity Analysis of Building Envelopes and Solar Panels Using Intelligent Algorithms. *Buildings* **2024**, *14*, 3134. https://doi.org/10.3390/buildings14103134.
93. Ebrahimi-Moghadam, A.; Ildarabadi, P.; Aliakbari, K.; Fadaee, F. Sensitivity Analysis and Multi-Objective Optimization of Energy Consumption and Thermal Comfort by Using Interior Light Shelves in Residential Buildings. *Renew. Energy* **2020**, *159*, 736–755. https://doi.org/10.1016/j.renene.2020.05.127.
94. Kakati, D.; Biswas, S.; Banerjee, R. Parametric Sensitivity Analysis of Split Injection Coupled Varying Methanol Induced Reactivity Strategies on the Exergy Efficiency Enhancement and Emission Reductions Objectives in a Biodiesel Fuelled CI Engine. *Energy* **2021**, *225*, 120204. https://doi.org/10.1016/j.energy.2021.120204.
95. Albatayneh, A. Sensitivity Analysis Optimisation of Building Envelope Parameters in a Sub-Humid Mediterranean Climate Zone. *Energy Explor. Exploit.* **2021**, *39*, 2080–2102. https://doi.org/10.1177/01445987211020432.
96. Hong, T.; Chou, S.K.; Bong, T.Y. A Design Day for Building Load and Energy Estimation. *Build. Environ.* **1999**, *34*, 469–477. https://doi.org/10.1016/S0360-1323(98)00035-3.
97. Hou, X.; Tian, Z.; Niu, J.; Wu, X.; Lu, Y. Research on Design Day Generation Method for Air-Conditioning System Design Considering the Coincidence of Hourly Variation Coefficient. *Energy Build.* **2022**, *270*, 112300. https://doi.org/10.1016/j.enbuild.2022.112300.