Spatial Thermal Autonomy (sTA): A New Metric for Enhancing Building Design Towards Comfort, Heat Resilience and Energy Autonomy

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Abstract

Achieving thermal comfort in buildings while maintaining energy efficiency is a critical challenge in architecture and engineering design and operation. Traditional thermal comfort metrics used in the early stages of design tend to neglect two key aspects: spatial variability of thermal conditions within buildings and the promotion of passive design strategies over active conditioning systems. This oversight leads to localized discomfort, excessive energy use, and increased vulnerability to overheating. To address these issues, we propose a novel metric called spatial Thermal Autonomy (sTA). The sTA metric has two advantages over existing metrics. Firstly, it captures spatial variability in thermal conditions. Secondly, it quantifies how much a building is able to provide thermally comfortable conditions without the use of active sources of energy. We performed a simulation case study evaluating sTA for different thermal zone sizes, passive design levels, and climate scenarios. Our findings suggest that buildings with high spatial thermal autonomy tend to use less energy, demonstrate greater thermal resilience during extreme weather or power outages, and experience fewer local discomfort problems. Optimizing building designs for spatial Thermal Autonomy encourages passive design strategies in key decisions related to building form, envelope, conditioning strategies, and HVAC system design. In buildings with reduced heating and cooling loads, this approach supports the increased adoption of local low-energy personal comfort solutions, such as fans or local heating solutions, and can lead

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to more adaptive, resilient, and comfortable indoor environments in a changing climate.

Keywords: Thermal comfort, Building performance simulation, Thermal autonomy

1. Research context

Indoor thermal comfort is strongly associated with occupant well-being (Altomonte et al., 2020), overall satisfaction (Graham et al., 2021), and energy use in buildings (Yang et al., 2014). As such, accurately projecting operational thermal comfort is a critical aspect of building design.

In traditional design workflows, thermal comfort assessments rely heavily on simulation data. Typically, these data points form the basis for calculating hourly thermal comfort indices, e.g., the Predicted Mean Vote (PMV), which are then aggregated into a single-value annual metric (see Figure 1). Common long-term metrics based on this approach include the *Percentage of Time Outside a PMV Range* and the *Percentage of Time Outside an Operative Temperature Range*, both featured in ISO-7730, EN-16798, and ASHRAE-55 (ISO, 2005; European Committee for Standardization (CEN), 2019; ASHRAE, 2023). Other measures adopted by global standards are the *Degree Hours* (ISO-7730, EN-16798) or the *Average PPD* (ISO, 2005) methods.

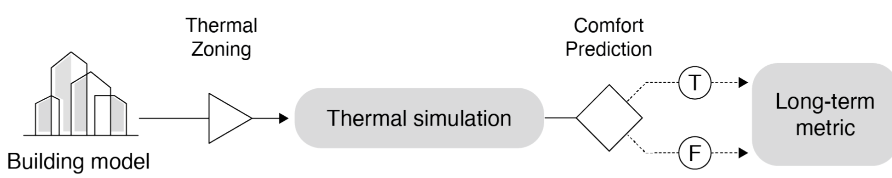


Figure 1: Traditional long-term thermal comfort prediction: The building model is divided into thermal zones and simulated in hourly time steps; simulated indoor climate data is then assessed using a thermal comfort index (e.g., PMV or operative temperature) and aggregated into a single-value long-term (e.g., annual or seasonal) metric.

Beyond the commonly used metrics found in building standards, research has introduced several alternative approaches. For example, based on continuous monitoring and post-occupancy evaluations in air-conditioned offices, Li et al. (2020) identified the percentage of time the daily temperature range exceeded a set threshold as a particularly effective index. This concept of temporal exceedance has also been explored by others (Borgeson & Brager, 2011; Nicol et al., 2009). Additional recommendations include evaluating the fraction of time within adaptive comfort limits (Albatayneh et al., 2019), using adaptive degree days (McGilligan et al., 2011), and tracking overheating degree-days (Estrella Guillén et al., 2019). In general, these metrics provide a broad annual assessment of thermal comfort and are instrumental in guiding key design decisions regarding the building's form and envelope, and in the design and sizing of HVAC systems.

However, despite the widespread adoption of standard thermal comfort workflows and metrics and continued research activity on identifying novel metrics, all presented methods share one substantial limitation, they typically capture only the temporal variability of thermal comfort while overlooking spatial differences within a thermal zone. This is a significant oversight, as is has been highlighted in (Mishra et al., 2016; Kramer et al., 2023).

We aim to introduce a new metric for the evaluation of building performance based on comfort: spatial thermal autonomy (sTA). Compared to traditional metrics, sTA offers two significant advantages: (a) it accounts for spatial thermal variability, ensuring a more comprehensive evaluation of comfort throughout a building, and (b) it quantifies how much a building is able to provide thermally comfortable conditions without the use of active sources of energy.

2. spatial Thermal Autonomy

Building on the initial concept proposed by Levitt et al. (2013) and a similar metric from the field of daylighting (Heschong et al., 2012), we define spatial Thermal Autonomy (sTA) as the "percentage of floor area where a thermal zone meets or exceeds a given thermal comfort criterion through passive means only". We suggest using both an hourly sTA index (see Equation (1)) and an annual single-value metric (Equation (2)). Since the sTA is calculated based on expected passive building performance and based on findings presented in this paper, we recommend using the adaptive comfort model to define the comfort criterion, but other comfort metrics could also be used.

$$sTA_t = \frac{\sum_{i=1}^{n} A_i \cdot 1_{\{i \in \text{comfort}\}}}{A_{total}} \tag{1}$$

$$sTA_{annual} = \frac{\sum_{t=1}^{T_{year}} 1_{\{\text{sTA}_t \geq 90\%\}}}{T_{\text{year}}} \tag{2}$$

Where:

- A_i is the area of grid point i.
- $1_{\{i \in \text{comfort}\}}$ is an indicator function that equals 1 if grid point i satisfies the comfort criterion, and 0 otherwise.
- A_{total} is the total area of the space.
- $1_{\{\text{sTA}_t \geq 90\%\}}$ is 1 if at hour t, the hourly spatial Thermal Autonomy sTA_t is greater than or equal to 90%, and 0 otherwise.
- T_{year} is the total number of hours in a year (usually 8760 h for a non-leap year).

Using sTA to guide building design captures both the temporal and spatial variability of dynamic indoor environments, offering deeper insights into building performance related to comfort. Traditional thermal comfort metrics tend to promote excessive energy use by prescribing narrow temperature ranges that frequently require active air conditioning systems (Arens et al., 2010). In contrast, sTA introduces a paradigm shift by prioritizing the evaluation and optimization of passive design strategies before resorting to active systems to mitigate uncomfortable conditions. This approach fundamentally shifts the focus to improving the passive performance of a building, prioritizing energy autonomy, and providing resilience to energy demands.

3. Case study

To evaluate spatial thermal autonomy for different thermal zone sizes and passive design levels, we performed a building performance simulation case study using EnergyPlus (Crawley et al., 2001) and Honeybee (Sadeghipour Roudsari & Pak, 2013).

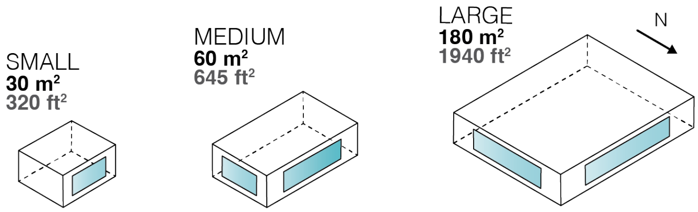
We focus on individual spaces in a typical office building in Sydney, Australia, and use two weather files: a typical meteorological year (TMY) and a future weather file for the year 2070 (RCP 4.5) provided by the Commonwealth Scientific and Industrial Research Organisation (CSIRO), Australia (Ren et al., 2021).

We modeled single thermal zones with typical office configurations using US Department of Energy (DOE) reference vintages and operational programs. To capture a range of building characteristics, we tested three zone sizes (30, 60, and 180 m^2) and three envelope construction scenarios — Standard, Medium, and Advanced — that differed in envelope properties such as U-values, window-to-wall ratios (WWR), and shading strategies (refer to Figure 2).

For each combination of zone size and construction standard, we performed an annual thermal simulation. In addition, using the same model and based on a spatial mapping algorithm developed by Mackey (2015), we computed spatially resolved mean radiant temperature (MRT) values on a 1-meter by 1-meter grid across the zones. We then ran the simulations model both passively to calculate spatial Thermal Autonomy (sTA) and with active conditioning to assess energy use for each scenario.

To assess the impact of different thermal comfort criteria on sTA (see Equation (2)), we evaluated three hourly indices: PMV, the adaptive model, and an empirical model. The empirical model is derived from field data in the ASHRAE Global Thermal Comfort Database II (Földváry Ličina et al., 2018; Parkinson et al., 2022). For this, we filtered the data to include only samples where the occupants expressed a thermal preference of 'No change' and identified the equivalent operative temperatures within the 10th to 90th percentile. This produced a comfort range of 21-28°C, which we applied as the target "comfort" range in the empirical model.

Furthermore, to evaluate spatial thermal heterogeneity in the scenarios tested, we developed a thermal heterogeneity index (THI). Similarly to sTA, we define two versions: THI_a or THI_{area} (Equation (3)), which captures the hourly heterogeneity throughout the zone, and THI_p or THI_{point} (Equation (4)), which summarizes the annual temperature variations at individual points on the grid. In both cases, we used the median value to derive a single-value index.



Setting(s)	**Definition**		
Climates	Sydney, Australia (Cfa), TMY & 2070 (RCP 4.5)		
Constructions	*ASHRAE 90.1 2019, IECC 2021*, Steel-framed*		
Program	*Small Office**		
HVAC system	IdealAir system, Air conditioned		
Passive Design Level	a) **Standard**	b) **Medium**	c) **Advanced**
Natural Ventilation?	No	Yes	Yes
Envelope	$U_{win} = 2.0$ $U_{wall} = 0.35$ $WWR = 0.4$ No shading	$U_{win} = 1.3$ $U_{wall} = 0.2$ $WWR = 0.3$ No shading	$U_{win} = 1.3$ $U_{wall} = 0.2$ $WWR = 0.3$ Ext. shading
AC* setpoint range *Heating - Cooling*	22-24°C	22-24°C	22-24°C

Figure 2: Overview of main settings for simulated case study scenarios: Construction properties, loads and schedules were based on Department of Energy (DOE) reference building information. (AC* - Air Conditioning (if used), WWR - Window-to-Wall-Ratio, U - U value in W/m²K)

$$THI_a = \text{median}\left(\max_n(T_{n,t}) - \min_n(T_{n,t})\right) \quad (3)$$

Where:

- $T_{n,t}$ is the temperature at spatial location n and time t.

- $\max_n(T_{n,t})$ is the maximum temperature across locations n at each hour t.
- $\min_n(T_{n,t})$ is the minimum temperature across locations n at each hour t.

$$THI_p = \text{median}\left(\max_t(T_{p,t}) - \min_t(T_{p,t})\right) \tag{4}$$

Where:

- $T_{p,t}$ is the temperature at point p and time t.
- $\max_t(T_{p,t})$ is the maximum temperature across time t (over the year) for each point p.
- $\min_t(T_{p,t})$ is the minimum temperature across time t (over the year) for each point p.

Lastly, to aid post-processing and analyze and visualize spatial indoor data, we developed an array-based Python module called comfortSIM. Custom functions in comfortSIM help to explore spatial thermal heterogeneity, calculate sTA based on various thermal comfort indices from the pythermalcomfort package (Tartarini & Schiavon, 2020), and evaluate the resilience of the building during passive operation by looking at the hourly temperature distribution across the thermal zone. The beta version of comfortSIM used for the analysis is openly accessible on GitHub.

4. Results

4.1. Spatial thermal heterogeneity

Our analysis revealed significant spatial variations in thermal conditions in different zone sizes and construction standards. As shown in Figure 3, all zones show temperature fluctuations throughout the year, with larger zones more susceptible to spatial thermal heterogeneity. This is evident from the heatmaps, which show more pronounced variations in mean radiant temperature (MRT) throughout the grid, and from the calculated THI_a, which was highest for the largest zones in each scenario.

We also observed that higher construction standards consistently reduced thermal heterogeneity, leading to smaller annual temperature variations for each zone size. Notably, envelope improvements such as better U values and especially added shading contributed to more uniform thermal conditions.

Thermal heterogeneity was particularly influenced by window positioning and size. The highest thermal variations occurred near the windows, especially in the medium-sized zone, where this effect resulted in consistently elevated THI_p values. This spatial gradient near windows highlights the importance of passive design strategies in controlling localized, potential discomfort on the perimeter.

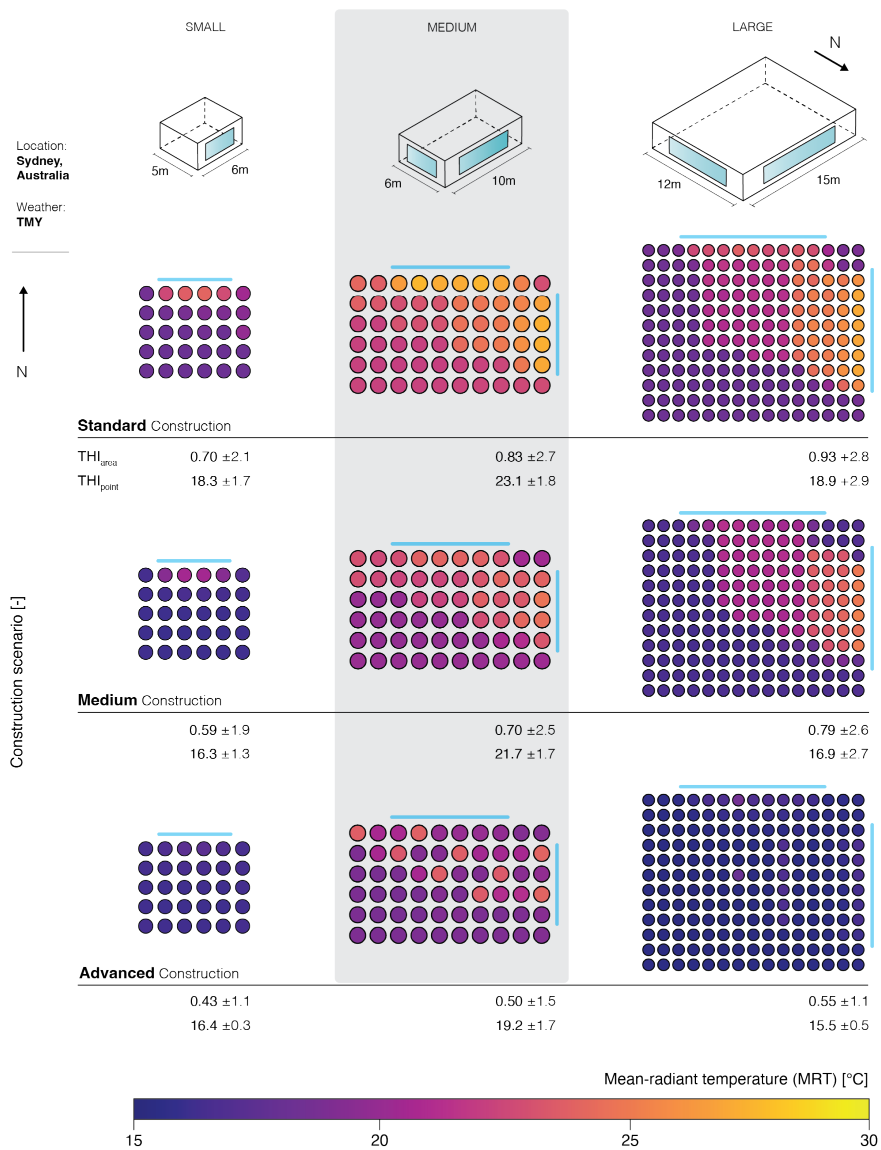
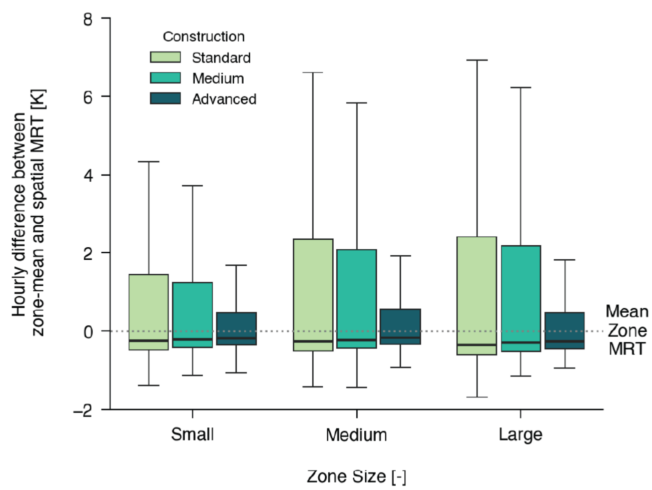


Figure 3: Annual mean radiant temperature variation and Thermal Heterogeneity Indices (THI) across different zone sizes and construction standards: Mid-sized to larger space show a higher spatial thermal heterogeneity with individual grid-points underlying annual temperature variations of up to 29 °C.

In Figure 4, we further explore the variation of indoor temperatures in the thermal zones. Here, we specifically compare the hourly temperature variation across the grid with the conventional standard of only evaluating zone conditions based on a single-point zone mean MRT in the zone center. The results show significant hourly variations between the mean zone MRT and individual grid points, as summarized in the table of percentile distributions in Figure 4. The combined insights from the box plot and table indicate that these deviations are most pronounced in zones with lower construction standards, where the differences between the mean zone MRT and spatial MRT are consistently higher across all percentiles, and in larger spaces, where the plot reveals a considerably wider range of deviations. This reinforces the finding that both zone size and envelope quality play a critical role in moderating thermal conditions.



Construction	min	2.5%	25%	50%	75%	97.5%	max	std
Standard	-1.0	-1.0	-0.5	-0.3	+2.0	+8.7	+8.7	+2.9
Medium	-0.8	-0.8	-0.5	-0.3	+1.8	+8.2	+8.2	+2.7
Advanced	-0.7	-0.7	-0.4	-0.2	+0.5	+5.5	+5.5	+1.4

Figure 4: Distribution of hourly differences between zone-mean MRT and spatially-resolved MRT: Simulating temperature only for the center of the zone (traditional method) overlooks significant thermal fluctuations within the space.

4.2. Impact of thermal comfort indices

In Figure 5.a, we present the distributions of the predicted sTA values hourly using three different thermal comfort indices: PMV, Adaptive, and an Empirical approach based on the ASHRAE Global Thermal Comfort Database II. Across all construction standards tested, the PMV index consistently resulted in the lowest hourly sTA values, with a nearly binary distinction between comfortable and uncomfortable conditions. In contrast, the Adaptive and Empirical models led to generally higher sTA predictions, reflecting a smoother and more gradual transition between low and high hourly sTA values. Moreover, as construction standards improved, we observed an increase in the ratio of higher sTA values, particularly when using the Adaptive and Empirical models. These indices appeared to be more sensitive to changes in envelope performance, capturing the impact of passive design measures more effectively than the PMV index.

Figure 5.b compares the annual sTA values calculated using the three thermal comfort indices, considering different thresholds of the area ratio (see Equation (2)). Similarly to the hourly analysis, the PMV index led the lowest annual sTA in all thresholds tested. Only when a low area ratio threshold of 50% was applied did the sTA values exceed 0.5. In comparison, the adaptive model again consistently predicted higher annual sTA values, independent of construction standards. An improvement in those further enhanced the sTA, with thresholds as high as 80% still producing sTA values above 0.6, and in the case of high standards, up to 0.8.

The empirical model generated the highest overall sTA values. For the highest construction standards, all area ratio thresholds resulted in sTA values above 0.9, indicating wider comfort ranges and a stronger alignment between passive design and thermal autonomy under this model.

4.3. Energy use and resilience

Figure 6.a illustrates the simulated cooling energy use, averaged across all zone sizes, as a function of construction standards and the two weather scenarios. We observed a significant increase in expected cooling energy demand for the 2070 weather scenario compared to the typical meteorological year (TMY). However, with better construction standards, the computed sTA_{annual} (based on operational hours) also increased, indicating improved thermal performance. Simultaneously, cooling energy use decreased as the construction standard improved, for both the TMY and 2070 scenarios. The reductions were substantial, with a drop of 46% for TMY and 37% for the

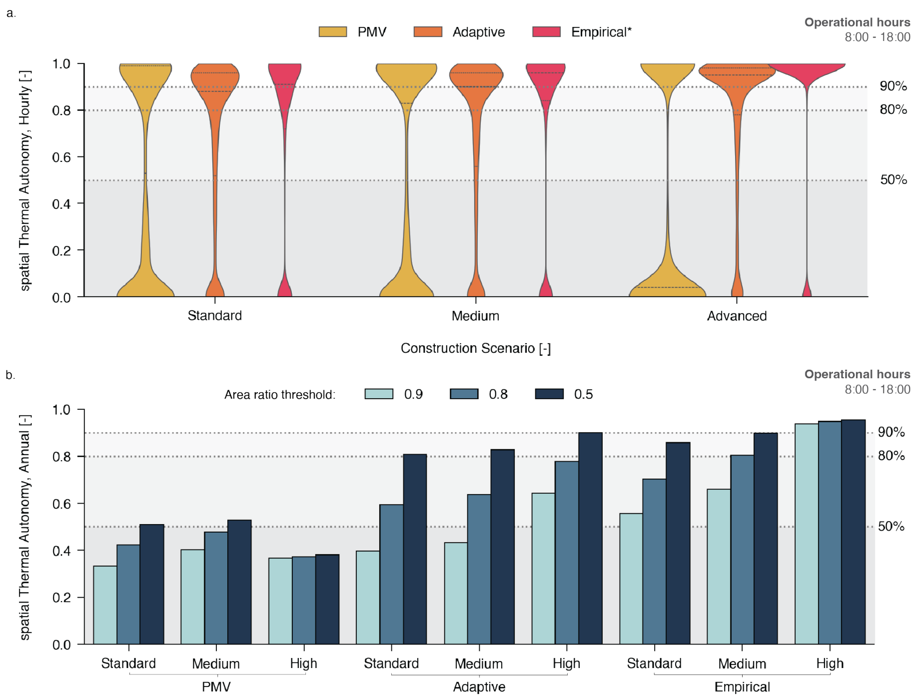


Figure 5: a) Hourly sTA distributions using PMV, Adaptive, and Empirical models for different passive design levels and medium zone size: Adaptive and Empirical model tend to predict higher sTA_{hourly} and are more sensitive passive design measures; b) Annual sTA comparison across comfort models for varying area ratio thresholds.: Adaptive and Empirical model consistently predict higher sTA_{annual} then PMV, independent of chosen area threshold.

2070 scenario, underscoring the potential for energy savings through enhanced building envelopes and higher sTA, even in future climate conditions.

In Figure 6.b, we compare the passive operative temperature distributions across the simulation grid for each construction standard and the weather scenario. A considerable portion of the operative temperature values exceeded 28 °C, particularly in the 2070 weather and standard construction scenarios. However, as the level of passive design elements improves, the range of operating temperatures narrows, and the proportion of elevated temperatures decreases.

For the advanced construction standard, at least 75% of the operative temperature values falls below 28 °C for both TMY and 2070, reflecting a significant impact of enhanced passive design on maintaining comfortable indoor conditions, even in future climates, and indicating improved thermal resilience when optimizing sTA.

Supplementary information, all underlying data and the Python code used for analysis and to generate figures are available on the public GitHub repository for this paper.

5. Conclusion

5.1. Summary of the findings

The spatial Thermal Autonomy (sTA) metric proposed in this paper offers several advantages that make it a valuable tool for optimizing thermal comfort and energy efficiency in building design. First, it leads to a more precise representation of indoor thermal comfort by capturing the spatial variability of thermal conditions. Unlike conventional metrics and workflows, which provide a single point temporal assessment of comfort over time, sTA offers a more nuanced and comprehensive view by accounting for spatial thermal differences within zones. Our findings reveal that larger zones experience more thermal heterogeneity, while buildings with higher construction standards consistently show reduced temperature variations and higher sTA values. This suggests that improving construction quality can mitigate local discomfort by creating awareness of existing thermal heterogeneity.

Moreover, using adaptive or field-data-driven comfort models resulted in higher sTA values and responsiveness to temperature changes compared to traditional PMV-based metrics. Based on our findings, the PMV lacks sensitivity to account for spatial differences. This could be caused by the significant number of PMV input parameters that are not directly affected by spatial temperature differences, especially clothing and metabolic rate, which are often assumed and treated as constants for long-term thermal comfort assessment. Moreover, PMV has been shown to have low prediction accuracy (Cheung et al., 2019). This is why we recommend using the adaptive model as the comfort criterion for sTA.

In addition, sTA encourages the use of passive design solutions and establishes a clear link between passive design quality, long-term thermal resilience, and energy performance. Our analysis showed that improved construction standards and higher

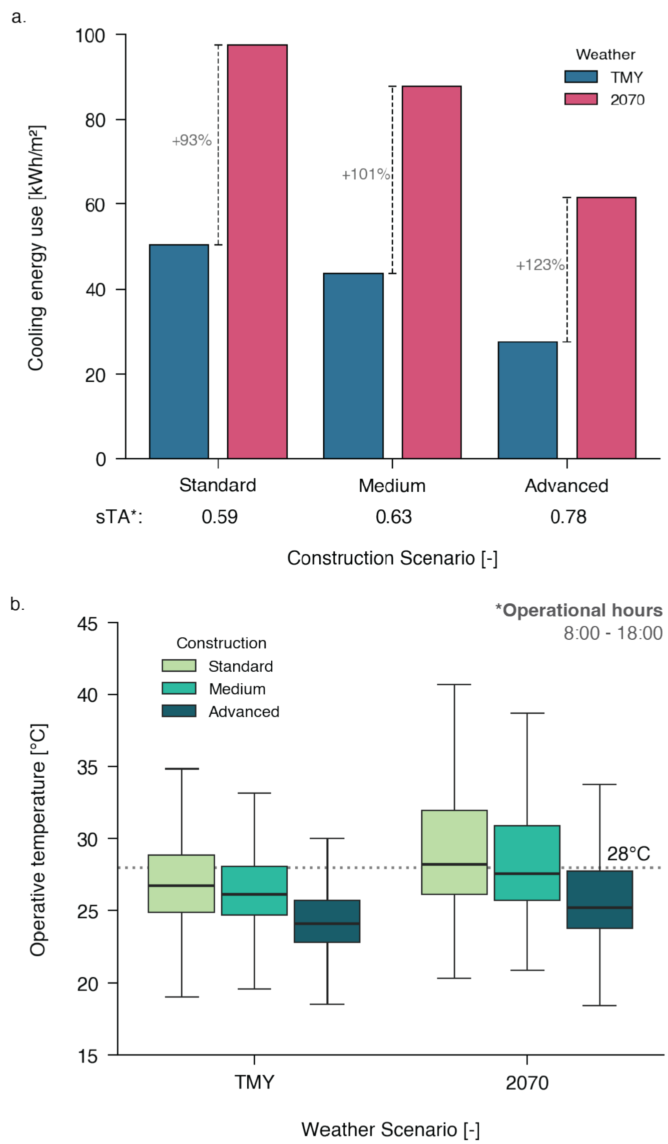


Figure 6: a) Simulated cooling energy use for different construction standards and weather scenarios (Adaptive model, area threshold of 0.8 for sTA$_{annual}$): Higher annual sTA correlates with lower energy use for both TMY and 2070 scenario; b) Passive operative temperature distribution across the grid for different construction standards and weather scenarios.: Higher annual sTA correlates with lower operative temperatures when free-running, indicating higher thermal resilience in both TMY and 2070 scenario.

sTA significantly reduced cooling energy demand, with energy savings of up to 46% under current climate conditions and 37% in future climate scenarios. This highlights the potential of sTA to support energy-efficient building design that adapts to both present and future climate challenges.

Furthermore, our results show that optimizing building design towards higher sTA can mitigate the effects of rising temperatures, both over time and across zones. The analysis of passive operative temperature distributions highlighted that the design guided by sTA contributes to maintaining comfortable indoor environments, even under more extreme future weather conditions. In practice, this might improve building resilience and shows that occupants can remain comfortable with minimal reliance on active conditioning systems in passively well-designed buildings.

5.2. Implications for building design

The spatial Thermal Autonomy (sTA) metric offers a novel approach to improving thermal comfort and energy efficiency in building design. By capturing spatial variability, sTA enables a more accurate representation of indoor thermal conditions compared to conventional, PMV-based metrics, which only assess single-point comfort over time. This enhanced representation allows for better identification and management of thermal heterogeneity, particularly in larger zones or areas with high exposure, such as near windows, and can help mitigate potential local discomfort. Buildings with higher sTA values consistently demonstrated reduced temperature variability, particularly when construction standards were improved, which suggests that enhancing building envelopes can effectively address these comfort issues.

In addition to optimizing comfort, sTA encourages passive design strategies that reduce energy demand. Prioritizing elements such as improved insulation, shading, and optimal window placement can lead to significant reductions in cooling energy use. Our findings show that buildings optimized for higher sTA values experienced energy savings of up to 46% in current climates and 37% under future climate scenarios. This strong correlation between sTA and energy performance underscores its utility in guiding long-term energy-efficient design.

sTA also offers a forward-looking tool to address future climate challenges. By simulating spatial thermal heterogeneity, sTA helps architects and engineers assess how a building will perform under extreme weather conditions, supporting decisions that enhance resilience. Buildings designed with higher sTA values showed better performance in maintaining comfort during future climate scenarios, demonstrating the potential to reduce reliance on active conditioning systems and improve overall thermal resilience.

The emphasis of the metric on passive design strategies and spatial variations aligns well with the growing use of personal comfort systems (PCS), such as fans and localized heating solutions. sTA highlights areas where personal comfort systems can be effectively integrated into building operations, helping to minimize energy use while maintaining occupant comfort in spaces with varying thermal conditions.

In general, our findings suggest that by incorporating sTA early in the design process, building projects can effectively balance thermal comfort, energy efficiency, and resilience. This holistic approach to design addresses current and future climate challenges and promotes indoor environments that are adaptive, sustainable, and comfortable over time and space.

5.3. Limitations & future work

While this study demonstrates the potential of spatial Thermal Autonomy (sTA) in optimizing thermal comfort and energy efficiency, there are several limitations that need to be addressed in future research.

Firstly, the analysis focused on a specific building typology and climate zone — namely, Sydney, Australia. To broaden the applicability of sTA, future studies should investigate different building types and climates to ensure that the metric is robust and adaptable in various contexts.

Secondly, although sTA provides a spatially resolved comfort metric, it relies heavily on thermal simulations, which may not fully capture the complexities of dynamic occupant behavior. Incorporating better models of adaptive behaviors into future studies would provide a more comprehensive understanding of comfort and further validate the use of sTA in diverse building environments.

Finally, this study separately assessed passive and active conditioning systems. Investigating hybrid systems and personal comfort systems in relation to sTA could provide valuable insights into how these approaches interact to enhance thermal autonomy, comfort, and energy efficiency, especially in future climate scenarios.

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