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Defining weather scenarios for simulation-based assessment of thermal resilience of buildings under current and future climates: A case study in Brazil

Amanda F. Krelling[1 2], Roberto Lamberts[1], Jeetika Malik[2], Wanni Zhang[2], Kaiyu Sun[2], Tianzhen Hong[2]

[1]Laboratory for Energy Efficiency in Buildings, Federal University of Santa Catarina, Florianopolis, SC, Brazil, [2]Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, Berkeley, CA, USA

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Amanda F. Krelling [a,b,*], Roberto Lamberts [a], Jeetika Malik [b], Wanni Zhang [b], Kaiyu Sun [b], Tianzhen Hong [b]

[a] *Laboratory for Energy Efficiency in Buildings, Federal University of Santa Catarina, Florianópolis, SC, Brazil*
[b] *Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, Berkeley, CA, USA*

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ABSTRACT

In response to increasingly severe weather conditions, optimization of building performance and investment provides an opportunity to consider co-benefits of thermal resilience during energy efficiency retrofits. This work aims to assess thermal resilience of buildings using building performance simulation to evaluate the indoor overheating risk under nine weather scenarios, considering historical (2010s), mid-term future (2050s), and long-term future (2090s) typical meteorological years, and heat wave years. Such an analysis is based on resilience profiles that combine six integrated indicators. A case study with a district of 92 buildings in Brazil was conducted, and a combination of strategies to improve thermal resilience was identified. Results reflect the necessity of planning for resilience in the context of climate change. This is because strategies recommended under current conditions might not be ideal in the future. Therefore, an adaptable design should be prioritized. Cooling energy consumption could increase by 48 % by the 2050s, while excessive overheating issues could reach 37 % of the buildings. Simple passive strategies can significantly reduce the heat stress. A comprehensive thermal resilience analysis should ultimately be accompanied by a thorough reflection on the stakeholders' objectives, available resources, and planning horizon, as well as the risks assumed for not being resilient.

1. Introduction

Climate uncertainty has been pushing for a paradigm shift in how we approach building design. Hazards that are familiar in one place may, now or in the future, occur where they never did before (OECD, 2021). An example is the unprecedented heat that marked the summer in 2022 in Europe (Ballester et al., 2023; Serrano-Notivoli et al., 2023), followed by a similar pattern in July 2023 in North America, Europe, and China (Zachariah et al., 2023). In São Paulo, Brazil, outpatient care and hospitalizations from heat exposure more than doubled in the first seven months of 2023, compared to 2022 (Secretaria de Estado da Saúde de São Paulo, 2023). A trend toward overheating hazards seems nonetheless inexorable (Zhang et al., 2022), as air conditioning is already the fastest-growing use of energy in buildings (IEA, 2018), and extreme heat events are projected to occur more often and severely in the future (Wedler et al., 2023). The conventional design practice of optimizing performance and cost needs to be updated to include a resilient design that seeks to minimize risks and increase adaptability (Holzer et al., 2022).

Thermal resilience is *the ability of the built domain — and all its constituent socio-ecological and socio-technical networks across temporal and spatial scales — to maintain or rapidly return to desired indoor thermal conditions in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity* (adapted from Meerow et al. (2016)). Thermal resilience of buildings is mainly assessed through building performance simulation, which allows one not only to learn from past experiences but especially to explore and project different conditions looking into the future. In fact, the uncertain nature of overheating risks under climate change requires various evaluation scenarios to be considered to assess resilience (Kesik et al., 2022). In Flores-Larsen and Filippín (2021), the limited number of hot periods considered to analyze resilience was highlighted as a limitation of the study because they may not cover enough factors influencing the indoor thermal conditions. Having analyzed resilience under a historical

* Corresponding author at: Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, Berkeley, CA, USA.
E-mail address: akrelling@lbl.gov (A.F. Krelling).

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event when a hurricane caused an extreme heat disaster, (Sun et al., 2020) also included the consideration of different weather events as a recommendation for future work. The minimum set of weather and climate scenarios to comprehensively evaluate thermal resilience of buildings and occupants, however, remains a research gap (Hong et al., 2023).

In Brazil, several cities are expected to experience highly dangerous heat for most of the year in the 2050s (Kommenda et al., 2023). Such a projection is likely to compound the urban heat risk in Brazil, given the low level of air-conditioning system ownership to cope with extreme heat (Eletrobras, 2019), a significant prevalence of energy poverty (Bezerra et al., 2022), and informal settlement issues (Ren, 2018). Additionally, appropriate codes and standards are either missing or not sufficiently enforced, with minimal incorporation of resilience into local codes (GlobalABC, IEA, UNEP, 2020), while decarbonization plans primarily focus on deforestation and transportation issues (Instituto Talanoa, 2023). In this context, there is a strong need to quantitatively understand the indoor overheating risks and evaluate effective measures to improve the building stock for safeguarding occupant health and well-being. Understanding the impacts of different weather scenarios can provide valuable insights for building retrofits and inform policy-making and decision-making for governments and utilities seeking to improve climate resilience in Brazil's buildings sector.

1.1. Scope and contributions

There are a few dimensions to consider when defining scenarios to assess resiliency (Hong et al., 2023):

- Occupant characteristics (e.g., healthy adults, children, or elderly)
- Building operation constraints (e.g., electric power availability)
- Evaluation time frame (i.e., short [days or months] or long [an entire year])
- Weather data:
  a. Time scale of the weather data (i.e., historical or projected future)
  b. Type of weather file (e.g., typical meteorological year or hot year)

This article addresses the essential dimension of weather data for building thermal resilience modeling and evaluation. We use the term "weather scenarios" throughout to illustrate its definition, methodology, and applications in resilience modeling and analysis.

This study assessed thermal resilience of buildings in Brazil using building performance simulation to understand the indoor overheating risk, and evaluated technologies or design strategies to improve thermal safety for occupants. A set of weather scenarios was defined, considering current conditions and future climates. In this context, we aimed to shed light on best practices when designing buildings to be resilient to future climate and extreme weather events.

This study offers valuable insights in three key areas:

1. **Impact of weather scenarios on thermal resilience:** We explore how different weather scenarios influence multiple key performance indicators that reflect a building's thermal resilience.
2. **Definition of weather scenarios by use case and stakeholder:** We discuss the application of scenarios that consider various objectives simultaneously.
3. **Implications in a resilience-oriented design:** We provide a deeper understanding of the implications of designing buildings for thermal resilience under a changing climate.

Given the uncertainty of future climate conditions, establishing the impact of possible scenarios is crucial. Firstly, it helps us understand how buildings will fare under different conditions and allows us to proactively design and adapt to minimize risks and ensure occupant well-being. Additionally, it provides valuable insights for policymakers and decision-makers, enabling them to prioritize interventions and allocate resources effectively to improve climate resilience in Brazil's buildings sector. Ultimately, the expected impact is to enhance the adaptability and resilience of buildings to withstand future climate challenges and ensure the sustainability of the built environment.

1.2. Weather scenarios for resilience assessment

Historical weather data have largely been used for building performance simulation to assess the thermal performance and energy efficiency in buildings, especially in the form of typical meteorological years (TMY) —that is, considering median weather conditions (ISO, 2005). Other types of weather files, such as an eXtreme Meteorological Year (XMY) (Crawley & Lawrie, 2015; Crawley & Lawrie, 2019) and historical heat wave data (Sun et al., 2020) have been adopted to reflect extreme conditions. Sengupta et al. (2023) analyzed the impact of heat waves and system shocks on a nearly zero-energy educational building. They found that heat waves had 20 to 93 times more critical impact than the worst system failure (e.g., failure on mechanical ventilation systems), with future climate scenarios being the most extreme shock.

Climate projections based on the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2023) scenarios have been adopted in the assessment of buildings looking into the future (Rahif et al., 2022; Sengupta et al., 2023). Future weather data are generated by downscaling general circulation models through techniques such as morphing, interpolation, and dynamic downscaling (Belcher et al., 2005). The adoption of regional climate models (RCMs), obtained through dynamic downscaling, allows a better simulation of mesoscale weather processes and improved reliability. However, the generation of future weather files can be computer-intensive and requires expertise in the field, therefore it is not accessible to all stakeholders of thermal resilience. Additionally, the creation of weather scenarios may involve a large amount of measured weather data from the selected location across several years. Measured data are used not only for identifying typical meteorological years in the historical period, but also for bias-correction of future climate projections from RCMs.

Initiatives like that of the Weather Data Task Force of the International Energy Agency's (IEA) EBC Annex 80—Resilient Cooling of Buildings—can help to bridge this gap by providing future weather files for cities in major climate zones across the world. In Brazil, a similar initiative generated a dataset with future weather files for all 26 state capitals in the country and the Federal District (Bracht et al., 2023). This dataset includes weather files considering three global climate models (GCMs) as driving models and two nested RCMs for dynamic downscaling under representative concentration pathways (RCP) 8.5 and 2.6. Still, a user-friendly tool to curate these weather files is missing, often limiting its use within the scientific domain.

Alternatively, the morphing method (Belcher et al., 2005) is one of the most straightforward techniques for developing future weather files, with the CCWorldWeatherGen (Jentsch et al., 2013) being a useful tool that applies such a method. The open-source, cross-platform developed by Rodrigues et al. (2023) is another alternative to generate future weather files for building performance simulation. However, a number of limitations are associated with morphing, including neglecting the growing severity and frequency of extreme weather events, and not ensuring consistency among climate variables (Eames et al., 2012; Jentsch et al., 2013).

Weather data can be used not only to curate typical future years, but also to identify extreme weather events such as heat waves. Still, there's no standard definition of how to detect heat waves (Hong et al., 2023). Flores-Larsen et al. (2022) compared three existing popular detection methods and found Ouzeau's (Ouzeau et al., 2016) to be the most suitable for building applications. This method is further described in Section 2.2.2.

To analyze thermal resilience, it is also conceivable that synthetic extreme weather data could be generated, but there is not a universal recipe to curate these data since a building's vulnerabilities are dependent on design (Kesik et al., 2022). Thus, even though one can intuitively select extreme weather data to test resilience, specific impacts of different weather scenarios still need further study. Also, practitioners often do not want to focus on resilience to extreme events at the expense of other annual metrics such as energy and carbon emissions (Bucking et al., 2022), which requires a comprehensive evaluation through multiple weather scenarios and metrics.

1.3. Current state of building energy modeling for thermal resilience

Building energy modeling (BEM) is one of the most important tools to design, operate, and retrofit buildings aiming at energy efficiency and carbon emission reduction (Pan et al., 2023). Physics-based models can replicate a building thermal dynamic to investigate the effect of different events and disruptions to the indoor thermal environment, which is especially useful in a thermal resilience analysis. For instance, BEM has been used to assess buildings exposed to multiple events, especially heat (Borghero et al., 2023; Baniassadi et al., 2018) and cold (Homaei & Hamdy, 2021) waves and future climate scenarios (Rahif et al., 2022).

Scaling from individual buildings to communities has formed a prominent field of study that can feed many stakeholders, from design and operation to policy making, with quantitative insights about neighborhoods, districts, and cities (Hong et al., 2020; Reinhart & Davila, 2016). Urban Building Energy Models (UBEM) simulate the performance of a group of buildings exposed to the urban environment and its dynamics (Hong et al., 2020).

Bottom-up physics-based UBEM consider detailed end-use information from which building models are constructed and simulated according to thermodynamic principles (Li et al., 2017). This approach should be suitable to evaluate thermal resilience, already counting with consolidated and freely available tools. However, Ferrando et al. (2020) thoroughly reviewed bottom-up physics-based UBEM tools and, among the features described, one characteristic stands out: restricted opportunities to evaluate thermal performance apart from energy use. This may compromise an appropriate modeling and evaluation of communities where passive strategies are prioritized. For instance, natural ventilation is the preferred strategy to improve indoor air quality in Brazilian households (Ramos et al., 2020); only 17 % of households are equipped with an air conditioning system (Eletrobras, 2019). Thus, to appropriately represent such a context, a UBEM tool would need to consider the effect of multi-zone airflows, as well as incorporate inputs describing building operation concerning ventilative cooling or other passive strategies. Considering that many of these tools (e.g., urban modeling interface [UMI], CityBES, and URBANopt (El Kontar et al., 2020; Hong et al., 2016; Houssainy et al., 2020; Reinhart et al., 2013)) rely on EnergyPlus (which already offers this functionality) as the simulation engine, adaptations are theoretically possible. However, it is uncertain whether an adequate simulation of airflows would be obtained in overly simplified building zones (e.g., UMI's Shoeboxer (Dogan & Reinhart, 2017)). Moreover, there's a potential overestimation of benefits from natural ventilation since EnergyPlus, as well as other similar engines, simplifies the wind sheltering effect from surrounding objects (Costanzo et al., 2019).

To better evaluate the thermal resilience of buildings and groups of buildings, it would be necessary to:

- Allow modeling of diverse hazards and disruptions (e.g., power outages, heat waves, and the heat island effect).
- Allow modeling of multiple strategies to respond to hazards and disruptions, including passive strategies such as ventilative cooling.
- Provide suitable indicators to assess thermal resilience or provide the means for calculating these indicators; for example, by reporting (at least) hourly outputs regarding the indoor thermal environment and energy use.

The addition of all these features could overburden an already cost-intensive computer simulation (Chen et al., 2017; Huber & Nytsch-Geusen, 2011) and would require certain trade-offs (Ferrando et al., 2020). For instance, increased model details may require an expressive reduction in the sample size and/or long periods to run the simulation.

There is a growing interest in the resilience of buildings and communities; thus, it seems opportune to consider a resilience assessment as an additional challenge that can be covered by urban building energy modeling. Despite the challenges, with the prospects of rapid development of system resources, big data, and the Internet of Things it is expected that UBEM will be able to increasingly provide value to communities regarding energy efficiency, sustainability, and resilience (Hong et al., 2020). By scaling the resilience diagnosis from individual buildings to the urban level through UBEM, many other stakeholders, such as urban planners, insurance companies, and first responders can benefit in the future.

2. Method

We investigated the thermal resiliency of buildings through a case study composed of 92 real buildings located in Florianopolis, Brazil. In the context of this article, this group of buildings is addressed as a community.

The community was analyzed under two conditions: the baseline condition and the optimized retrofit condition. The latter was developed through the application of multiple design strategies to improve its thermal resiliency. Both community conditions were then evaluated under multiple weather scenarios. Fig. 1 summarizes the method, which is further described in Sections 2.1 through 2.4.

2.1. Building energy modeling workflow and thermal resilience assessment

A dataset was created containing information about each building—number of floors, building height, year of construction, and the building footprint polygon—and inputted into the web-based platform CityBES (Hong et al., 2016). CityBES was used to generate the first version of the building baseline models, which can be downloaded through the platform as an input data file (.idf) for EnergyPlus. Each building has its own input file where surfaces of buildings in the proximity are modeled as shading elements. A Python code was developed to further adjust the building models to better represent the characteristics of buildings in Brazil. These adjustments followed the workflow shown in Fig. 1(A).

Previously, we modeled this group of buildings using a different set of UBEM tools, UBEM.io and UMI, as part of our involvement in a workshop aimed at advancing carbon reduction technology pathways for buildings across multiple countries (Ang et al., 2022; Ang et al., 2023). However, our previous modeling attempts faced challenges to represent natural ventilation strategies due to the simplified zoning method and limitations to create building templates associated with these tools. Thus, buildings have been modeled as fully air-conditioned throughout the year, which does not properly represent how they are operated in Brazil. While this approach was deemed acceptable for evaluating compliance with decarbonization goals in the context of our previous study, it would not be suitable for assessing thermal resilience, as it fails to account for potential overheating issues. In this study, we have addressed these limitations by refining our modeling approach to better represent natural ventilation and by reducing zone simplification.

The thermal resilience assessment followed the framework described in Krelling et al. (2023), which proposes the creation of resilience profiles for buildings and communities composed of a set of comprehensive key performance indicators (KPIs). See the illustration in Fig. 1(B). These indicators were selected and tailored to describe the building performance in each of the three stages of resilience against overheating:

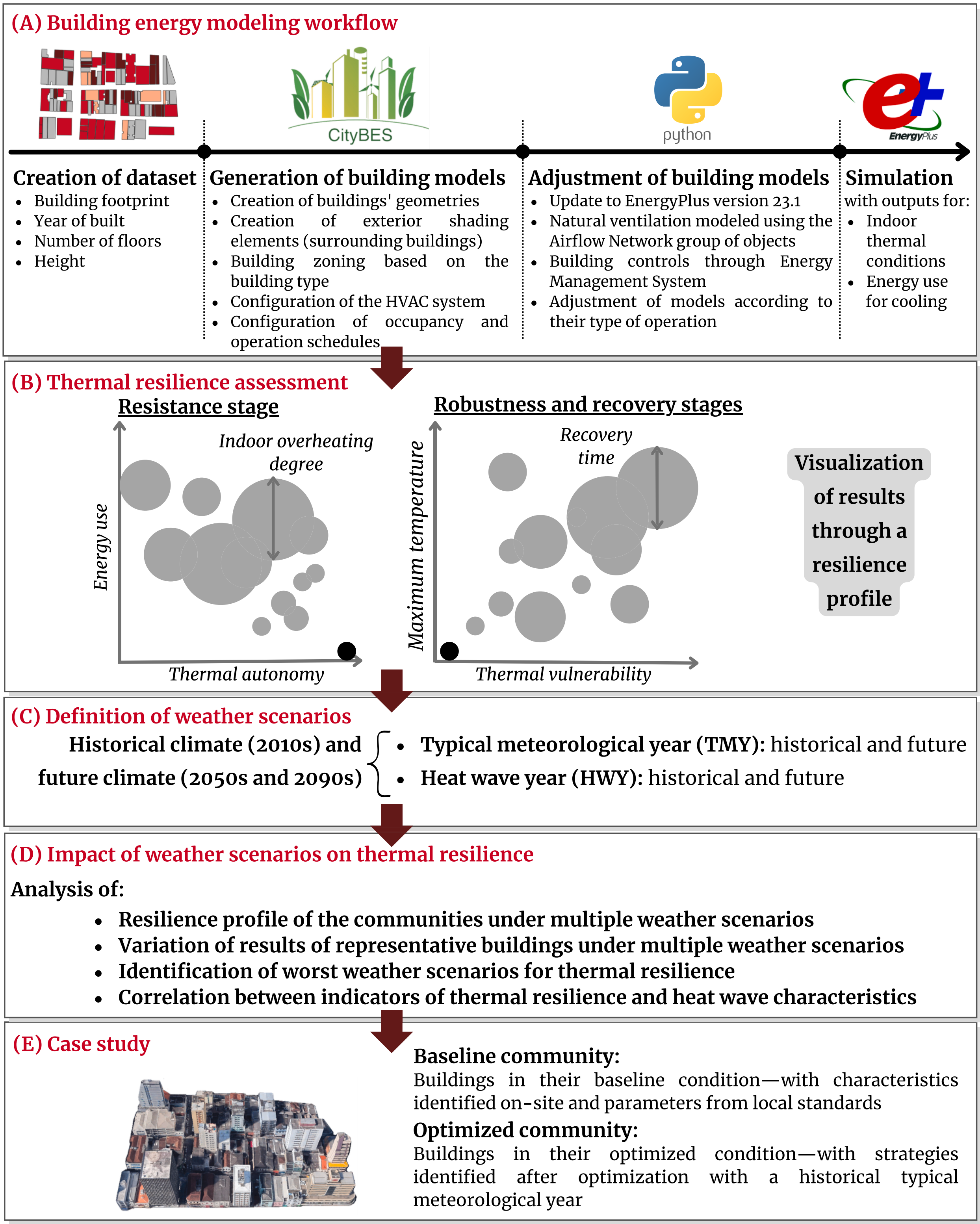

Fig. 1. Illustration of the methodology and workflow.

1. **Resistance stage:** the ability to maintain initial (minimum) conditions and prevent disturbances from translating into impact. Resistance is measured by thermal autonomy, energy consumption for cooling, and indoor overheating degree. These indicators provide three relevant information: (1.1) how frequently a building provides acceptable indoor thermal conditions passively (i.e., without the aid of mechanical cooling); (1.2) when not operated passively, what is the consequent energy burden; (1.3) and, when minimum thresholds are not ensured, what is the deviation from acceptable conditions.
2. **Robustness stage:** the ability to absorb shocks and the cumulative effects of slow-onset challenges in ways that avoid catastrophic failure if thresholds are exceeded. During the robustness stage, buildings experience the breakdown of their features and strategies. Despite this failure, a robust building can withstand critical

conditions and adapt its performance, transitioning into the recovery stage. The indicators considered are thermal vulnerability and annual maximum operative temperature, which communicate (2.1) the frequency with which a building provides extreme unsafe thermal conditions to its occupants and (2.2) the intensity of these extreme conditions.

3. **Recovery stage:** the ability to reorganize and to re-establish function and sense of order following a failure. In the recovery stage, buildings transition from critical conditions to restoring minimum thermal conditions. This is measured through the recovery time.

If one intends to assess resilience against overcooling instead, these KPIs could be adapted considering thresholds related to cold stress. For example, instead of analyzing the maximum temperature (Tmax), the minimum temperature (Tmin) would be used. KPIs and stages of resilience are described in Table 1 and Eq. (1). This equation was proposed in Hamdy et al. (2017).

$$\mathrm{IOD} \equiv \frac{\sum_{zn=1}^{Z}\sum_{i=1}^{N_{occ}(zn)}\left[\left(\mathrm{T}_{fr,i,zn}-\mathrm{TL}_{accept,i,zn}\right)^{+}\times \mathrm{t}_{i,zn}\right]}{\sum_{zn=1}^{Z}\sum_{i=1}^{N_{occ}(zn)}\mathrm{t}_{i,zn}} \tag{1}$$

Where: *zn* is building zone counter; *Z* is the total number of zones in a building; *i* is occupied hour counter; *t* is time step (1 hour); $N_{occ(z)}$ is total occupied hours in a given calculation period; T_{fr} is free-running indoor SET at the time step *i* in zone *zn; TL_{accept}* is the acceptable temperature limit at the time step *i* in zone *zn*. The IOD, as given by Eq. (1), indicates the average degree that the indoor thermal conditions would surpass acceptable thresholds if overheating were evenly distributed throughout all occupied hours in a zone or building.

Table 1
Key performance indicators for each stage of resilience.

Stage of Resilience	KPI	Calculation Procedure for Single Zones	Calculation Procedure for Multi Zones
Resistance Stage	Thermal autonomy (TA) [%]	Proportion of occupied hours with SET within acceptable thresholds (i.e., 12.2 °C and 30 °C)	Average value between all zones
	Indoor overheating degree (IOD) [°C] (Hamdy et al., 2017)	According to Eq. (1)	Same equation adopted for single zones—Eq. (1)
	Energy consumption for cooling [kWh/m^2]	Summation of the zone's annual HVAC electricity consumption	Summation of values of all zones divided by the conditioned floor area
Robustness Stage	Thermal vulnerability (TV) [%]	Proportion of occupied hours with SET above the acceptable upper threshold (i.e., 30 °C)	Highest value between all zones
	Maximum temperature (Tmax) [°C]	Maximum SET value registered in the evaluated period during occupied hours	Highest value between all zones
Recovery Stage	Recovery time (t_R) [h]	Amount of time between the moment of maximum annual temperature (Tmax) and the time when the space reaches an acceptable SET threshold (i.e., 30 °C)	Amount of time the zone with highest Tmax takes to recover

Notes: SET is Standard Effective Temperature in °C; kWh/m^2 is kilowatt-hours per square meter.

The Standard Effective Temperature (SET) (ASHRAE, 2020) was adopted as the parameter to describe the indoor thermal environment and used to calculate the KPIs. The SET requires six parameters for calculation, including indoor air velocity, humidity, occupant metabolic rate, and clothing insulation. It is an equivalent temperature that hypothesizes a standard environment combining multi-factor effects to reflect the physiological regulation mechanism of the human body and the heat exchange with the environment (Ji et al., 2022). Besides being a comprehensive parameter to describe the indoor environment, it is especially useful within this study for taking into account the cooling effect provided by elevated airspeed. The SET has long been included in ASHRAE 55 (Thermal Environmental Conditions for Human Occupancy) (ASHRAE, 2020) and is also considered in the Leadership in Energy and Environmental Design (LEED) v4.1 credit for "Passive Survivability and Backup Power During Disruptions," which defines livable conditions with a SET between 12.2 °C and 30 °C (USGBC, 2023). These thresholds were also adopted in this study.

2.2. Definition of weather scenarios

The evaluation of weather scenarios consists of simulating the baseline community and the optimized community under multiple weather conditions, encompassing typical historical and projected future climates, as well as historical and projected future heat waves.

2.2.1. Historical and future climates

Historical and future weather files, in .epw format, were developed based on a method structured by the Weather Data Task Group, which is part of the IEA EBC Annex 80—Resilient Cooling of Buildings (Machard et al., 2020). Three time frames were considered—historical (2001–2020), medium-term future (2041–2060), and long-term future (2081–2100); the latter two were projected considering the representative concentration pathway (RCP) 8.5 (highest baseline emissions scenario) (IPCC, 2013).

The approach consists of using regional climate models (RCMs), which are climate models obtained from global climate models (GCM) after a dynamic downscaling to improve spatial resolution (10 to 50 km) (Machard et al., 2020). RCMs were obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012) in the Coordinated Regional Downscaling Experiment (CORDEX) (Giorgi et al., 2022) database, where worldwide multiyear projections are available for RCP 4.5 and 8.5. Although CMIP6 GCM datasets are already available, CMIP5 remains the most detailed and widely used dataset for South American local scale impact studies (Teichmann et al., 2021).

A step-by-step procedure to create historical and future weather files is described in Machard et al. (2020), and can be summarized in four main steps: (1) collection of hourly historical data from a local weather station; (2) extraction and interpolation of CORDEX data; (3) bias-adjustment of CORDEX data using measured data; (4) creation of typical meteorological years following EN ISO 15927–4:2005 (ISO, 2005) or heat wave weather years (HWY) (see Section 2.2.2).

In our study, we implemented a bias-adjustment procedure—step (3)—to address expected disparities between observations and raw outputs from regional climate models. This involved utilizing historical hourly observations spanning from 1991 to 2021 to derive correction factors. These correction factors were then applied to both historical and future climate data, enabling adjustments to the distribution functions of climate variables, including both averages and extremes, to better align them with observed data. A key assumption underlying this procedure is the constancy of the correction factor across changing climates, although the possibility of variations in model bias in the future introduces an additional layer of uncertainty (Machard et al., 2020).

2.2.2. Heat waves

Scenarios that consider heat waves were simulated with weather files of specific years when heat waves have been detected. These heat wave years (HWY) were selected among those generated after bias-adjustment described in Section 2.2.1, considering historical, medium-term future, and long-term future periods.

The screening process to identify heat wave years followed the method proposed by Ouzeau et al. (2016). Detection is made by analyzing daily mean temperatures from a given period (i.e., historical or future) in comparison with three temperature thresholds: Spic, Sdeb, and Sint. These thresholds represent percentiles equal to 99.5 %, 97.5 %, and 95 % of the daily temperature distribution over the historical period, respectively. Detection and delimitation of a heat wave consider the following, according to Ouzeau et al. (2016):

- A heat wave is detected when temperature reaches the Spic threshold
- The beginning of this event is considered from the moment temperature crosses the Sdeb threshold
- The end is marked by temperature staying below Sdeb for at least three consecutive days, or once temperature falls below the Sint threshold

After detection, heat waves can be characterized by three values: duration (number of days); maximum mean temperature during the event; and global intensity (i.e., severity of the event). The global intensity is defined by the cumulative difference between daily mean temperature and the Sdeb threshold, divided by the difference between Spic and Sdeb (Ouzeau et al., 2016). These indicators were used to select three years among each period (historical or future periods) where the following can be found: (1) the **most intense heat wave**, with the highest maximum mean temperature; (2) the **most severe heat wave**, with the highest global intensity; and (3) the **longest heat wave**, with the highest duration. In the end, up to nine heat wave years can be developed, considering three periods and three heat wave types. It is possible, however, that the same heat wave is the most intense and severe, for example, which would lead to fewer heat wave years being generated. Apart from Ouzeau et al. (2016), Machard et al. (2020), and Flores-Larsen et al. (2022), who put this procedure into practice, it was also adopted by the Annex 80 Weather Data Task Group to generate historical and future heat wave years.

2.3. Impact of weather scenarios on thermal resilience

The impact of weather scenarios on the thermal resilience of buildings was analyzed through the generation of resilience profiles. See an example of a resilience profile plotted in Fig. 1 (B), where black-colored bubbles illustrate ideal performances for thermal resilience. These profiles aggregate all six KPIs from Table 1, divided into two sides related to the resilience stages: (1) resistance, and (2) robustness and recovery. The best results are located in the center of the plot; that is, in the lower right corner of the resistance stage, and in the lower left corner of the robustness and recovery stages. The smaller the size of the bubble, the better the performance. Each bubble in these graphs represents a single building. Each bubble (building) on the left side has a correspondent bubble on the right side.

We analyzed the variation of results across weather scenarios as a comparison with Scenario 1 (historical TMY). With respect to energy consumption, values correspond to a percentage change, whereas all other KPIs were analyzed through the absolute difference (the result in a certain Scenario minus the result in Scenario 1).

Worst-weather scenarios for thermal resiliency were also ranked, considering the different building types and operation modes. A multi-objective optimization was performed to identify possible optimal solutions, known as Pareto-optimal front (Wang & Rangaiah, 2017); however, in this case "optimal" corresponds to the worst results with respect to all indicators. This procedure was repeated for each subset of building type and operation type (i.e., air-conditioned, naturally ventilated, or hybrid). It should be highlighted that the Pareto front might indicate multiple scenarios that are equally leading to the worst performance but due to different indicators. This analysis was developed using the R software (R Core Team, 2020) with R-Studio (RStudio Team, 2021) interface and the package "rPref" (; Borzsony et al., 2001; Kießling, 2002; Roocks, 2016).

Finally, we also performed a correlation analysis aiming to identify what characteristics of heat waves might be related to specific impacts on thermal resilience. This was done by calculating the strength of association between these two variables, as well as the direction of the relationship. The Spearman rank correlation test was adopted for not carrying any assumptions about the distribution of the data. Results vary between -1 (strong correlation with a negative relationship) and $+1$ (strong correlation with a positive relationship). See Section 2.2.2 for heat wave characteristics: duration (number of days), intensity (maximum mean temperature), and severity (global intensity).

2.4. Case study

To illustrate how weather scenarios influence resilience modeling results, we conducted a case study with a group of 92 buildings located in the downtown area of Florianopolis, Brazil. Florianopolis is the capital of southern Brazil's Santa Catarina state. Its climate is classified by ASHRAE 169 as 2A (ASHRAE, 2020), and as humid subtropical according to Köppen-Geiger climate classification. Fig. 2 shows hourly values of dry-bulb temperature and relative humidity throughout the year in Florianopolis, considering a typical meteorological year from historical years between 2001 and 2020.

The downtown area was selected for having different building types of an older vintage compared to the rest of the buildings in the city, which are good candidates for retrofitting. These buildings are further described in Fig. 3 by four building types: office, residential, restaurant, and retail. These data were directly provided by the city hall of Florianopolis.

We conducted a field survey to verify and complement the data provided by the city hall. Every single building was verified during this survey, which was conducted in July 2022. The main information obtained was the mode of operation in terms of controlling the indoor air temperature. Three options were considered: fully air-conditioned buildings (AC), naturally ventilated buildings (NV), and hybrid buildings (natural ventilation and air conditioning being used interchangeably). They represent 12 %, 22.8 %, and 65.2 % of the buildings, respectively.

Two simplifications during the development of the case study should be highlighted: (1) all rooms inside the same building were considered having the same operation mode, and (2) only one building type was attributed to each building, which constituted the prevalent type between all rooms and floors.

Building envelope characteristics were adopted following local building standards: the Inmetro's normative instruction for the energy efficiency classification of commercial, service, and public buildings (INI-C) (Inmetro, 2022), and the Brazilian building performance standard, NBR 15575–1:2021 (ABNT, 2021). INI-C establishes the energy efficiency labeling scheme for commercial buildings in Brazil, and NBR 15575 presents a simulation path to assess the thermal performance of residential buildings. Building characteristics are presented in Table 2 and Fig. 4. Occupancy schedules and internal heat gains of residential buildings were adopted as described in NBR 1,575–1:2021 (ABNT, 2021). Commercial buildings have internal heat gains according to INI-C (Inmetro, 2022) and schedules following United States Department of Energy (DOE) prototype models (DOE, 2023).

Air-conditioned and hybrid buildings were equipped with mini-split air conditioners, which is the prevalent cooling equipment adopted in offices (Scheidt & Westphal, 2023) and residential buildings in the region (Eletrobras, 2019). Given the importance of passive building operation in Brazil (Buonocore et al., 2023), natural ventilation was represented using the most advanced model available in EnergyPlus, composed of the *Airflow Network* group of objects. The *Airflow Network*

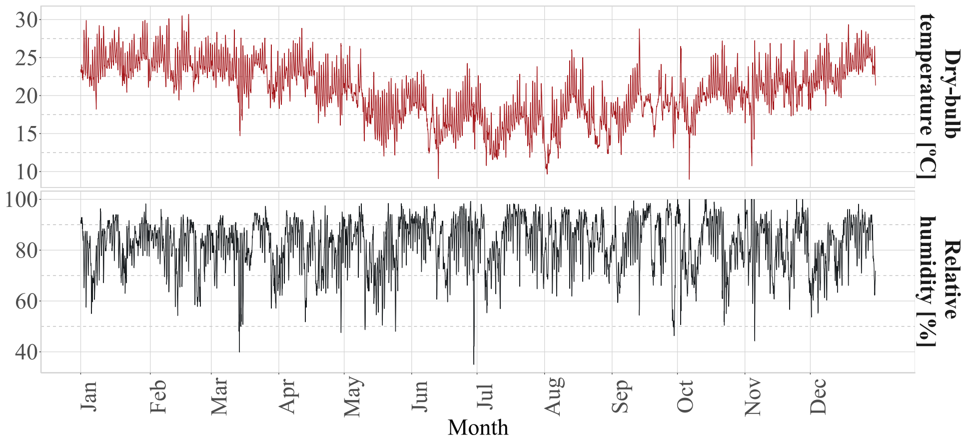

Fig. 2. Dry-bulb temperature and relative humidity for a typical meteorological year in Florianopolis.

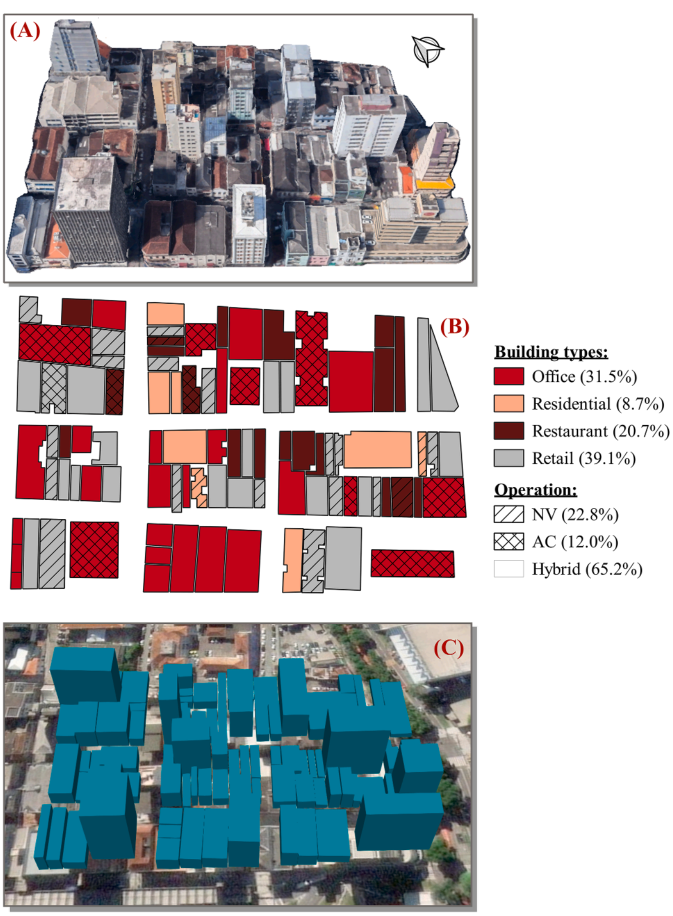

Fig. 3. Buildings within the case study represented in 3D (A) as footprints (B), and as illustrated in CityBES (C), colored and hatched according to the building type and operation.

models air changes inside the building according to wind data from the weather file. Detailed controls using EnergyPlus's *Energy Management System* (EMS) were considered to operate the air conditioning system and windows for natural ventilation. In addition to natural ventilation and/or air-conditioning, fans were also considered as a typical device used to improve thermal comfort in Brazilian buildings. They were included in all residential building models and all naturally ventilated buildings, irrespective of the building type. The effect of fans was considered through an adjustment of the airspeed from 0.2 m/s to 0.9 m/s.

Detailed control criteria were considered to operate windows and air-conditioners aiming to realistically represent a building's operation dynamics and capacity to respond as this is highly relevant in a thermal resilience analysis. Controls vary with the type of operation:

- *Naturally ventilated buildings:* Windows are open when the indoor thermal conditions are within the adaptive comfort thresholds from ASHRAE 55 (ASHRAE, 2020), considering 80 % acceptability, and the outdoor environment is simultaneously colder than the indoor environment. Windows close outside these conditions. When buildings are equipped with fans, the upper limit threshold is extended by 1.8 °C to account for a broader acceptance of operative temperature due to increasing airspeed (ASHRAE, 2020). Fans are used when the room surpasses the upper limit threshold.
- *Air-conditioned buildings:* Windows are always closed and the air-conditioning system is operated during occupied hours to meet a set point of 24 °C.
- *Hybrid buildings:* The same criteria from naturally ventilated buildings apply, but the air-conditioning system is activated once the upper limit of the adaptive comfort thresholds is surpassed. If a fan is available, it is used before turning on the air conditioning, which is used only if it exceeds the extended threshold. To avoid an unrealistic behavior of turning on and off the air-conditioning in a short timeframe, once this system is in use it is only turned off if: (1) the room temperature has reached set point and the outside air is colder than the indoor air; or (2) the room becomes unoccupied.

To obtain an optimized design with resilience-oriented solutions, eight strategies were considered (as described in Table 3): seven passive strategies and one active strategy. These strategies were applied in representative buildings within the community aiming to define an optimized combination that fosters thermal resilience. One optimized combination of strategies was defined for each building type, which could reflect, for instance, the application of possible new building codes in the region.

A cluster analysis was adopted to identify three representative cases within each building type, aiming to appropriately cover the variability within each type. Twelve representative buildings were defined based on results of all six KPIs (Table 1) in the baseline scenario. Strategies from Table 3 were combined parametrically and assigned to the selected representative cases, resulting in 2304 models, including the baselines. Building models were simulated using a historical TMY developed according to Section 2.2.1. This analysis was developed using the R software (R Core Team, 2020) with the R-Studio (RStudio Team, 2021) interface and the package "cluster" (Maechler et al., 2022).

Optimal solutions were identified through the Pareto-optimal front

Table 2
Description of building envelopes in the baseline.

	Description	Thermal Transmittance [W/(m^2.K)]	Thermal Capacity [kJ/(m^2.K)]	Solar Absorptance [dimensionless]
Exterior Walls				
All buildings except for residential	Burnt clay brick masonry and stucco finishing	2.39	150	0.50
Residential buildings	100 mm wall	4.40	220	0.58
Roof				
All buildings except for residential	Concrete slab (100 mm) with a hip roof composed of fiber cement roof tiles	2.06	233	0.80
Residential buildings	Slab (100 mm) with a hip roof composed of 6 mm roof tiles	2.10	229	0.65

	Description	Thermal Transmittance [W/(m^2.K)]	Solar Heat Gain Coefficient [dimensionless]	Window-to-Wall Ratio [%]
Glazing				
Office	Single pane window with clear 6 mm glass	5.7	0.82	50
Retail	Single pane window with clear 6 mm glass	5.7	0.82	20
Restaurant	Single pane window with clear 6 mm glass	5.7	0.82	40
Residential	Single pane window with clear 3 mm glass	5.7	0.87	Variable, equivalent to 17 % of the floor area

Notes: W/(m^2.K) is watts per square meter-kelvin; kJ/(m^2.K) is kilojoules per square meter-kelvin.

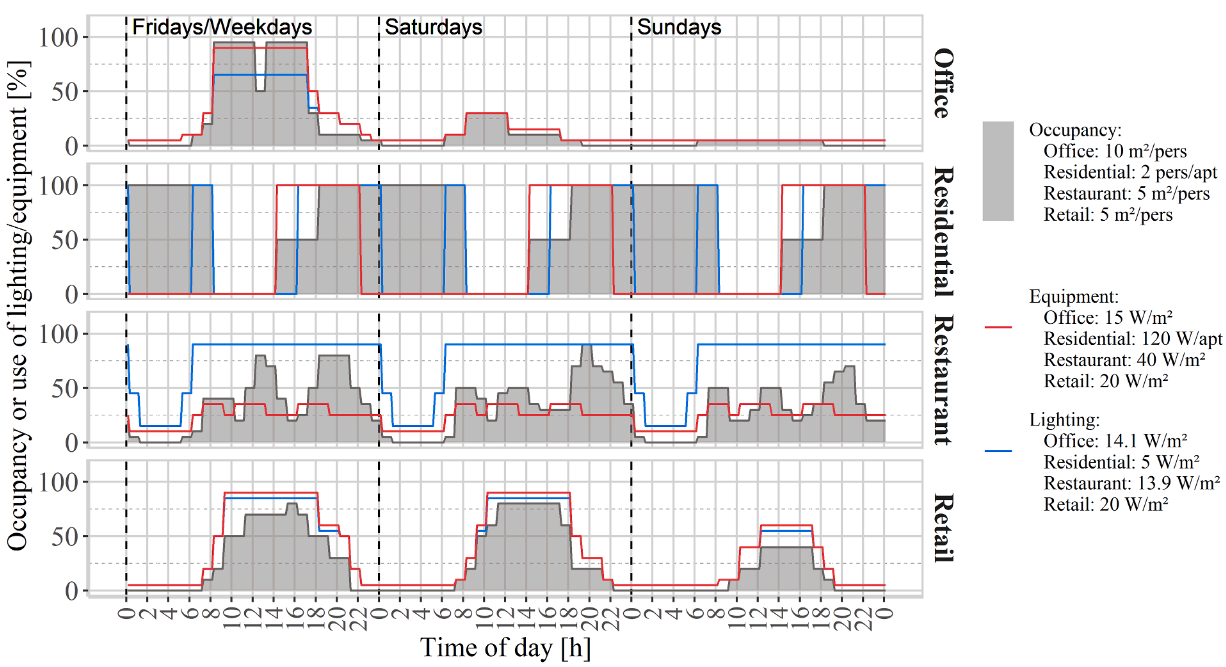

Fig. 4. Occupancy and operation schedules, and internal heat gains.

(Wang & Rangaiah, 2017), this time considering the best combination of results—i.e., closer to the black-colored bubble in Fig. 1(B). The selection of the final solution for each building type used a tiebreaker, the ease of application of the strategy, described in the right column of Table 3.

3. Results

3.1. Weather scenarios

In total, nine weather scenarios were generated, three TMYs for the 2010s, 2050s, and 2090s; and six heat wave years (HWYs), as show in Table 4.

Fig. 5 (TMYs) and Fig. 6 (HWYs) show the variation in heat index throughout the year between these meteorological years. The heat index combines dry-bulb temperature and relative humidity to represent the thermal sensation when humidity is high or low and needs to be considered (NOAA, 2022). All nine scenarios were considered in the next steps of this analysis. Each scenario received a number from one to nine, as shown previously.

3.2. Case study

3.2.1. Quality check of results

Metered data of the actual buildings was not available for the entire community, prohibiting calibration of the simulation results at the individual building level. Also, this neighborhood has been impacted by the COVID-90 pandemic, with multiple buildings still vacant or sub-

Table 3
Strategies for resilient design optimization.

Strategy	Description	Application
Cool roofs	Cool roof coating with solar absorptance equal to 0.29 and thermal emissivity equal to 0.88	Easy
Cool walls	Cool paint with solar absorptance equal to 0.41 and thermal emissivity equal to 0.89	Easy
Advanced glazing	Window film that, installed in a clear glass, results in a solar heat gain coefficient (SHGC) equal to 0.4	Easy
Advanced glazing	Double-pane window	Hard
Solar shading	Overhang 0.5 m deep	Hard
Insulation (roofs)	Thermal insulation under the roof with 2.56 (m^2.K)/W of thermal resistance	Hard
Insulation (walls)	Exterior insulation finishing with thermal resistance equal to 2.38 (m^2.K)/W	Hard
Increased window openable area	Replacement of windows with opening factor equal to 90 %. Only applied to naturally ventilated and hybrid buildings	Hard
Pre-cooling	Activation of air conditioning 1 hour before occupancy. Only applied to fully air-conditioned buildings	Easy

Table 4
Description of weather scenarios.

Scenario	Type of weather file	Period	Description
1	TMY	*2010s*	Historical TMY between 2001 and 2020
2	TMY	*2050s*	Medium-term future TMY between 2041 and 2060
3	TMY	*2090s*	Long-term future TMY between 2081 and 2100
4	HWY (SL)	*2010s*	Year with the most severe (S) and longest (L) heat wave in the historical period
5	HWY (I)	*2010s*	Year with the most intense (I) heat wave in the historical period
6	HWY (I)	*2050s*	Year with the most intense heat wave in the mid-term future
7	HWY (SL)	*2050s*	Year with the most severe and longest heat wave in the mid-term future
8	HWY (SL)	*2090s*	Year with the most severe and longest heat wave in the long-term future
9	HWY (I)	*2090s*	Year with the most intense heat wave in the long-term future

utilized. We further discussed these issues as limitations of the study in Section 4.4.

To check the reasonability of the simulation results, we compared simulated whole-building energy consumption with a comprehensive database (EPE - Energy Research Office, n.d.) of measured energy consumption of the Brazilian non-residential building stock. This database is explored by Soares Geraldi et al. (2022), whose data has been generously shared with us, as shown in Fig. 7. This figure compares simulated and metered annual energy intensities. Metered data encompasses buildings located in the Southern Brazilian region—where Florianopolis is located—and covers three building types, office, restaurant, and retail. In Soares Geraldi et al. (2022), these building types are described as "office," "food services," and "mercantile," respectively. Fig. 7 is centered on metered data up to the 75th percentile, but Geraldi's database includes consumptions up to 1408 kWh/m^2.

We verified that simulated median energy use intensities fall close to metered data reported in Soares Geraldi et al. (2022) for offices and restaurants, and they are also within metered 25th and 75th percentiles. Our results for retail buildings are higher than the metered 75th percentile, but still within the entire range of metered data. One possible explanation is that this building type might operate passively more frequently than considered. In this case study, most retail buildings have very large openings that are not totally enclosed throughout opening hours, which might help release indoor heat and foster natural ventilation, which consequently reduces HVAC energy use. Such characteristics are difficult to reflect on building models, particularly in UBEM, and were not incorporated into the models of this study.

For residential buildings, we compared simulated annual energy consumption with median metered data from consumers within the state of Santa Catarina between July 2018 and April 2019. This information is provided by the Electrical Appliances Possession and Usage Habits Research for the Residential Sector (PPH 2019) (Eletrobras, 2019). The median difference between simulated and reported data is −6.0 % (e.g., models are mostly consuming less energy) and the average difference is −8.6 %. It should be noted that we were not able to compare energy use intensities for residential buildings (i.e., in kWh/m^2), but rather annual energy use (i.e., in kWh). This prevents a direct comparison as the housing size will influence the results. Thus, such a comparison is only performed to check if our results are within an acceptable range from usual consumption.

Considering that these are uncalibrated models that adopt standardized schedules and internal loads, as well as simplified zoning methods, we considered the results reasonable to proceed with the analysis.

3.2.2. Baseline and optimization

Results for the community in the baseline condition under a historical typical meteorological year (Scenario 1) are shown in Fig. 8 through a resilience profile. This profile combines the six KPIs from Table 1 into two sides: resistance and robustness/recovery. Optimal performance is in the lower center, with smaller bubbles indicating better performance. Each bubble represents a building, with pairs on each side.

Thermal autonomy of buildings in this community varied from 4 % to 100 %, which describes their capacity of providing acceptable indoor thermal conditions without the assistance of air conditioning. Energy consumption for cooling varied from 0 (mostly naturally ventilated buildings) to about 50 kWh/m^2. The worst indoor overheating degree (IOD) obtained was equal to 0.48 °C, which means this building would be constantly surpassing the acceptable thresholds by 0.48 °C if overheating were distributed throughout all occupied hours, considering all thermal zones. Some extreme conditions can be identified in the robustness and recovery stages, with one retail naturally ventilated building reaching about 40 % of thermal vulnerability. That is, this building has at least one zone that exhibits 40 % of occupied hours with SET surpassing 30 °C. Occupants in this building experience at least 60 continuous hours (2.5 days) in such conditions, considering the recovery time (t_R) from 37.5 °C (Tmax) until reaching 30 °C again.

The representative cases highlighted in Fig. 8 are those identified through the cluster analysis. In total, 12 representative buildings were identified (three per building type). These cases were used to test strategies from Table 3 to find the combinations attributed to the optimized community. Fig. 9 shows results for the three representative retail buildings, highlighting the baseline results (blue) and the combination of strategies giving optimal results considering all six indicators (red). Bubbles in shades of gray represent combinations of strategies that have not been selected.

Fig. 10 shows results for the optimized community once all representative buildings were analyzed. For instance, it was possible to significantly improve the thermal vulnerability of the retail building previously mentioned from 40 % to about 10 %. The best combination of strategies selected for retail buildings was applying a cool paint or coating on both walls and roof, and installing overhangs for solar shading and double-pane windows with increased openable area for natural ventilation. The same strategies were selected for office buildings, along with adding insulation to the roof. For restaurants and residential buildings, windows would not need to be replaced; applying a window film to existing windows would be enough to improve resilience. All building types benefited from cool surfaces.

It is important to highlight that in a few cases, performance slightly

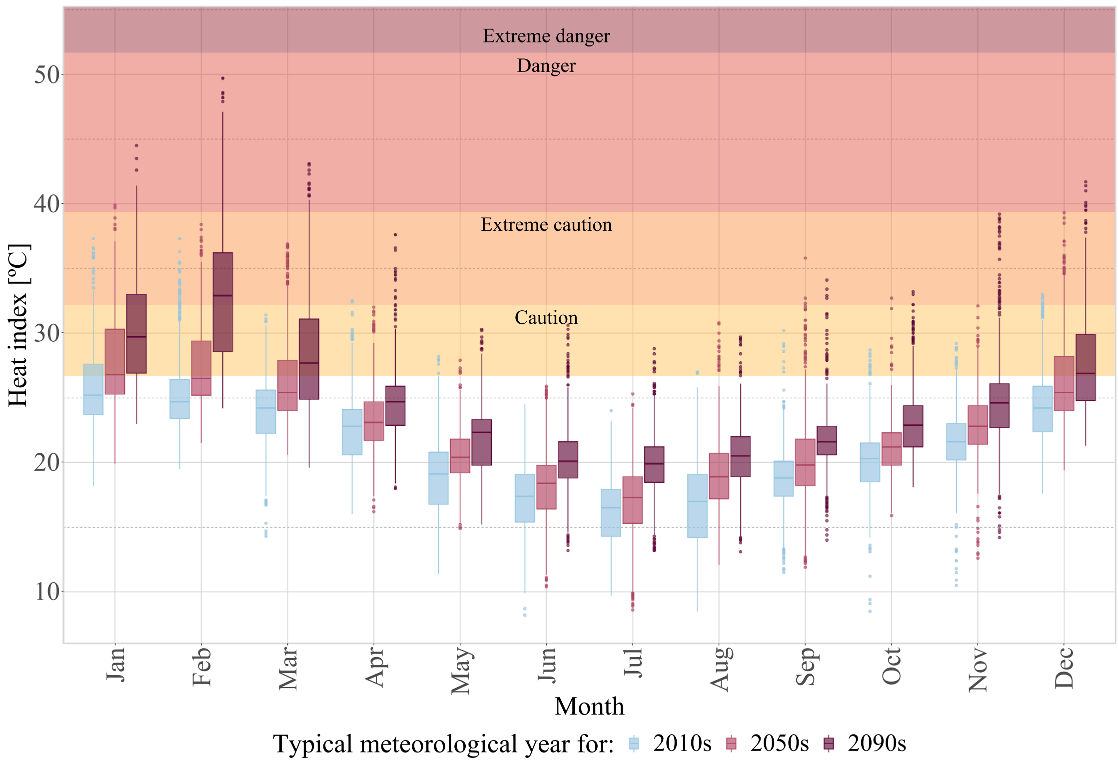

Fig. 5. Monthly variation in heat index of typical meteorological years for the 2010s, 2050s, and 2090s (Scenarios 1–3) throughout a year, juxtaposed with heat index levels from caution to extreme danger.

worsened with respect to some KPIs. This is because the selected combinations of strategies were defined based on representative buildings, and only one combination was attributed by building type. Thus, it can be expected that these strategies would not be ideal for all buildings within this group. However, considering that this is how most building policies are enforced around the world, especially prescriptive standards and codes, such an approach of recommending retrofit solutions based on the building type (and not for each individual building) would be closer to reality. An alternative would be to optimize thermal resilience for every single building, which would follow the same procedure described herein, but with a considerably higher computational cost.

3.2.3. *Impact of weather scenarios*

Quantifying the impacts of weather scenarios on thermal resilience is complex, as it involves multiple metrics. The six KPIs adopted in this study were influenced not only by the weather, but also by the building type and operation. Residential buildings, even when naturally ventilated, showed high thermal resilience with respect to most indicators even when exposed to future extreme events. Two important factors influencing these results are the low indoor heat gains in residential buildings and the use of fans to increase airspeed. In fact, fans were used on average 18 % of the occupied hours throughout the year, which translated into lower SET outputs and consequently higher thermal autonomy. Nonetheless, when extreme indoor thermal conditions could not be avoided through ventilation or air conditioning, these buildings presented the highest increase in maximum temperature in relation to Scenario 1. Other building types (non-residential) often presented lower thermal resilience, in part due to their high internal heat gains and floor area that reduced the impact of strategies applied to the façade. Large buildings, especially when in close proximity to surrounding buildings, often had reduced area for natural ventilation, decreasing thermal autonomy and increasing energy use for cooling. This is because windows were not applied to exterior walls close to or in contact with neighboring building's façades, reflecting another problem of dense urban areas.

Fig. 11, Fig. 12, and Table 5 illustrate the effect of multiple weather scenarios in the two communities: baseline and optimized. The adoption of simple strategies allowed reducing the median energy intensity for cooling between 11 and 17 kWh/m^2.year for both historical and future typical meteorological years, which means consuming 59 % and 48 % less energy by the 2050s and 2090s, respectively. Extreme indoor thermal conditions were also mitigated, with thermal vulnerability improving up to 25 percentage points for the year with the most severe and longest heat wave in the long-term future (Scenario 8). Maximum SET was also reduced across buildings in the optimized community. The baseline community reached over 40 °C, taking weeks or even months to recover. "Weeks or months" is used in Fig. 11 to represent any recovery time longer than a month. In Fig. 12, results for the recovery time within 0 and 72 h are plotted to improve visualization of the boxes, thus not showing all values above the 75th percentile.

Fig. 13 shows the variation of results of the 12 representative buildings for each indicator in relation to the results obtained for the same building in Scenario 1 (historical TMY). IOD was not included because it showed very little variation across the scenarios. The bars represent results for the baseline community, and the dots show results for the optimized community.

The main message from Fig. 13 is that design optimization for a historical typical weather scenario will not necessarily translate into a lower impact to buildings when exposed to different and more extreme scenarios. At least, not with respect to all indicators. Take the example of the three representative retail buildings (their results are also shown in Fig. 9). Building 79 was already highly resilient in Scenario 1. Its thermal autonomy was reduced by up to 10 percentage points (pp), and thermal vulnerability increased by up to 10 percentage points when considered in other scenarios in the baseline condition. These results were improved to about half the impact for the optimized condition (i.e., smaller resiliency reduction). On the other hand, weather scenarios proportionally impacted the optimized Building 10 more than its baseline for most of the KPIs. For example, Tmax is about 1.7 °C higher in the optimized Building 10 when comparing scenarios 2 and 1, while the baseline is only 0.5 °C higher. Also, energy consumption varied more in

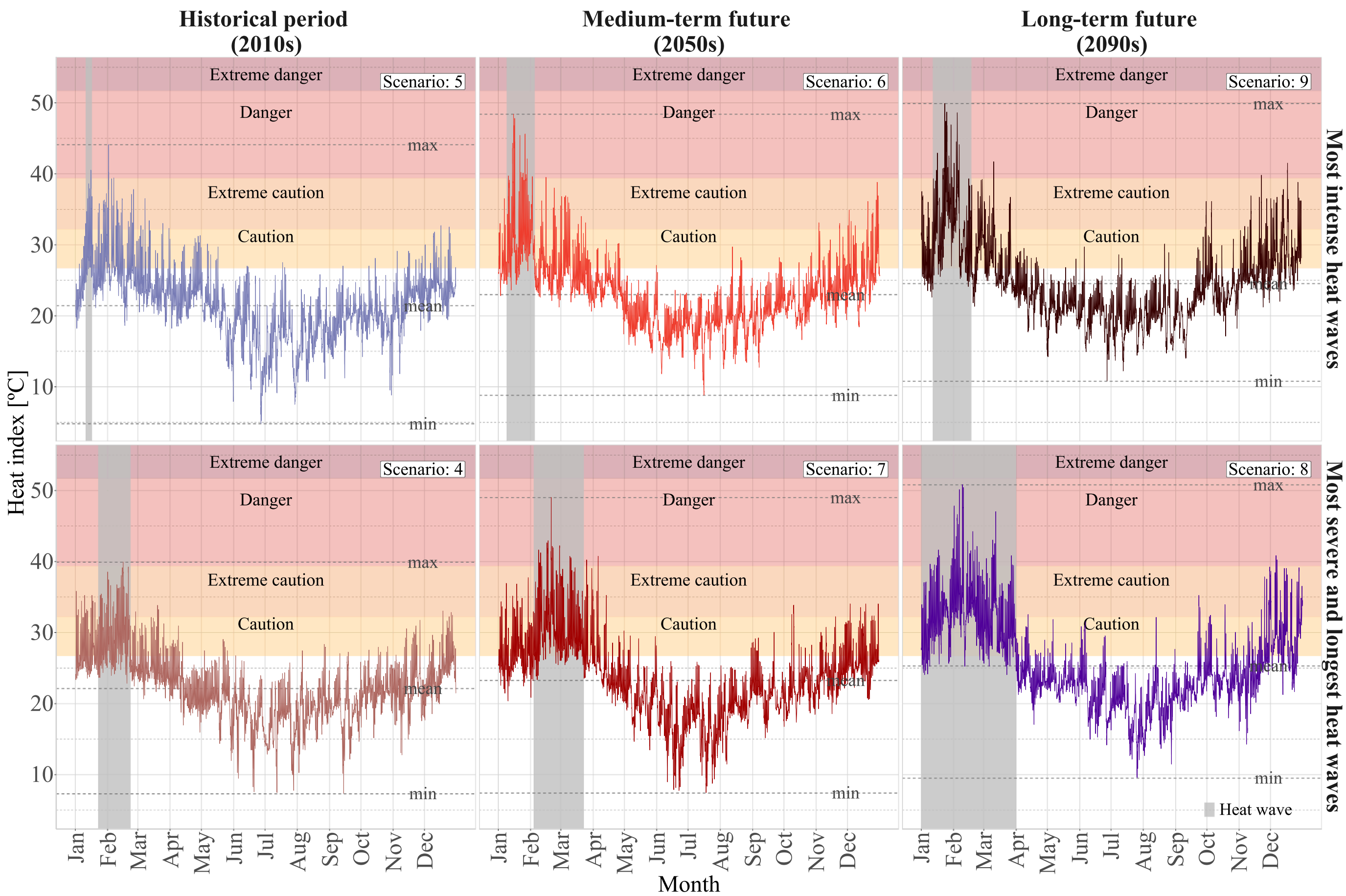

Fig. 6. Hourly values of heat index of heat wave years in the 2010s, 2050s, and 2090s (Scenarios 4–9), juxtaposed with heat index levels from caution to extreme danger.

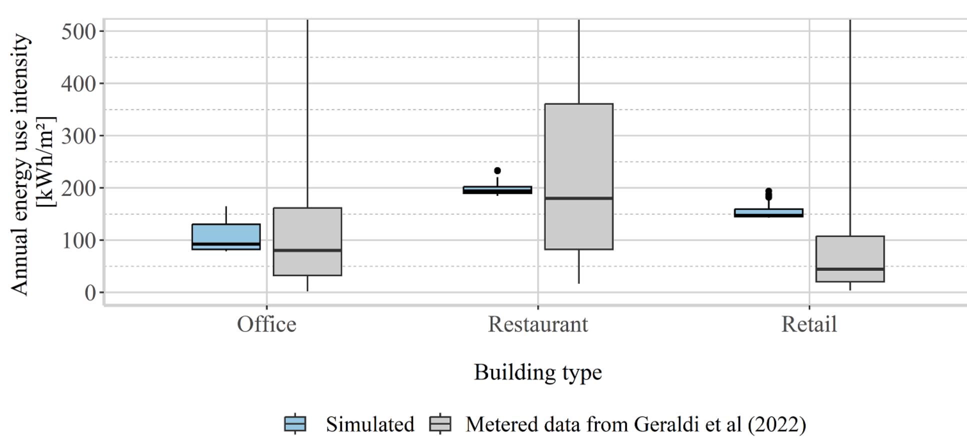

Fig. 7. Comparison between simulated and metered energy use intensities for non-residential buildings.

the optimized condition, but absolute values are still lower than those of the baselines. Such a pattern also can be observed by comparing absolute median values and the variation of median results compared to Scenario 1 in Table 5. The same is generally true for all the indicators: optimization improved most of the results. Still, some KPIs were harder to improve than others, especially those related to extreme indoor thermal conditions, and particularly the Tmax and recovery time. Fig. A.1, in the Appendix, shows absolute results for each KPI of representative buildings.

Results for the recovery time of Building 27 were not included in Fig. 13 because of their high variability in comparison to all the other buildings, compromising visualization and comparison. The reader is referred to Fig. A.1 for absolute results. In summary, this building is highly vulnerable in its baseline condition and in future climate scenarios, with at least one zone with continuous exposure to extreme indoor conditions throughout several weeks. The main reason behind this performance is its high internal loads coupled with a large footprint area in comparison to the window opening area, which hinders the effect of natural ventilation. Air conditioning is not available in Building 27.

Fig. 14 ranks weather scenarios from the least to the most impactful for the thermal resilience of each building, which ultimately splits them in groups of different time frames—first scenarios in the 2010s, then

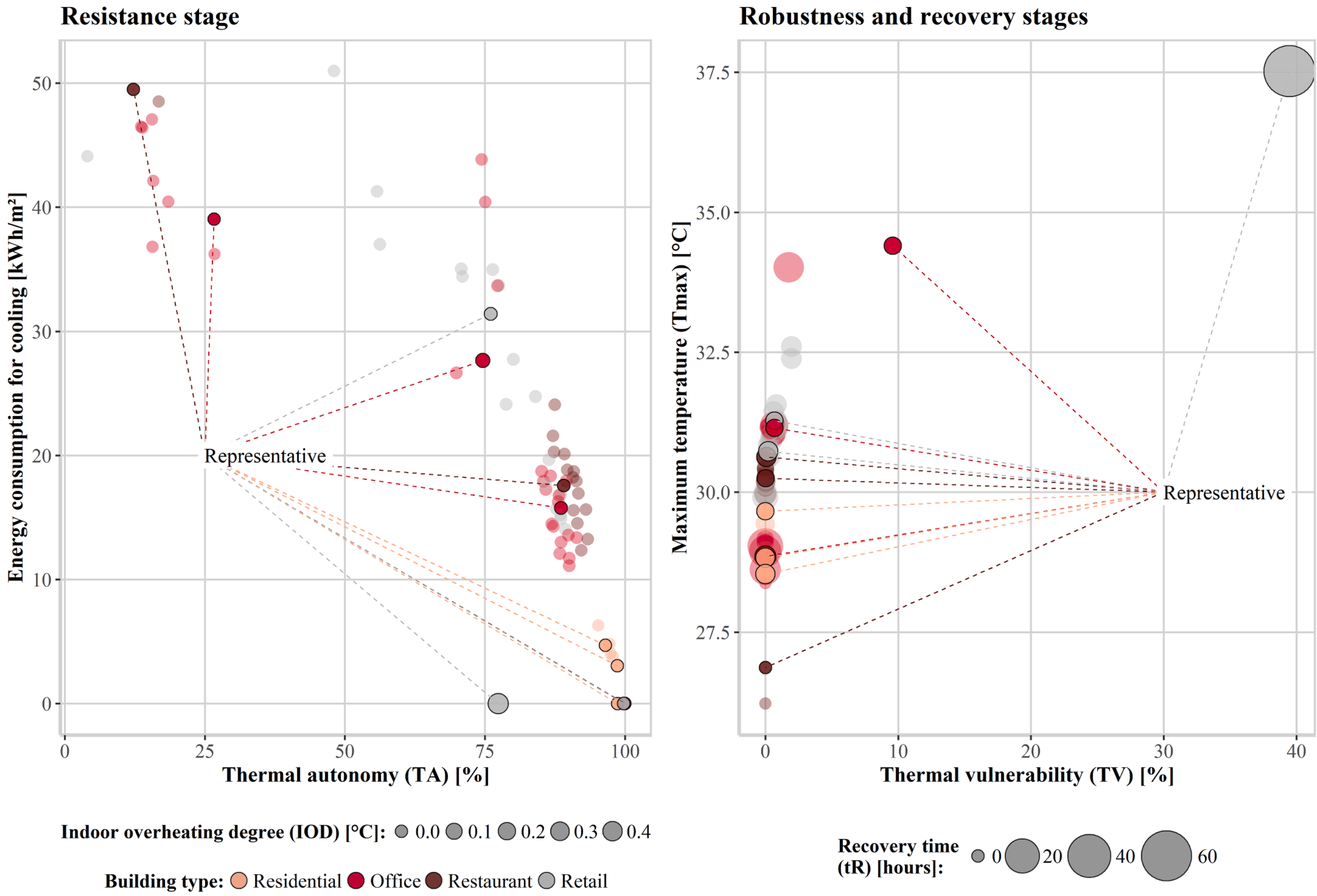

Fig. 8. Resilience profile of the baseline community under Scenario 1.

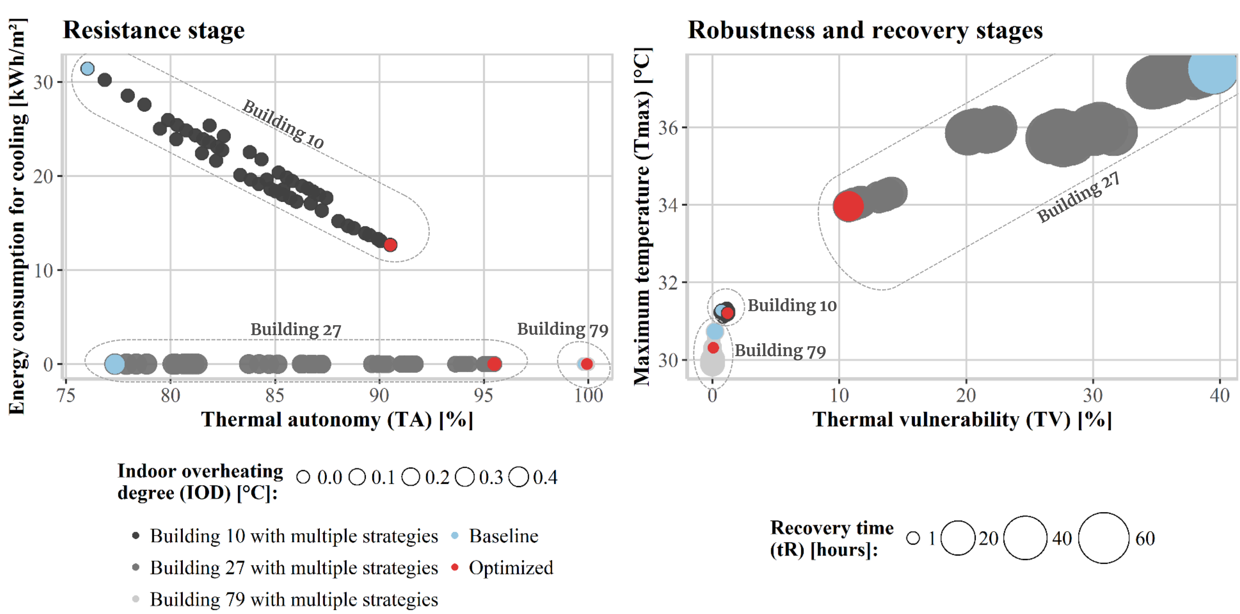

Fig. 9. Optimization of representative retail buildings.

2050s, and 2090s—as could be expected. As previously observed, Scenario 8, the most severe and longest heat wave in the 2090s, was identified as the most impactful for nearly all buildings, irrespective of the type, operation mode, and the strategies applied (i.e., optimization). However, if one is not interested in analyzing buildings in such a distant future, the most severe and longest heat wave in the 2050s (Scenario 7),

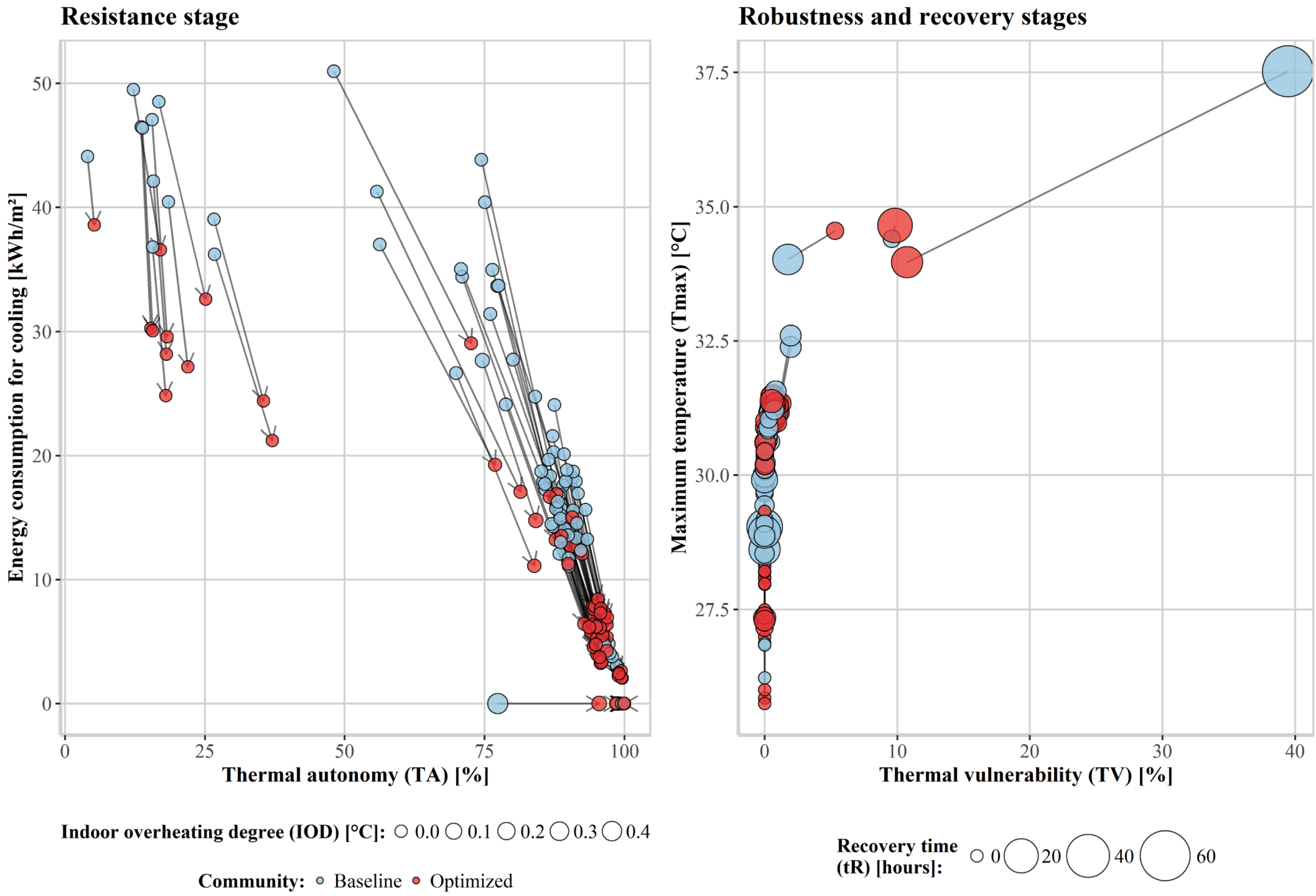

Fig. 10. Resilience profile linking baseline and optimized buildings within a community.

or the most intense heat wave in the historical period (Scenario 4) could be used. Scenario 7 also compromised resilience of the majority of hybrid residential buildings in the baseline condition. This was driven especially by the increase of the recovery time in the most severe and longest heat wave. Such a problem was mitigated in the optimized community, where Scenario 7 did not appear among the worst.

The intensity of each scenario's impact on buildings is highly dependent on the building type and operation, but also on other design characteristics, such as floor area and window-to-wall ratio. This becomes evident by looking at the hybrid operation in Fig. 14, where scenarios in the historical period can be as impactful as in the 2090s to some buildings.

Still seeking to identify the ideal situations in which each scenario could be preferred, Fig. 15 shows the correlation between the KPIs and characteristics of the heat waves across different building types and operations. This figure only considers Scenarios 4 to 9, which are heat wave years. Only significant correlations were included, considering a significance level of 5 %. The severity, duration, and intensity of heat waves correlated almost exclusively to the thermal autonomy and energy consumption of air-conditioned buildings, which may indicate that variability in the other KPIs is not explained by the type of heat wave. For the remaining buildings, the severity was the heat wave characteristic most strongly correlated to most KPIs. Additionally, in naturally ventilated buildings, the higher the intensity of the heat wave, the higher the maximum SET values (Tmax). This indicates that, if one aims to identify extreme temperatures inside buildings during heat waves, the events with higher intensity could be prioritized. Severe heat waves are also relevant to finding high Tmax values, especially in hybrid buildings.

4. Discussion

4.1. Impact of weather scenarios on thermal resilience

If we consider that a building is overheating when thermal vulnerability surpasses 3 % (adapted from CIBSE (2013)) of the occupied hours, two of the 92 buildings (2.2 %) would fail this criterion in the baseline condition under Scenario 1 (TMY 2010s). Even though this value corresponds to the most impacted zone in the building, a conservative approach may be recommended to safeguard occupant's health, as it is not guaranteed that they would be able to commute to other safer areas inside the building. In commercial buildings, such a condition could also lead to decreased productivity and limitation on service provision.

Maintaining baseline conditions in a typical year in the 2050s could result in 37 % of the buildings being subject to overheating. Even though median thermal autonomy in buildings improved by up to 10 % across all scenarios with the application of strategies, and median energy use for cooling was reduced by up to 60 %, extreme indoor thermal conditions persist. That is, a similar number of buildings would be subjected to overheating, considering thermal vulnerability values.

Indicators communicating resistance of buildings (i.e., in the resistance stage), particularly thermal autonomy and energy use, showed higher sensibility to the application of strategies, whereas Tmax (i.e., in the robustness stage) was harder to mitigate. Thermal vulnerability (TV) could be significantly reduced when the baseline condition obtained remarkably high results. TV up to about 10 % was much harder to reduce, especially through multi-objective optimization. This means that trade-offs between indicators will often need to be considered, as an improvement in resistance might come at the expense of robustness and

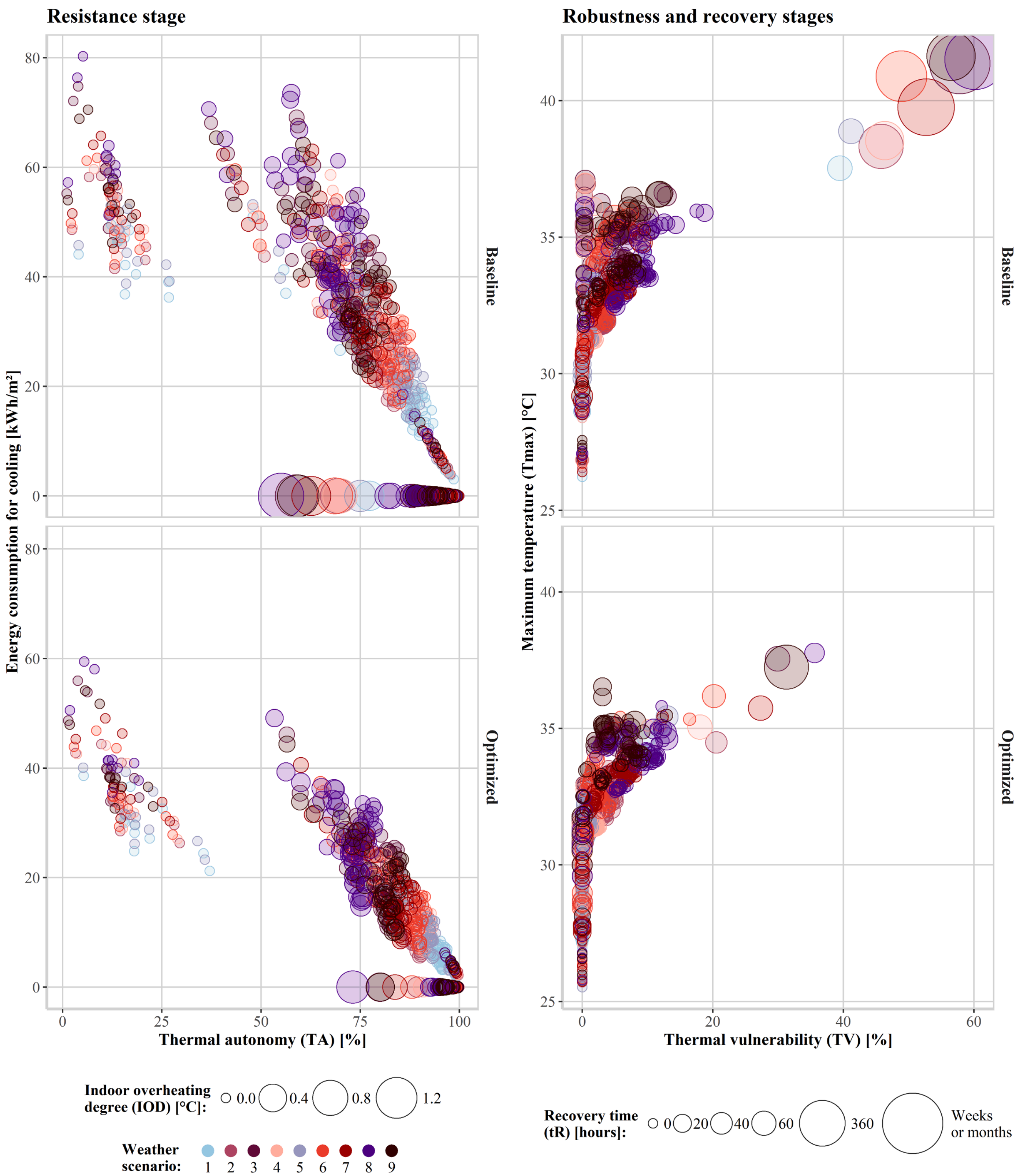

Fig. 11. Resilience profile of the communities under multiple weather scenarios.

recoverability. See Fig. 9 and Fig. 10 for examples. Thus, emergency plans should be available to respond to the most extreme conditions due to the difficulty of mitigating these events solely through passive strategies. Such response might come from active strategies, emergency kits, or commuting to safer zones within the building, when possible. This is also relevant when sizing HVAC systems considering future extreme weather scenarios and higher peak loads, which prompts another important discussion on trade-offs between thermal resilience, energy efficiency, and cost (both capital and operational).

Design optimization for resilience also should be performed within

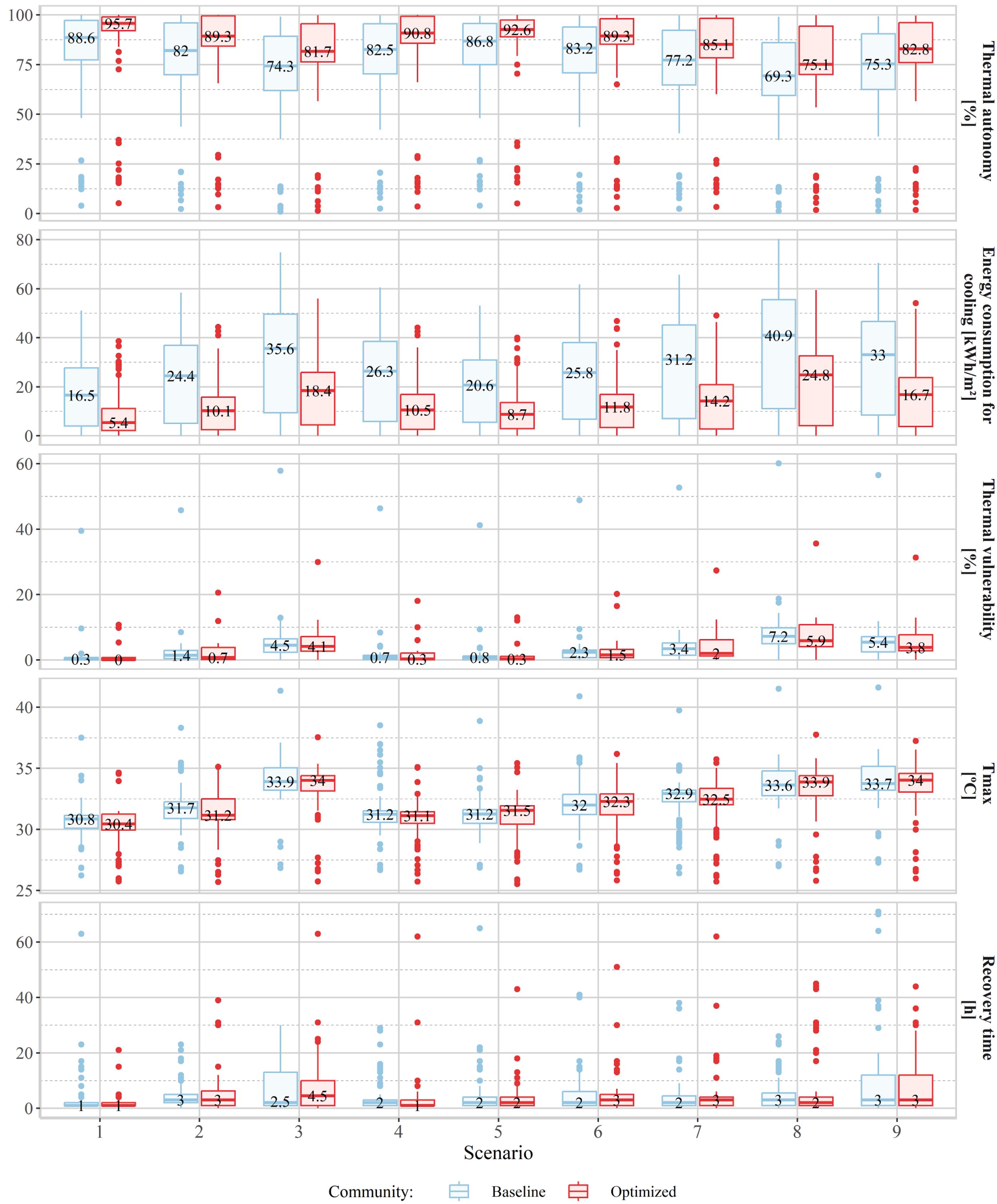

Fig. 12. Box and whisker plot showing the variation of results depending on the scenario.

Table 5
Median results and variation of median results (between parentheses) by KPI in comparison to Scenario 1.

KPI	Community	Scenario							
		2	3	4	5	6	7	8	9
Thermal autonomy [%]	Baseline	82 (−6.5 pp)	74.3 (−14.3 pp)	82.5 (−6.1 pp)	86.8 (−1.8 pp)	83.2 (−5.3 pp)	77.2 (−11.3 pp)	69.3 (−19.3 pp)	75.3 (−13.3 pp)
	Optimized	89.3 (−6.4 pp)	81.7 (−14.1 pp)	90.8 (−4.9 pp)	92.6 (−3.1 pp)	89.3 (−6.4 pp)	85.1 (−10.6 pp)	75.1 (−20.7 pp)	82.8 (−12.9 pp)
Energy consumption for cooling [kWh/m^2]	Baseline	24.4 (48 %)	35.6 (115 %)	26.3 (59 %)	20.6 (25 %)	25.8 (56 %)	31.2 (89 %)	40.9 (148 %)	33.0 (100 %)
	Optimized	10.1 (89 %)	18.4 (243 %)	10.5 (95 %)	8.7 (63 %)	11.8 (119 %)	14.2 (164 %)	24.8 (363 %)	16.7 (212 %)
Thermal vulnerability [%]	Baseline	1.4 (1.1 pp)	4.5 (4.2 pp)	0.7 (0.5 pp)	0.8 (0.5 pp)	2.3 (2.1 pp)	3.4 (3.2 pp)	7.2 (6.9 pp)	5.4 (5.1 pp)
	Optimized	0.7 (0.7 pp)	4.1 (4.1 pp)	0.3 (0.2 pp)	0.3 (0.2 pp)	1.5 (1.5 pp)	2.0 (1.9 pp)	5.9 (5.8 pp)	3.8 (3.8 pp)
Maximum temperature [°C]	Baseline	31.7 (0.9 °C)	33.9 (3.1 °C)	31.2 (0.4 °C)	31.2 (0.4 °C)	32.0 (1.1 °C)	32.9 (2.1 °C)	33.6 (2.8 °C)	33.7 (2.9 °C)
	Optimized	31.2 (0.7 °C)	34.0 (3.6 °C)	31.1 (0.7 °C)	31.5 (1.1 °C)	32.3 (1.8 °C)	32.5 (2.0 °C)	33.9 (3.4 °C)	34.0 (3.6 °C)
Recovery time [h]	Baseline	3.0 (2.0 h)	2.5 (1.5 h)	2.0 (1.0 h)	2.0 (1.0 h)	2.0 (1.0 h)	2.0 (1.0 h)	3.0 (2.0 h)	3.0 (2.0 h)
	Optimized	3.0 (2.0 h)	4.5 (3.5 h)	1.0 (0.0 h)	2.0 (1.0 h)	3.0 (2.0 h)	3.0 (2.0 h)	2.0 (1.0 h)	3.0 (2.0 h)

the context of a changing climate. This is because recommended strategies under historical weather scenarios might differ in future conditions, especially with the increasing frequency of extreme events. Thus, building design should provide flexibility to adapt throughout the building life cycle in tandem with current sources of stress. Ideally, maintenance and retrofitting plans can guide adaptation strategies if developed using a comprehensive assessment framework of resilience with multiple weather conditions.

4.2. *Definition of weather scenarios by use case and stakeholder*

Even though worst weather scenarios might differ depending on the building, a pattern was identified: thermal resilience tends to reduce further into the future, with years of the most severe and longest heat wave being the worst, followed by the year with the most intense heat wave or a typical meteorological year. This is a pattern we were expecting to verify, but it does not mean that a resilience analysis should simply adopt the worst possible weather scenario in the 2090s.

For building design, the choice of scenario also depends on the available resources, expected life cycle, and future adaptation plans. For instance, some of the buildings analyzed are already over 30 years old. With a building life cycle expected to last at least 50 years in Brazil, a retrofit analysis considering a typical year in the 2050s might be enough. For 25 % of air-conditioned office buildings and nearly 50 % of hybrid retail buildings, a TMY in the 2050s was already among the worst weather scenarios, even comparable to scenarios in the 2090s. When designing new buildings, severe heat waves in the 2050s could be considered as well, as they can be highly correlated to increased thermal vulnerability and maximum SET. Ideally, this information should be shared with other stakeholders responsible for developing systems manuals and emergency plans to better operate buildings and respond to extreme events.

To forecast the impact of weather scenarios on the power grid, severe heat waves may be adopted, as they are highly correlated to increasing energy consumption. However, we verified that the community's peak cooling demand occurred during the most intense heat waves (i.e., high maximum daily mean temperature), not during the most severe and longest events. We also identified that the intensity of a heat wave correlates with the maximum indoor temperature (Tmax) and thermal vulnerability (TV) in naturally ventilated and hybrid buildings. Thus, these intense events might be suitable for applications such as developing evacuation plans during extreme events.

A thermal resilience assessment including scenarios in the 2090s might be more suitable for policymakers to use to identify the pathways to policy change. For instance, incentivized heat mitigation and heat management strategies in building policies can evolve over time, gradually adapting to climate changes. A long-term resilience analysis could help create smooth and gradual steps throughout time to facilitate compliance.

By addressing the thermal resilience of a real community, instead of prototypical isolated buildings, it is possible to map vulnerabilities and develop action plans to respond during extreme events. For example, assistance to buildings with higher Tmax and recovery time could be prioritized by emergency responders. Such information would be particularly useful if combined with other health and comorbidity data; for example, to identify buildings with high thermal vulnerability occupied by the elderly or people with reduced mobility. Nonetheless, a detailed analysis at the building scale remains essential, especially when performed by design teams. These professionals could look at buildings in detail to identify the zones most affected and what is causing such vulnerability, thus providing tailored solutions to each context. In both cases, however, the framework remains useful given the comprehensive set of indicators adopted, which can also be calculated and analyzed for single zones inside buildings.

4.3. *Implications in a resilience-oriented design*

Besides shedding light on weather scenario choices within building performance simulation applications, we highlight practical implications for decision-making, policymaking, and urban planning:

- Median energy consumption for cooling could increase by 48 % in a typical 2050s scenario if resilience strategies were not applied. This value reached 115 % in the 2090s and up to 148 % during a heat wave year. Such increased demand can heavily strain the power grid and should be addressed through policies with long implementation

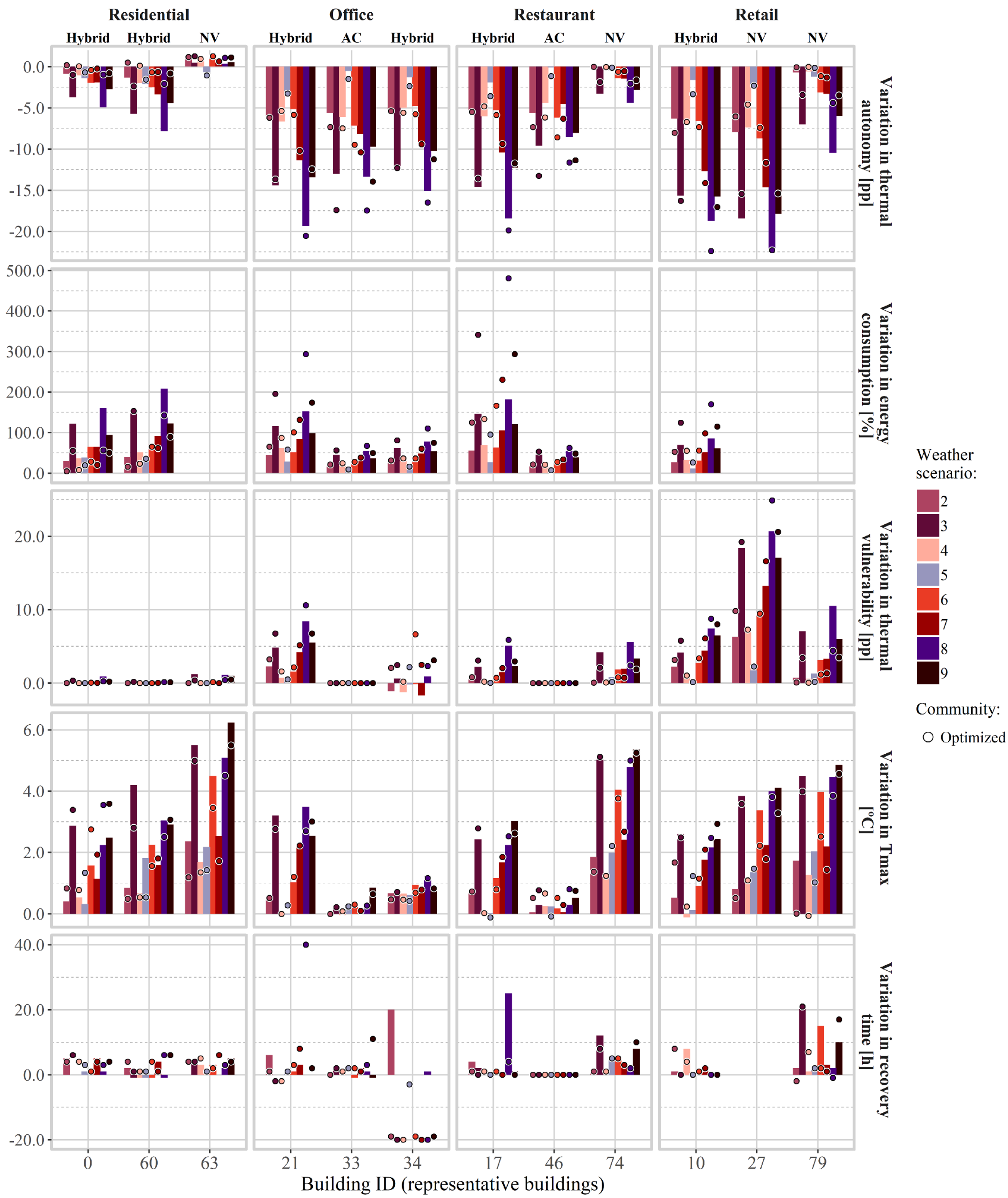

Fig. 13. Variation of results of representative buildings under multiple weather scenarios.

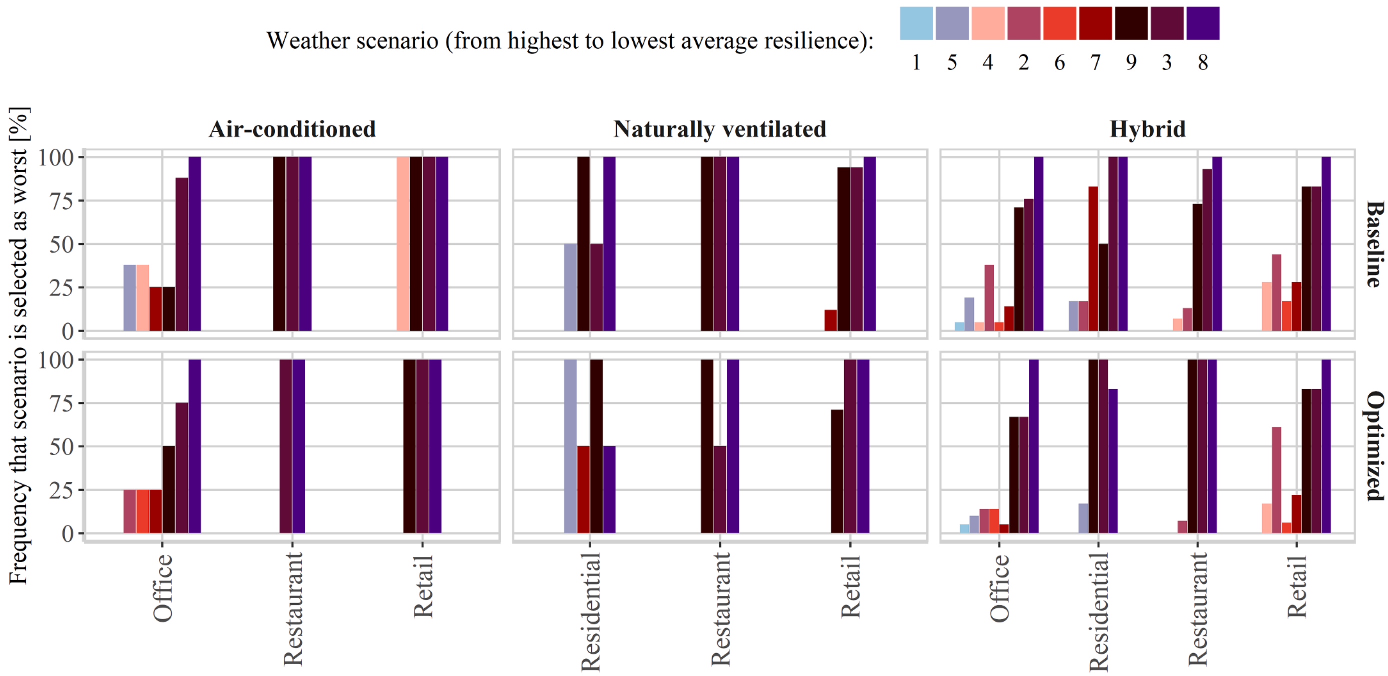

Fig. 14. Identification of worst weather scenarios for thermal resilience.

timelines. Nonetheless, median energy consumption could be reduced by 59 % and 48 % by the 2050s and 2090s, respectively, in comparison to baseline results, if simple passive strategies are fostered.

- In Brazil, an important step to addressing the thermal performance of residential buildings was taken in 2021 with the revision of the Brazilian standard, NBR 15575–1. This national standard considers a building simulation path with key performance indicators including thermal autonomy (also known as PHFT), cooling load, and maximum temperature, thus providing the foundations to also address thermal resilience with further updates. However, a similar standard for commercial buildings still does not exist, and NBR 15575–1 is often only applied to large multi-family residential buildings due to a lack of enforcement. Considering the expected increase in overheating issues in buildings, like those identified in this study, the development and enforcement of new policies are essential to face the effects of climate change. The resilience assessment adopted herein could help guide such a process.
- Resilience needs to be treated through long-term maintenance and retrofitting plans because ideal strategies and technologies might change over time as the climate changes. For designers, this might require analyzing solutions both at the historical period and a mid-term future (2050s) to verify what the best strategies are and if they differ in the future. If they do, ideally a flexible design would be developed; for example, by designing an appropriate structure to support installation of exterior shading devices in the future, or defining a time frame in which a cool coating should be applied on walls or roof tiles. For policymaking, on the other hand, the long-term future (2090s) also could be considered to define paths for smooth policy changes/transition.
- Extreme indoor thermal conditions are likely to become more intense and last longer in the future, which is directly reflected in higher thermal vulnerability, especially in naturally ventilated buildings with high internal heat gains (e.g., retail buildings, restaurants, and offices). Such conditions require emergency planning at the community scale. Thus, mapping vulnerable groups is important to speed up assistance. Such mapping could be developed using a severe heat wave in the 2050s, as we verified that it can be highly correlated to increased extreme indoor thermal conditions, such as thermal vulnerability and maximum temperature.
- Increased thermal vulnerability might trigger more deployment of air-conditioning for buildings that currently do not have such units installed, increasing energy use and carbon dioxide emissions. Therefore, increased demand for air-conditioning needs to be quantified to predict the incentives and rebates necessary to make this equipment more accessible to disadvantaged populations, including discounts on the energy bill. This energy burden is relevant given that in August 2023, utility bills represented more than 24 % of Brazilians' debt defaults (SERASA, 2023).

4.4. Limitations and future work

The findings and conclusions drawn in this article are limited by the building characteristics, occupation and operation patterns, and modeling assumptions considered in the case study, as well as the geographic location, weather data, and method to generate future climate scenarios. Other important limitations are related to the urban microclimate. Weather data did not reflect the possible urban heat island in the location, and the wind sheltering effect caused by the urban canyon was not considered, which should impact the natural ventilation potential as a strategy for thermal autonomy. Future studies could further explore the microclimate using tools like the Urban Weather Generator (UWG) (Bueno et al., 2013). It is also relevant to create alternatives to easily couple UBEM models to this or similar tools to facilitate representation of the urban heat island effects when locally measured weather data are not available.

Simplification of building models also limited the analysis. For instance, many real buildings within this case study are mixed use (e.g.,

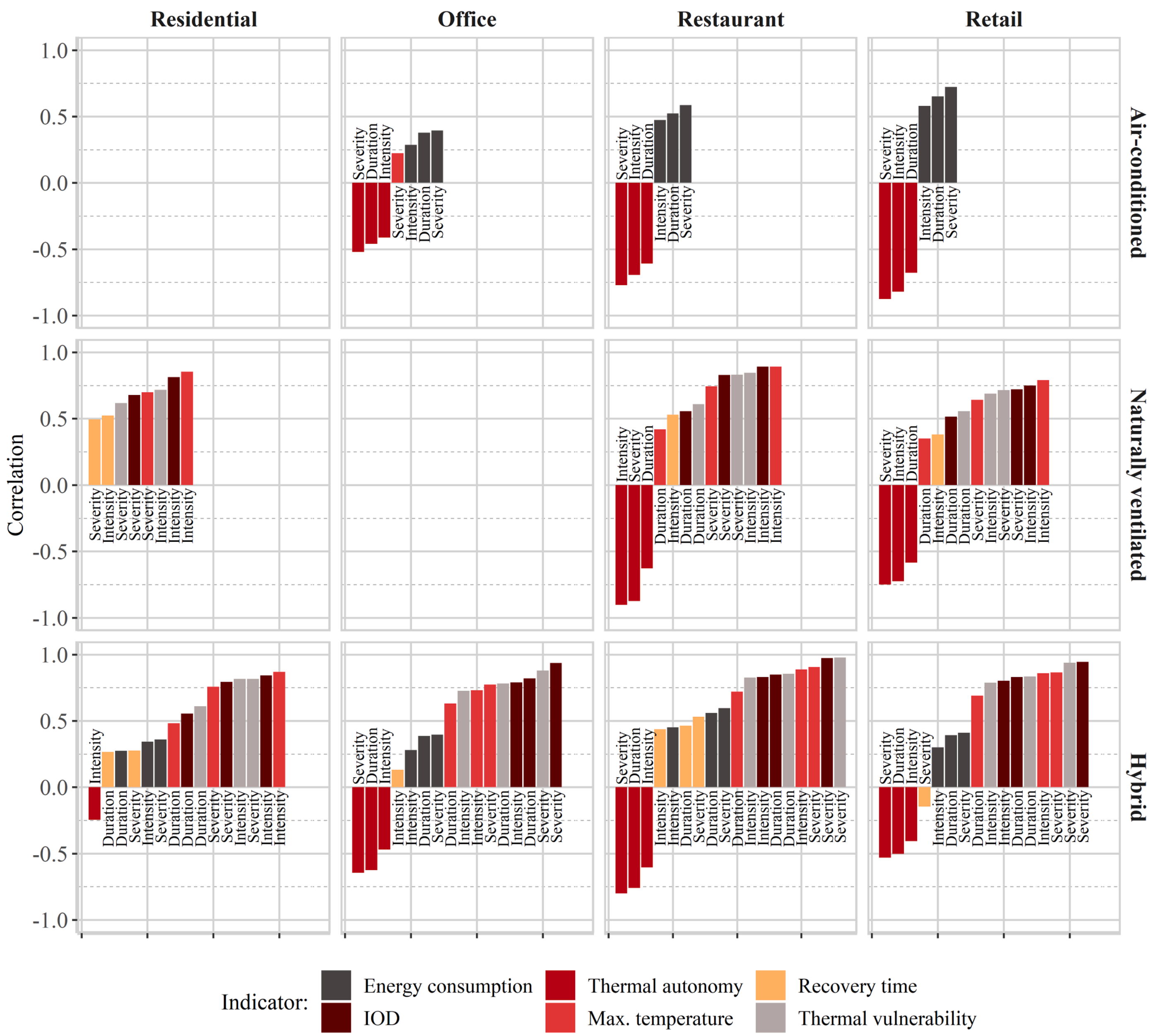

Fig. 15. Correlation between indicators of thermal resilience and heat wave characteristics.

retail enterprises on the first floor and residences on the remaining floors). We adopted the predominant type. Additionally, we verified that multiple small businesses inside these buildings permanently closed during the COVID-19 pandemic. We adopted the most recent building type, but some buildings or floors have remained inactive ever since, which hinders validation of results. Validation of indoor thermal conditions is still a challenge in building performance simulation, especially when analyzing multiple buildings within a community. Future studies could investigate alternatives to improve the verifiability of thermal resilience metrics, particularly for disadvantaged communities where this type of analysis is most needed and data are limited.

Future studies could also investigate other disturbances to thermal resilience, such as power outages, technical systems failures, and operational constraints (e.g., restricted ability to open windows due to outdoor air pollution, noise, or security issues), as well as diversity of populations (e.g., healthy adults, elderly, and children). When doing so, and especially when analyzing longer time frames (e.g., until the 2090s), analyses should consider how existing buildings age over time and that new buildings might be already improving as a result of evolving regulations. How to properly reflect such a passage of time in thermal resilience analyses is still to be further explored across different socioeconomic, regulatory, and climatic contexts.

5. Conclusions

This study first proposed a framework to define and curate various weather scenarios for building thermal resilience modeling and analysis. It then investigated the impacts of weather scenarios on the thermal resilience of buildings and communities against overheating within the context of climate change and increased occurrence of extreme events. We also explored the effect of multiple design strategies to improve thermal resilience.

Our results reflect the necessity of planning for resilience. This is because, often, strategies and technologies recommended under current weather conditions might not be ideal in the future. Therefore, flexible design, maintenance, and retrofit planning are key. Also, different stakeholders' objectives might require diverse weather scenarios, sometimes even resulting in trade-offs between improving resistance or the robustness of buildings. For instance, we verified that the same strategies that were improving thermal autonomy and reducing energy consumption (i.e., increased resistance) could lead to higher indoor maximum temperatures and thermal vulnerability during extreme weather conditions (i.e., reduced robustness).

Overall, the years with the most severe and longest heat waves within a period (historical, mid-, or long-term future) impacted thermal resilience the most with respect to all six analyzed key performance indicators combined. However, specific applications may benefit from adopting intense heat waves; especially for identifying extreme indoor thermal conditions and peak energy demand. Such a decision should ultimately be accompanied by a thorough reflection on the objectives of quantifying resilience, available resources, planning horizon, and the risks that would be assumed by not being resilient.

There also is a strong need to define and curate a standard set of various scenarios of weather data for major locations across the world (Annex 80 achieved a portion of this goal), to ensure consistent weather data are used in thermal resilience modeling and analysis so simulation results from different studies can be compared and analyzed to inform policymaking on climate resilience for buildings and communities.

Based on our findings, we offer the following specific and actionable recommendations for policymakers, designers, and researchers:

1. Policymakers:
   a. Implement long-term policies aimed at reducing energy consumption for cooling, particularly in response to projected increases in demand during heat waves. These policies should include incentives for the adoption of simple passive strategies in building design and retrofitting projects.
   b. Strengthen enforcement of building standards, such as NBR 15575–1 in Brazil, to ensure comprehensive coverage across residential and commercial buildings. Additionally, consider updating these standards to incorporate thermal resilience metrics to address the effects of climate change effectively.
   c. Develop emergency response plans at the community level to mitigate the impact of extreme indoor thermal conditions, especially for vulnerable populations. This could involve mapping vulnerable groups to facilitate targeted assistance during heat waves.
   d. Explore strategies to make air-conditioning equipment more accessible to disadvantaged populations through incentives and rebates.
2. Designers:
   a. Incorporate flexibility into building designs to accommodate future climate changes and evolving thermal resilience strategies.
   b. Conduct thorough analyses of potential solutions for both current and future climate scenarios to identify the most effective strategies.
3. Researchers:
   a. Continue studying the impacts of climate change on indoor thermal conditions and energy consumption to inform future policy and design decisions.
   b. Investigate the correlation between severe heat waves and extreme indoor thermal conditions, such as thermal vulnerability and maximum temperature, to refine emergency planning efforts and improve assistance to vulnerable populations.

These recommendations carry significant implications for the field, emphasizing the urgent need for proactive measures to address the challenges posed by climate change on building thermal performance and energy consumption. Policymakers, designers, and researchers must collaborate to develop and implement effective strategies that enhance building resilience and mitigate the adverse impacts of extreme thermal conditions.

CRediT authorship contribution statement

Amanda F. Krelling: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Roberto Lamberts:** Writing – review & editing, Supervision. **Jeetika Malik:** Writing – review & editing. **Wanni Zhang:** Software, Data curation. **Kaiyu Sun:** Data curation, Software, Writing – review & editing. **Tianzhen Hong:** Supervision, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix

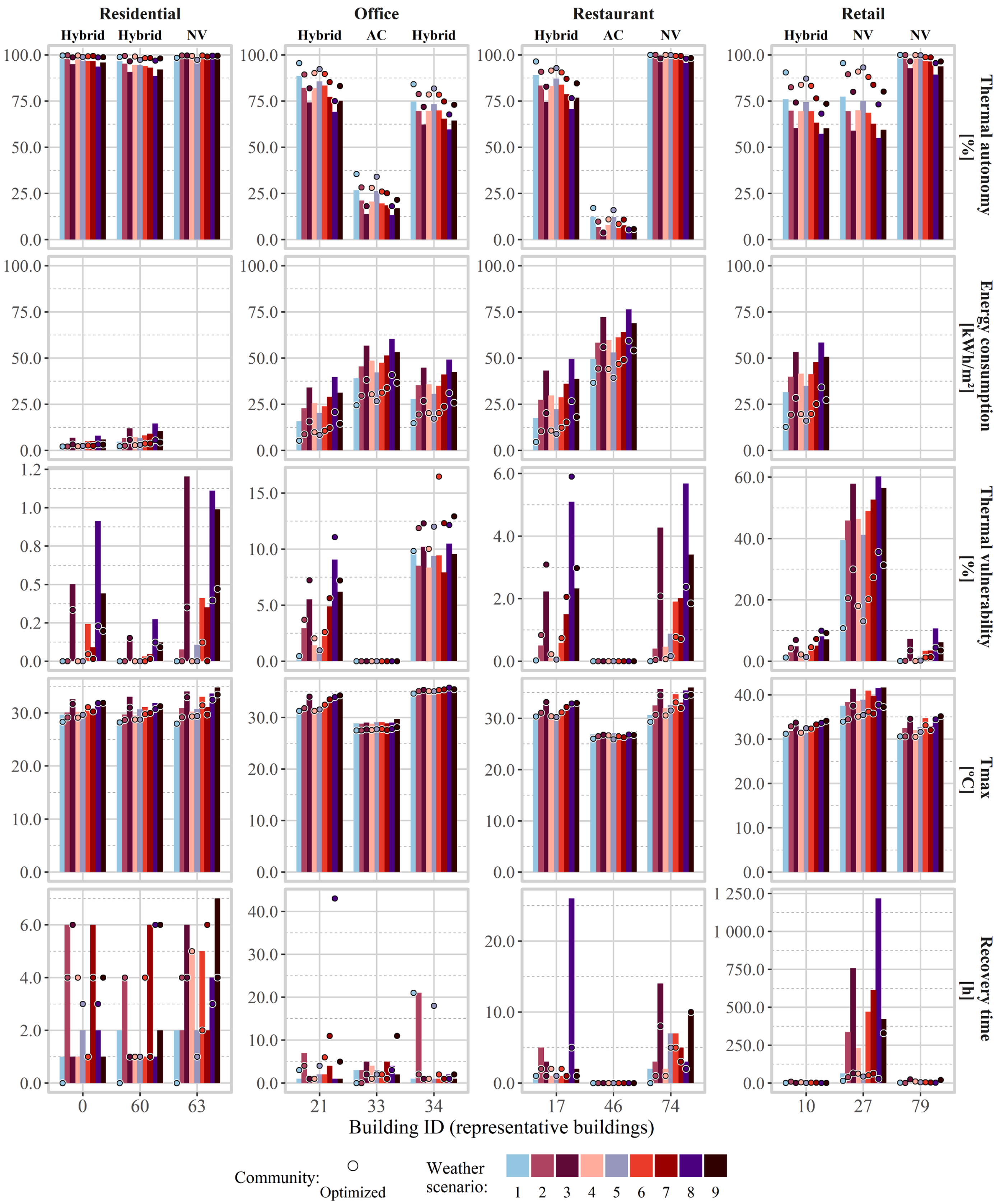

Fig. A.1. Results of representative buildings under multiple weather scenarios.

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