Optimising Sensor Deployment in Open-Plan Offices Using Ordinary Kriging for Spatial Indoor Temperature Mapping

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SUMMARY

This study demonstrates the potential of geostatistical spatial interpolation, specifically ordinary kriging, to support thermal comfort mapping in complex open-plan office environments using a limited number of sensors. By analysing temperature distributions across contrasting climatic seasons and occupancy states, the research highlights how spatial coherence, interpolation accuracy, and uncertainty are strongly influenced by operational conditions and internal heat dynamics. The findings show that while kriging is effective for reconstructing broad spatial thermal patterns, its performance is constrained under occupied conditions where short-range variability and localised effects dominate. Variogram analysis further reveals that indoor thermal environments are characterised by short spatial correlation lengths, underscoring the importance of both sensor density and strategic placement. Overall, the work provides a methodological framework for interpreting spatial thermal data in buildings, offering insights into how interpolation-based approaches can be applied sensibly to support indoor environmental assessment while acknowledging their limitations for comfort-critical diagnostics.

KEYWORDS

Ordinary Kriging, Sensor Distribution, Indoor Temperature Mapping, Thermal Comfort

1 INTRODUCTION

This research deals with the challenge of thermal comfort mapping in open-plan office spaces. Following the SARS-CoV-2 (COVID-19) pandemic and the widespread adoption of hybrid working arrangements, increased emphasis has been placed on indoor air quality and thermal comfort as key factors influencing office space utilisation. Recent findings by Suliman et al. (2023) indicate that occupants experiencing thermal discomfort report it as a critical factor in their decision to work from home rather than attend the office, which ultimately contribute to energy waste in underutilised or vacant spaces.

Thermal comfort, as widely reported in the literature, is typically quantified using empirical models that incorporate personal preferences and subjective factors, which can vary considerably between individuals (Fanger, 1970; de Dear and Brager, 1998). In contrast, indoor environmental monitoring commonly relies on temperature measurements collected at a limited number of locations, effectively representing thermal conditions at a macroscale. Such an approach may overlook local thermal variations in high or multi-occupancy spaces arising from factors such as HVAC configuration, internal heat gains, and building envelope heat transfer characteristics. However, to monitor these micro-conditions, many sensors are required to accurately measure the IEQ factors within a space, which carries many disadvantages such as initial cost and poor space utilisation (Jin et al, 2018).

Spatial interpolation methods have been increasingly applied to model and visualise indoor air quality (IAQ) in open-plan spaces. Yu et al. (2021) evaluated a range of spatial interpolation techniques and found that methods such as inverse distance weighting with a power function, kriging, minimum curvature, and modified Shepard's method are well suited for indoor air temperature mapping in buildings. Similarly, Choi et al. (2022) investigated the performance of spatial interpolation methods for various indoor environmental quality (IEQ) parameters, including volatile organic compounds (VOCs) and CO_2, under occupied conditions, demonstrating that these methods can effectively visualise internal environmental conditions. However, several limitations were identified, including short monitoring periods and the lack of consideration of varying climatic conditions. In addition, the reviewed studies were limited to single-floor open-plan spaces, with more complex multi-level geometries not addressed. Accordingly, the present study extends existing research by evaluating the performance of spatial interpolation methods across different climatic seasons and occupancy conditions within a multi-plane indoor environment.

2 MATERIALS/METHODS

2.1. The Case Study and Raw Data Collection

The case study is a Grade II listed university building located at the University of Oxford, UK, and is primarily used for educational purposes, including lecture rooms, common areas, laboratories, and office spaces for researchers and staff. For the purposes of this investigation, a former 20 x 11m chemical laboratory that was recently refurbished and converted into an open-plan office was selected. This space was chosen due to a recent retrofit aimed at improving both energy performance and indoor environmental quality, as well as being one of the most utilised spaces by occupants. The refurbished office is designed to accommodate approximately 40 occupants and comprises a combination of open-plan work areas and enclosed offices arranged over two levels, including an open mezzanine. The space is heated using four electric heaters located in the open mezzanine as depicted in figure 1

For the local temperature monitoring, the space was divided into six zones each containing a cluster of desks with the purpose of picking up the microclimatic temperature conditions in these zones. The sensor used to measure and log the temperature was a Hobo MX1104 which has a temperature range of -20° to 70°C and a measuring accuracy of ±0.21°C from 0° to 50°C. temperature readings were recorded every five minutes for a period of 10 months between November 2023 and September 2024. However, for the purpose of this investigation only data from the coldest month (December 2023), and the warmest month (August 2024) will be modelled, focusing only on the temperature extremes.

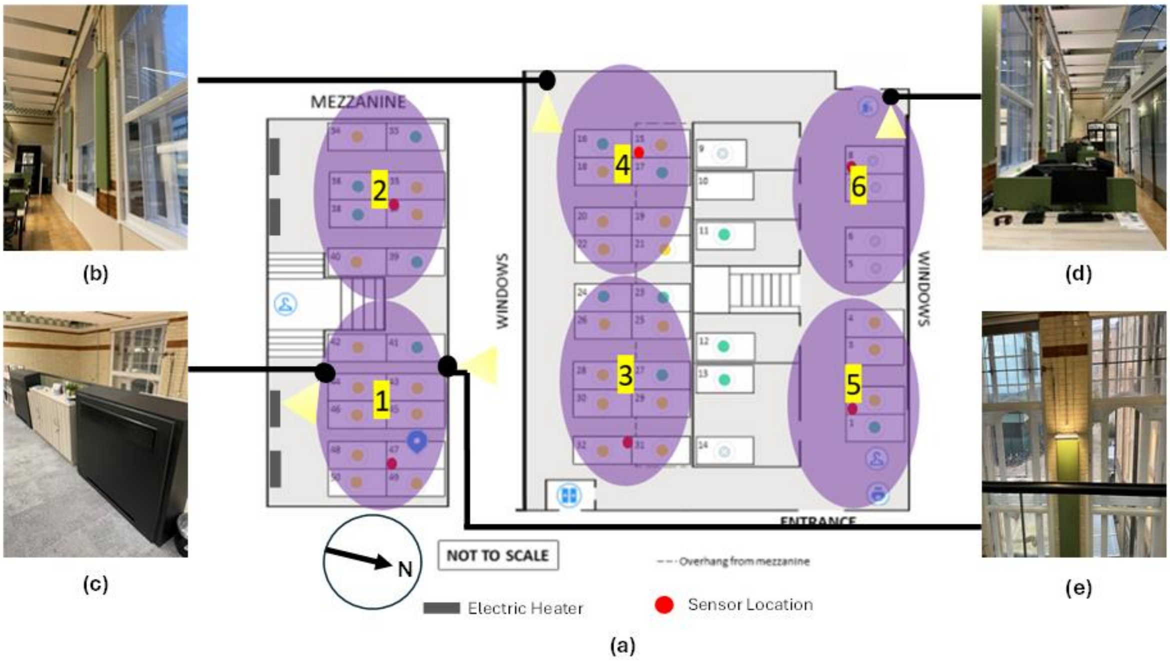


Figure 1. A visualisation of the case study including a) a floor plan with the marked location of sensors. b) an East facing view showing the south facing façade and zones 3 and 4. c) A visualisation of the electric heaters as located in the Mezzanine. d) an East facing view showing the north façade and zones 5 and 6. e) A view of the north facing façade from the mezzanine.

2.2. Ordinary Kriging and Variogram Development

Ordinary kriging remains one of the most used methods for spatial interpolation, it provides an estimate at unmeasured locations based on the spatial structure derived from available observations. In contrast to other less sophisticated approaches such as inverse distance weighting and linear regression, kriging incorporates spatial correlation among sampled points when estimating values across a spatial structure. The method relies on the observed spatial arrangement of the data and additionally produces an estimate of uncertainty for each prediction.

Ordinary kriging provides an estimate of the value of a variable at an unsampled location $\boldsymbol{x_0}$ as a weighted linear combination of measured values at surrounding locations, which can be calculated using equation 1:

$$Z(x_0) = \sum_i \lambda_i Z(x_i) \tag{1}$$

Where: $\boldsymbol{Z(x_0)}$ is the calculated estimate value at location $\boldsymbol{x_0}$. $\boldsymbol{Z(x_i)}$ represents the measured value at location $\boldsymbol{(x_i)}$, and $\boldsymbol{\lambda_i}$ is the kriging weight that is applied to each measured value. The weights are applied so each of the estimator remains unbiased, and variance estimation is minimised.

When using ordinary kriging, the kriging weights can be obtained by solving a series of linear equations that incorporates the spatial covariance structure of the data. These equations are note as follows (equations 2-3):

$$\sum_i \lambda_i C(x_i, x_j) + \mu = C(x_i, x_0) \;\; for\ all\ i \tag{2}$$

$$\sum_i \lambda_i = 1 \tag{3}$$

Where $\boldsymbol{C(x_i, x_j)}$ is the covariance between measured values at location $\boldsymbol{x_i}$ and $\boldsymbol{x_{j,}}$' while $\boldsymbol{C(x_i, x_0)}$ is the covariance between the measured values location and the prediction location. $\boldsymbol{\mu}$ denotes the LeGrange multiplier which implements the unbiasedness limits.

Furthermore, the spatial covariance required for solving Kriging equations is derived from the variogram (also referred to as semi-variance), which defines the spatial dependence of the variable as a function of the distance separating the measured observation points from the sensors. In this study, a spherical variogram model was employed and can be expressed by equation 4 as follows:

$$\gamma(h) = nugget + psill\left[1.5\left(\frac{h}{range}\right) - 0.5\left(\frac{h}{range}\right)^3\right] \quad (4)$$

Where $\boldsymbol{\gamma(h)}$ is the semivariance at separation distance $\boldsymbol{h}$, the ***nugget*** accounts for unresolved microscale variation and potential measurement error. The partial sill **(*psill*)** represents the portion of the total variance that is described by spatial correlation among the measured observations, by quantifying how much of the variability in the data can be attributed to the spatial arrangement rather than measurement or random errors. The ***range*** highlights the distance beyond which spatial correlation becomes insignificant. Therefore, the fitted variogram model was then ran to calculate the covariance values required for the ordinary kriging interpolation.

3 RESULTS AND DISCUSSIONS

3.1. Kriging and Thermal Mapping

Comparison of the occupied (08:00–18:00) and unoccupied (18:00–08:00) hours validation results for August (warmest month) as depicted in figure 2 demonstrates a clear reliance of the spatial model performance on operational conditions. During occupied hours, prediction accuracy is notably reduced (RMSE = 0.89 °C, MAE = 0.66 °C, R^2 = 0.47), with a model tendency to overestimate the temperatures at the higher end. This degradation reflects increased spatial and temporal heterogeneity driven by internal processes such heat gains, occupant behaviour, and localised HVAC system patterns, which cannot be fully determined by spatial interpolation based solely on fixed sensor locations. However, during unoccupied hours, the indoor thermal behaviour becomes more coherent and temporally stable, leading to noticeably improved predictive performance (RMSE = 0.59 °C, MAE = 0.56 °C, R^2 = 0.83). Under these conditions, temperature distributions are dominated by envelope heat transfer and thermal mass effects, which produce smoother gradients that are more responsive to kriging-based spatial analytical models.

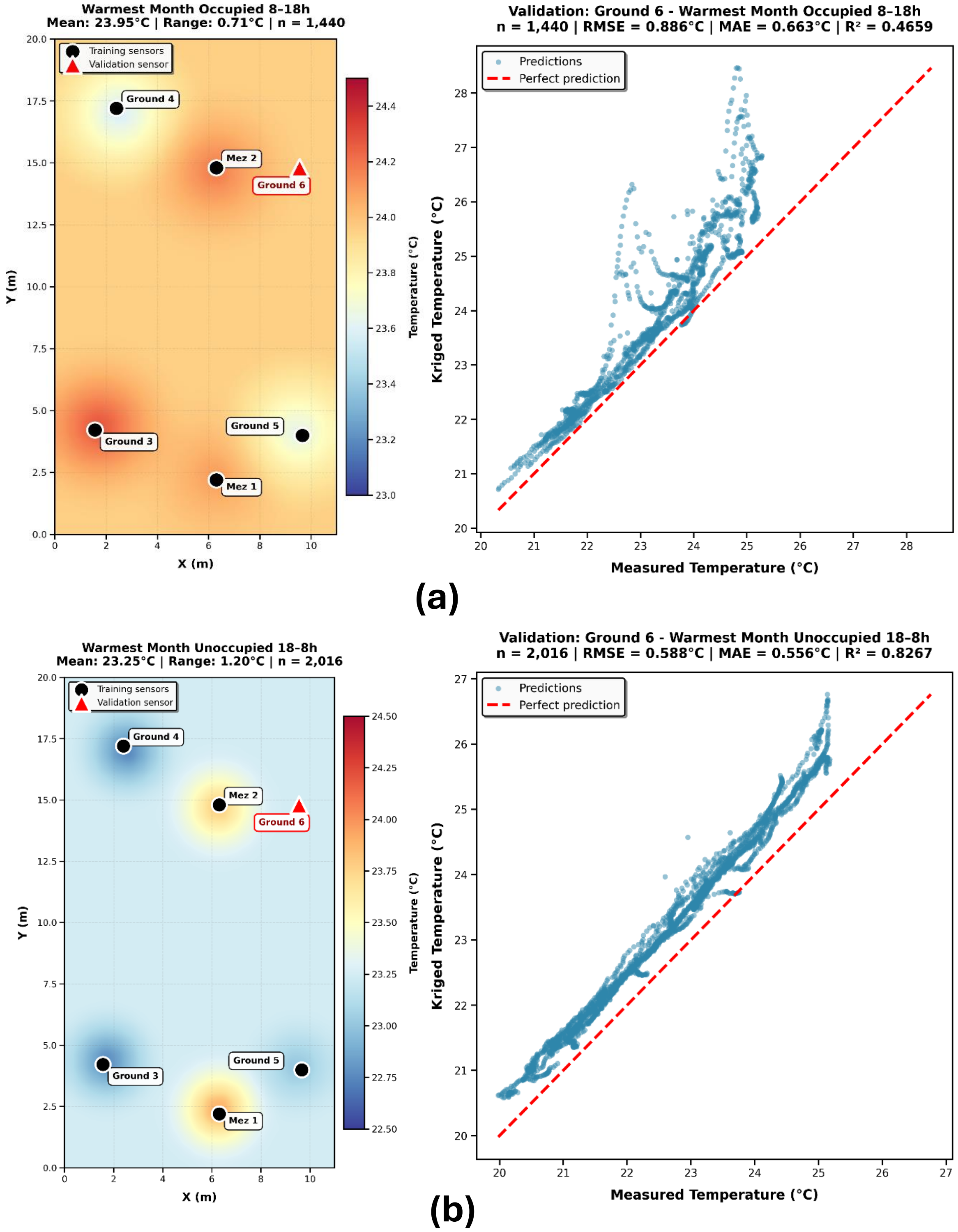
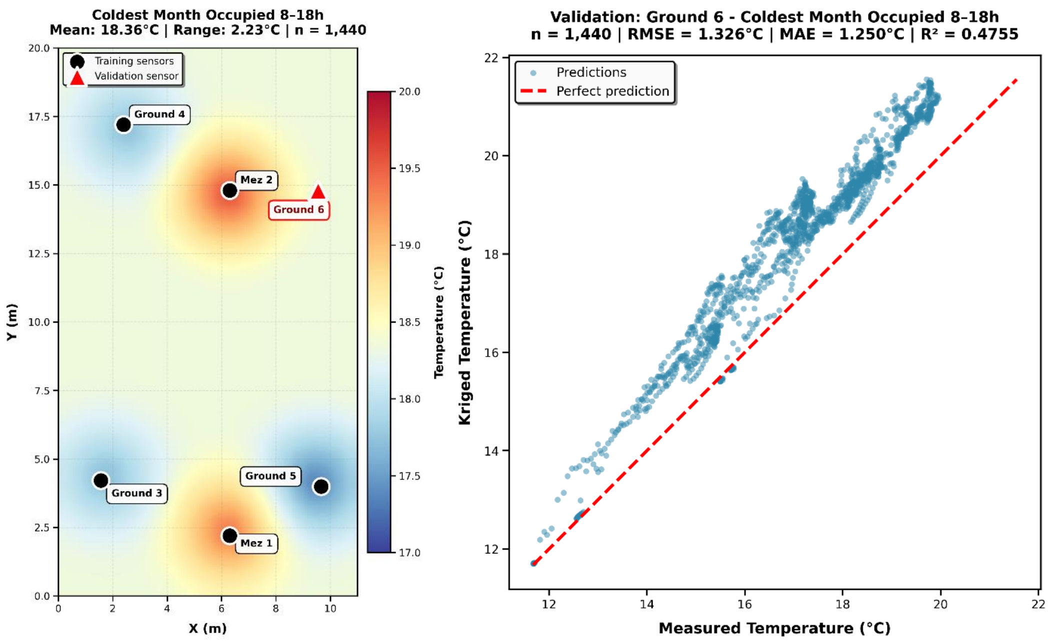
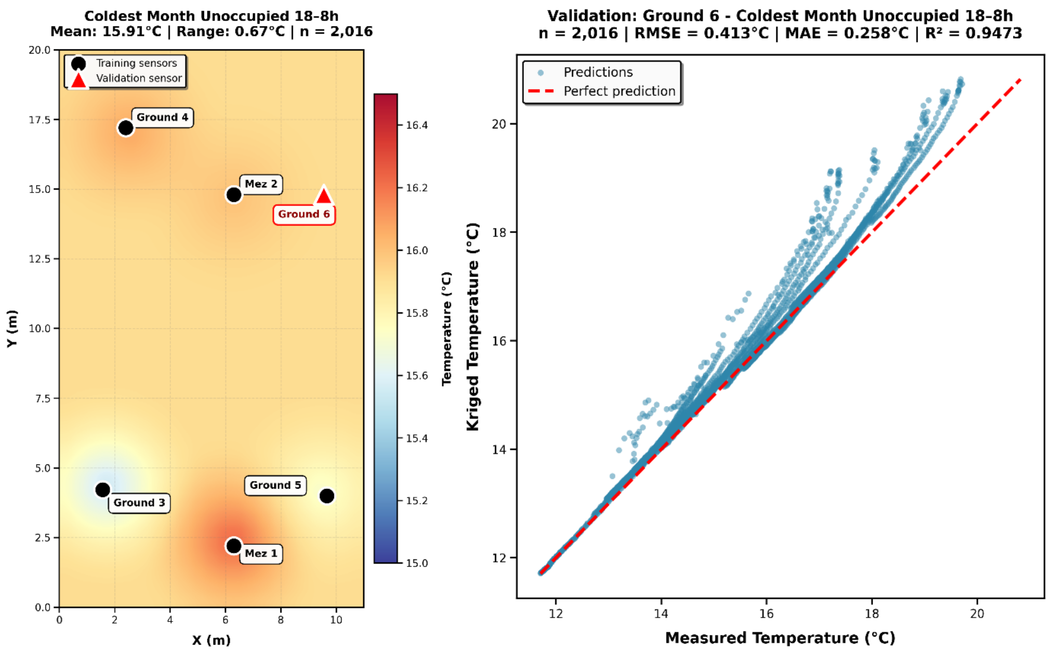


Figure 2. The temperature distribution map of the space and the validation plot for the kriged vs measured temperature for the validation (ground 6) sensor for the month of August during: **a.** occupied hours. **b**. non-occupied hours.

A similar reliance on occupancy is observed during the coldest month (December), as shown in Figure 3, but with more pronounced spatial contrasts and larger prediction errors during occupied periods. Under occupied daytime conditions, indoor temperatures exhibit stronger spatial gradients, with warmer regions concentrated near mezzanine zones and cooler pockets near ground-level peripheral areas, mainly driven by heating system distribution (close to the mezzanine), buoyancy-induced stratification, and glazing heat loses on the periphery of the room adjacent to the ground floor sensor location. These mechanisms further reduce spatial coherence and increase short-term variability, resulting in only moderate interpolation performance (RMSE ≈ 1.33 °C, $R^2 \approx 0.48$), which is poorer than that observed during occupied summer conditions. In contrast, during unoccupied nighttime periods, internal heat gains and airflow disturbances are minimal and thermal behaviour is dominated by the thermal mass storage and envelope heat transfer, producing a more uniform and temporally stable temperature field. Consequently, kriging performance improves substantially (RMSE ≈ 0.41 °C, $R^2 \approx 0.95$), indicating that spatial interpolation is highly reliable when indoor thermal conditions are governed primarily by steady-state heat transfer mechanisms.



(a)



(b)

Figure 3. The temperature distribution map of the space and the validation plot for the kriged vs measured temperature for the validation (ground 6) sensor for the month of December during: **a.** occupied hours. **b**. non-occupied hours.

From a thermal comfort viewpoint, these findings are critical where the periods of greatest modelling uncertainty coincide with times of highest occupant exposure. Comfort thresholds in standards (e.g. CIBSE and ASHRAE) typically operate within narrow temperature bands (±1 - 2 °C), meaning that prediction errors approaching or exceeding 1 °C as observed during both warm and cold occupied periods can materially affect comfort classification, detection of overheating or cold discomfort, and assessment of heating or cooling adequacy. In the warmest month of August, reduced predictive accuracy during occupied hours may lead to underestimation of localised overheating risk, while in December the tendency to overestimate temperatures may mask underheated microclimates, potentially underrepresenting occupant dissatisfaction or energy poverty risks in peripheral or poorly served zones. By contrast, during unoccupied periods in both seasons, prediction errors are substantially lower, and spatial fields are more coherent; however, these periods are less directly relevant to perceived comfort and instead primarily inform thermal storage behaviour and pre-conditioning requirements.

Moreover, the warm regions near mezzanine levels across both seasons suggests that stratification and direct solar gains contribute to simultaneous overheating at upper levels and underheating at occupied lower zones, a condition that spatially averaged metrics or sparsely distributed sensors would fail to capture. This vertical and zonal decoupling is particularly an issue during occupied winter conditions, when heating system operation amplifies buoyancy-driven gradients, but is also evident during summer occupancy when internal gains dominate. These results reinforce the need vertical temperature profiling, or more advanced hybrid modelling approaches that incorporate airflow patterns, occupancy, and HVAC system operation when evaluating thermal comfort and system performance. Although sparse-sensor spatial interpolation is effective for characterising general thermal behaviour and distribution in the space, reliance on sparse sensing and purely spatial models remains weak for comfort-oriented diagnostics, overheating and underheating risk assessment, and responsive control strategies under occupied conditions in both heating and cooling seasons.

3.2. Variogram and Spatial Dependence

Figure 4 presents the experimental semi variogram and fitted spherical model derived from temperature data aggregated across all the datasets. The variogram shows an effective spatial correlation range of approximately 2.56 m, beyond which temperature values exhibit weak spatial dependence. This suggests that, when averaged across the various building thermal states, indoor temperatures vary significantly over short distances, due to the varying local thermal behaviour, such as occupancy, HVAC and fabric heat losses. Furthermore, the fitted model yields a partial sill of 0.624 °C^2, representing the structured spatial component of variance, and a relatively small nugget value of 0.079 °C^2, indicating that most variability arises from physical spatial processes rather than sensor noise or unresolved microscale fluctuations. Elevated semi variance at short lag distances confirms that even closely spaced locations can experience appreciable temperature differences, while the plateau beyond the range reflects thermal decoupling between distant zones within the space.

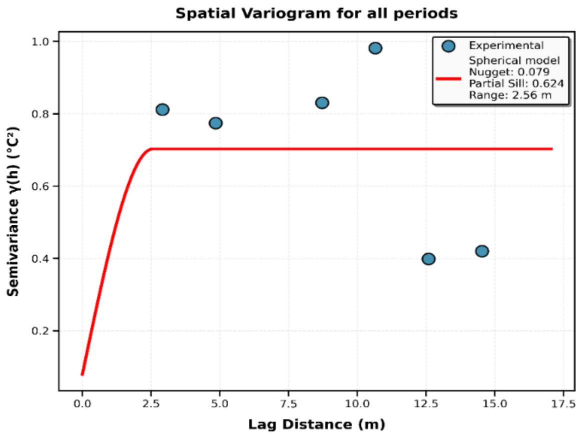


Figure 4. The spatial variogram plots for all periods including the calculated nugget, partial sill and range values.

These results support earlier validation findings, showing that short spatial correlation lengths make interpolation accuracy highly sensitive to sensor spacing. Consequently, sparse sensor networks struggle to resolve comfort-relevant microclimates during occupied periods, leading kriging to smooth local extremes such as cold perimeter zones or warm regions. While effective for visualising broad thermal patterns, the variogram analysis indicates that indoor thermal behaviour is dominated by short-range spatial variability. Improving accuracy therefore requires either increased sensor density or the integration of kriging with hybrid models that account for airflow and HVAC operation. Importantly, the results demonstrate that sensor placement is as critical as sensor density, with mezzanine-level sensors capturing stratification effects that ground-level measurements alone would likely miss.

5 CONCLUSIONS

This study shows that ordinary kriging can effectively support high-level visualisation of indoor thermal patterns in open-plan offices when sensing resources are limited. The results indicate that its applicability is strongly influenced by occupancy and seasonal operating conditions, with implications for how spatial models are interpreted in comfort-critical contexts. Rather than serving as a detailed comfort assessment tool, kriging is best suited to informing spatial diagnostics and identifying broad thermal trends. For building operators, the findings stresses the importance of informed sensor placement for maximizing insight while controlling monitoring costs. Overall, the work contributes practical guidance for deploying spatial interpolation methods as part of context-aware IAQ monitoring strategies in real buildings.

6 REFERENCES

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