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Spatial and Temporal Variation of Indoor Environmental Quality and Occupancy across a Five-Node Office Sensor Network

*[1]Ahmed Mohammed, [1]Mustapha Ismail, [1]Abdulhamid Ibrahim Nafada, [1]Muhammad Dawaki and [2]Mohammed Ajuji

[1]Department of Computer Science, Gombe State University, Gombe, Nigeria.
[2]Department of Physics, Gombe State University, Gombe, Nigeria.

*Corresponding authors' email: ahmedmhd686@gsu.edu.ng
ORCID iD: https://orcid.org/0009-0009-1394-1719

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ABSTRACT
Indoor environmental quality (IEQ) and occupancy are usually characterized for a single room, yet real buildings comprise many zones that may differ substantially, with direct consequences for zoned heating, ventilation and air-conditioning control. This study quantified the spatial and temporal variation of IEQ and occupancy across a five-node, low-cost sensor network deployed in five offices. Each node logged temperature, humidity, illuminance, motion and a fused occupancy state every minute, yielding 56,173 validated records over 8 days, from which the apparent temperature (heat index) and thermal-comfort compliance were derived. Differences between offices were tested with one-way analysis of variance, the non-parametric Kruskal–Wallis test and Tukey honestly-significant-difference post-hoc comparisons, and the offices were grouped by Ward hierarchical clustering. All four variables differed significantly between offices ($p < 0.001$). Temperature differed in 10 of 10 pairwise comparisons, mean temperature spanned 30.5–31.1 °C and occupancy ranged from 54% to 75% of the time. Temperature and humidity were strongly anti-correlated ($r = -0.78$). No office met the conventional comfort envelope for an appreciable share of the time, and the heat index exceeded the caution threshold almost throughout. Clustering separated one low-occupancy office from the rest. The results show that single-zone assumptions are unsafe and that spatially resolved monitoring is required for effective, zone-aware building management.

Keywords: Indoor Environmental Quality, Occupancy, Sensor Network, Smart Buildings, Spatial Variability

INTRODUCTION

Buildings consume close to 40% of global energy, much of it for heating, ventilation, air-conditioning (HVAC) and lighting that maintain indoor environmental quality (IEQ) (Pérez-Lombard et al., 2008). IEQ principally temperature, humidity and illuminance governs both energy use and occupant comfort, productivity and health (de Dear & Brager, 2002; Yang et al., 2014), and occupancy is the most actionable determinant of when conditioning is actually needed (Gunay et al., 2013; Hong et al., 2016). Low-cost Internet-of-Things sensing now makes it feasible to measure these quantities continuously and at scale (Adoga et al., 2025; Metallidou et al., 2020; Minoli et al., 2017; Mohammed et al., 2026; Verma et al., 2019).

Most of the monitoring and occupancy studies, however, characterize a single room or zone (Candanedo & Feldheim, 2016; Sahar et al., 2026; Sowmya et al., 2021; Usman et al., 2025). Real buildings comprise many zones whose orientation, use, equipment and occupancy schedules differ, so a building-wide average can conceal substantial spatial variation. This matters because modern control is increasingly zoned and occupant-centric: if zones differ, a single setpoint or schedule is necessarily suboptimal (Esrafilian-Najafabadi & Haghighat, 2021; Naylor et al., 2018; Park & Nagy, 2018). Reviews of occupancy measurement and building energy management repeatedly note the scarcity of multi-zone, comparative field evidence (Chen et al., 2018; Salimi & Hammad, 2019; Sun et al., 2020), and the need is sharper in warm, humid, naturally conditioned settings that are under-represented in the literature (Halhoul Merabet et al., 2021; Shaikh et al., 2014).

This study addresses that gap by quantifying, with formal statistical testing, how IEQ and occupancy vary across five simultaneously monitored offices served by a common low-cost sensor network (Dinmohammadi et al., 2025; Rocha et al., 2015). The objectives are to: (i) characterize and compare the distributions of temperature, humidity, illuminance and apparent temperature across the offices; (ii) test whether the differences are statistically significant and quantify their magnitude; (iii) compare occupancy and diurnal rhythms between offices; and (iv) group the offices by their environmental and occupancy signatures to reveal typologies relevant to zoned control. Establishing the extent of inter-zone heterogeneity provides the evidence base for spatially resolved, occupant-centric building management (Tien et al., 2022; Zhang et al., 2022).

MATERIALS AND METHODS

Sensor Network and Data

Five low-cost edge nodes, each combining an SHT45 temperature–humidity sensor (Sensirion AG, 2022), a VEML7700 ambient-light sensor (Vishay Semiconductors, 2019) and a passive infrared motion sensor on a Raspberry Pi, were deployed one per office and sampled every 60 s, logging temperature (°C), relative humidity (%), illuminance (lux), a binary motion flag and a fused occupancy state. After parsing, de-duplication and validation, 56,173 records spanning 8 days were retained; short, isolated gaps in illuminance were linearly interpolated.

Derived Comfort Indices

Thermal comfort was assessed against the conventional cooling-season envelope (23–26 °C, 30–60% relative humidity) (ASHRAE, 2017; Schiavon et al., 2014). The apparent temperature (heat index, HI) was computed from temperature T (°F) and relative humidity φ (%) using the Rothfusz regression (Rothfusz, 1990) (Eq. 1), converted to °C, with HI > 27 °C taken as the onset of heat caution:

$$HI = c_1 + c_2T + c_3\varphi + c_4T\varphi + c_5T^2 + c_6\varphi^2 + c_7T^2\varphi + c_8T\varphi^2 + c_9T^2\varphi^2 \quad (1)$$

where $c_1 \ldots c_9$ are the standard coefficients.

Statistical Analysis

Per-office distributions were summarized by mean, standard deviation and quartiles. Differences between offices were tested for each variable with one-way analysis of variance (ANOVA) and the non-parametric Kruskal–Wallis H test; effect size was reported as eta-squared (η^2). Pairwise differences were localized with Tukey honestly-significant-difference (HSD) tests at $\alpha = 0.05$. Pearson correlations quantified inter-variable coupling. Finally, the offices were grouped by Ward hierarchical clustering on standardized mean temperature, humidity, illuminance, occupancy and motion, to reveal environmental–occupancy typologies (Chen et al., 2018; Saha et al., 2019). Analyses used Python (pandas, SciPy, statsmodels, scikit-learn).

RESULTS AND DISCUSSION

Environmental Conditions Differ Between Offices

All five offices were warm and humid, but their distributions differed markedly (Figure 1, Table 1). Mean temperature ranged from 30.5 °C to 31.1 °C and mean humidity from 66.9% to 70.5%, while median illuminance varied several-fold, reflecting differing daylight exposure. One-way ANOVA confirmed highly significant between-office differences for temperature ($F = 802$, $p < 0.001$, $\eta^2 = 0.05$), humidity ($F = 1351$, $p < 0.001$), illuminance ($F = 160$, $p < 0.001$) and heat index ($F = 643$, $p < 0.001$), corroborated by the Kruskal–Wallis test (all $p < 0.001$; Table 2). Tukey HSD localized the temperature differences to 10 of 10 office pairs, confirming that the heterogeneity is pervasive rather than driven by a single outlier.

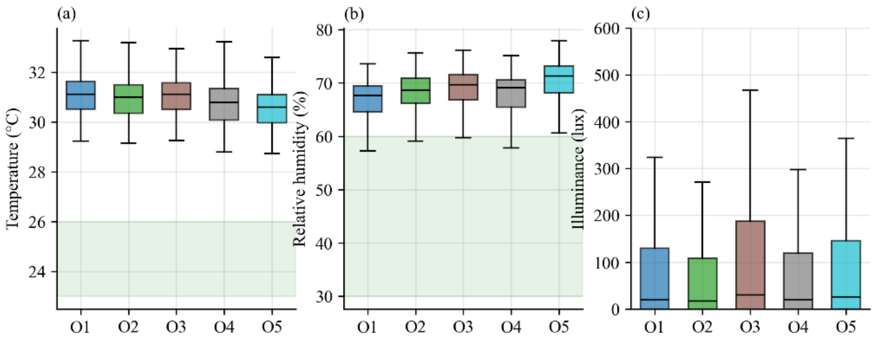

Figure 1: Distributions of (a) Temperature, (b) Humidity and (c) Illuminance by Office; Shaded Bands Mark the ASHRAE Comfort Ranges

Table 1: Per-Office Descriptive Statistics (Mean ± SD) and Occupancy

Office	Temp (°C)	RH (%)	Light (lux, median)	Heat index (°C)	Occupied (%)
O1	31.1 ± 0.7	66.9 ± 3.8	20	36.9	75
O2	31.0 ± 0.8	68.2 ± 3.8	17	36.9	54
O3	31.0 ± 0.7	69.0 ± 3.9	30	37.3	58
O4	30.9 ± 1.1	67.8 ± 4.5	20	36.6	66
O5	30.5 ± 0.7	70.5 ± 4.1	26	36.5	66

Table 2: Between-Office Difference Tests (ANOVA and Kruskal–Wallis)

Variable	ANOVA F	p (ANOVA)	Kruskal–Wallis H	p (KW)	η^2
Temp	802	<0.001	3304	<0.001	0.054
Hum	1351	<0.001	5869	<0.001	0.088
Light	160	<0.001	444	<0.001	0.011
HI	643	<0.001	2560	<0.001	0.044

Diurnal Rhythms and Occupancy Vary Spatially

The offices also differed in their daily rhythms (Figure 2). Temperature peaked in the afternoon in every office but with office-specific amplitude, and occupancy profiles were distinct in both level and timing. Aggregate occupancy ranged from 54% (Office 2) to 75% (Figure 3), and the motion-activity rate varied correspondingly. The office–hour occupancy heatmap (Figure 4) shows that peak-use windows are not aligned across offices, which is precisely the condition under which a single building-wide HVAC/lighting schedule wastes energy in some zones while under-serving others (Ghahramani et al., 2016; Mirakhorli & Dong, 2016; Pang et al., 2021).

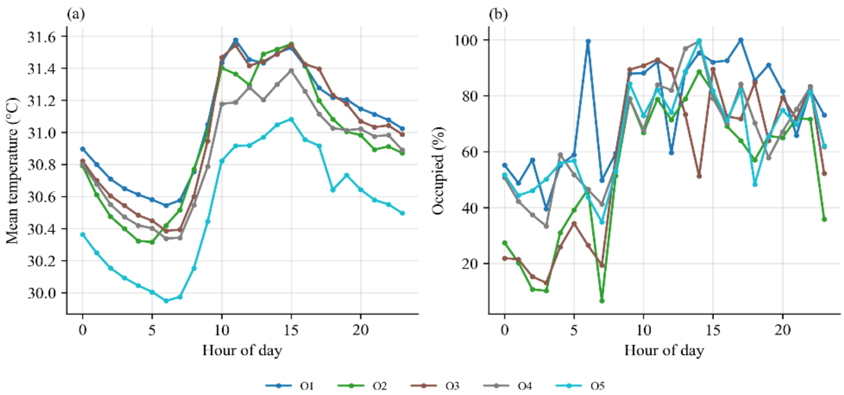

Figure 2: Diurnal Profiles by Office: (a) Mean Temperature and (b) Occupancy Probability Versus Hour of Day

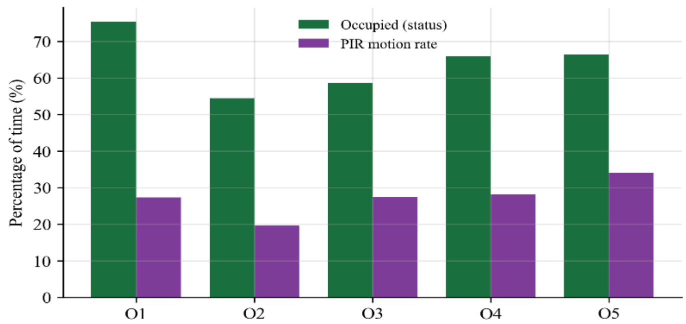

Figure 3: Aggregate Occupancy and PIR Motion-Activity Rate by Office

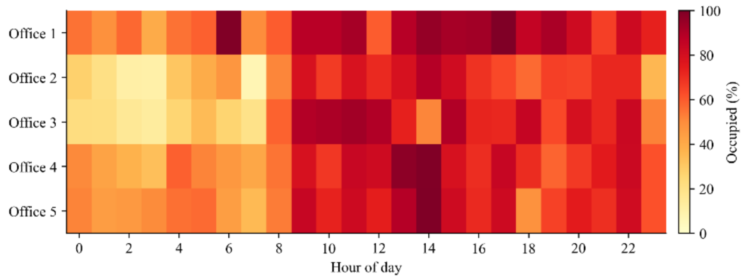

Figure 4: Occupancy Probability by Office and Hour of Day, Showing Misaligned Peak-Use Windows Across Zones

Thermal Comfort and Variable Coupling

No office met the combined comfort envelope for an appreciable fraction of the time, and the heat index exceeded the 27 °C caution threshold almost throughout in every office (Figure 5), confirming a building-wide comfort deficit on top of the spatial variation. Temperature and humidity were strongly anti-correlated across the pooled data (r = -0.78; Figure 6), the expected psychrometric signature, whereas illuminance and occupancy were only weakly coupled, indicating that lighting was driven more by daylight and fixed schedules than by presence (Candanedo & Feldheim, 2016; Rafsanjani et al., 2020).

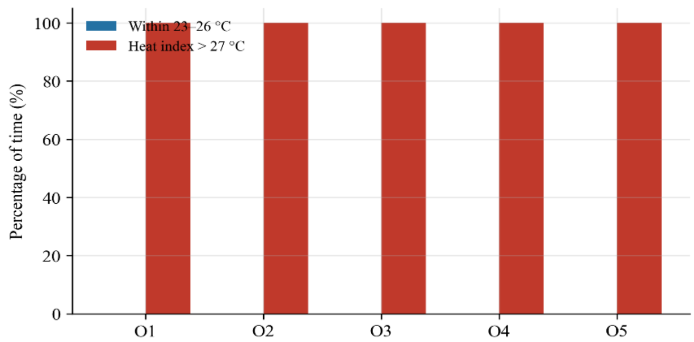

Figure 5: Thermal-Comfort Compliance by Office: Time Within 23–26 °C Versus Time with Heat Index Above 27 °C

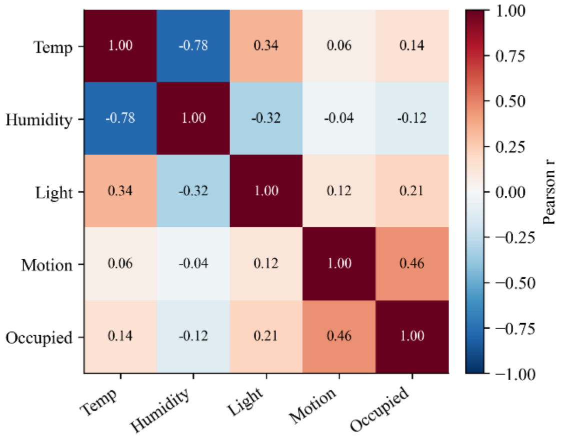

Figure 6: Pearson Correlation Matrix of Environmental and Occupancy Variables (Pooled Across Offices)

Office Typologies

Ward clustering on the standardized environmental–occupancy signatures separated the offices into two groups (Figure 7): a majority cluster of comparable, higher-occupancy rooms and a distinct low-occupancy, low-activity office (Office 5). This typology is actionable: zones in different clusters warrant different control strategies and commissioning priorities, and the outlier office is a candidate for schedule revision or re-purposing (Naylor et al., 2018; Salimi & Hammad, 2019). The finding operationalizes the central message of the study that spatially resolved monitoring exposes structure that single-zone studies cannot.

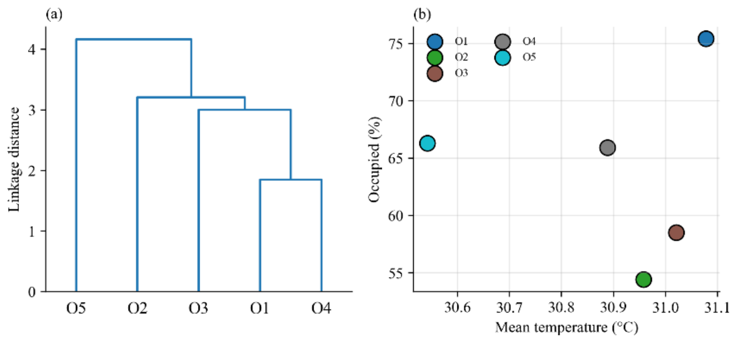

Figure 7: (a) Ward Dendrogram of Offices and (b) Office Positioning in the Temperature–Occupancy Plane, Separating One Low-Occupancy Office

Taken together, the results demonstrate statistically significant, pervasive spatial heterogeneity in both IEQ and occupancy across nominally similar offices in the same building. This challenges the single-zone assumption common in the literature (Candanedo & Feldheim, 2016; Sun et al., 2020) and supports zone-aware, occupant-centric control and commissioning (Esrafilian-Najafabadi & Haghighat, 2021; Park & Nagy, 2018; Tien et al., 2022). The short, single-site observation window is a limitation; longer, multi-building campaigns and the integration of these signatures into closed-loop control are important next steps.

CONCLUSION

Across a five-node office sensor network logging 56,173 minute-resolution records, indoor environmental quality and occupancy varied significantly between offices: all measured variables differed at $p < 0.001$, temperature differed in 10 of 10 office pairs, occupancy ranged from 54% to 75%, and clustering isolated one low-occupancy office. A building-wide comfort deficit (heat index above caution almost throughout) coexisted with this spatial variation. The findings show that single-zone characterizations are unsafe generalizations and that spatially resolved, low-cost monitoring is necessary for effective zone-aware building management. Limitations include the short, single-site window and the use of a firmware-derived occupancy label; future work will extend the campaign across seasons and buildings and couple the zone typologies to closed-loop HVAC and lighting control.

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