



RESEARCH ARTICLE

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Novel Parameterization of Building Storage Heat Flux for Urban Climate Modeling

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Key Points:

- A new OHM parameterization enable rapid estimation of urban storage heat flux (ΔQ_s) across diverse building material and weather condition
- Evaluation using SOMUCH measurements shows substantially improved ΔQ_s modeling accuracy
- Integration into SUEWS reveals building design impacts on neighborhood thermal environment

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Accurate estimation of building heat storage flux (ΔQ_s) is essential for modeling the urban surface energy balance and urban climates. The Objective Hysteresis Model (OHM) is a computationally efficient scheme that uses coefficients (a_1, a_2, a_3) that can be derived from standard thermal parameters for heat conduction. Currently, it is constrained by the scarcity of coefficients representative of diverse construction types and meteorological regimes. To address this problem, we develop a physically informed parameterization that links OHM coefficients to key construction properties and weather forcing. Using large ensembles of parametric EnergyPlus simulations, we fit regression models that map thermal-mass thickness and properties, insulation placement, and meteorological drivers to a_1 – a_3 . We demonstrate the dominant influence of insulation placement: materials located exterior to the insulation layer account for most heat storage and release. The derived coefficients are verified using field observations undertaken at the Scaled Outdoor Measurement of Urban Climate and Health (SOMUCH) platform, where ΔQ_s is independently estimated using the element surface temperature method (ESTM). OHM-modeled ΔQ_s agrees closely with observations. Implemented within the Surface Urban Energy and Water Balance Scheme (SUEWS), the new scheme enables assessment of how construction choices affect neighborhood-scale microclimate (e.g., air temperature, wind speed), underscoring the influence of insulation placement on both building and neighborhood climates. This approach offers a practical means to rapidly infer OHM coefficients from readily available building and meteorological data, broadening OHM's applicability across materials and climates and supporting improved urban design and heat-mitigation strategies.

Plain Language Summary Urban climate models need to estimate how much heat buildings store during the day and release at night to predict outdoor air temperatures. A commonly used approach, the Objective Hysteresis Model (OHM), is fast to run but depends on three coefficients that are currently limited by lack of data for diverse building materials and weather conditions. This limitation hinders the ability of models to assess how different construction choices affect the urban thermal environment. Here, we address this problem by developing a new, physically informed method that calculates these coefficients from basic building information (such as material thickness and thermal properties) and local weather, using a large set of building energy simulations and checks the results against field measurements. We find that the position of building insulation is a critical factor, with building materials outside of insulation layer are responsible for the majority of heat storage and release. This improved approach allows researchers and planners to rapidly estimate heat storage for various construction material and weather conditions, improving urban temperature estimates and supporting design choices for mitigating urban heating.

1. Introduction

Urban areas are complex and temporally dynamic environments, where built structure interacts with atmospheric processes. A critical component of the urban surface energy balance is the storage heat flux (ΔQ_s), which accounts for large fraction of daytime available energy input as net all-wave radiation (Roberts et al., 2006). The storage heat flux accounts for net uptake and release of energy in the urban canopy volume, which includes air, building, ground and water. This canopy volume extends from the top of roof level down to a depth in the ground where vertical fluxes are negligible (Grimmond & Oke, 1999; Grimmond et al., 1991).

As urbanization is characterized by replacing natural land surfaces with artificial materials such as concrete and asphalt, this profoundly alters urban climate. A notable consequence of this transformation is the urban heat island

(UHI) effect where urban regions experience warmer canopy layer air temperatures compared to their rural surroundings (Schlünzen et al., 2023). The UHI effect is largely driven by the increased thermal mass capacity of urban materials, which absorb more heat during the day (positive ΔQ_s) and release it slowly at night (negative ΔQ_s) (Oke et al., 2017). This thermal inertia slows the cooling of air temperatures in urban areas after sunset, thereby creating (or sometime prolonging) a temperature difference between urban and rural regions. The ΔQ_s varies with urban morphology and materials (Lindberg et al., 2020), which in turn impacts the urban surface energy balance and then atmospheric stability, dispersion of scalars and momentum, and the growth of the mixing layer within the boundary layer (Kawai & Kanda, 2010). These processes are crucial for understanding local climate dynamics, heat exposure, building energy demand and air quality management.

However, the complex three-dimensional structure and diversity of urban material make ΔQ_s difficult to measure directly and to model. Parameterization schemes, allow rapid estimation of ΔQ_s using pre-determined appropriate values for the material and morphology properties. For example, the objective hysteresis model (OHM) estimates ΔQ_s as the function of net all-wave radiation (Q^*) and surface characteristics (Arnfield & Grimmond, 1998; Grimmond et al., 1991). This scheme captures the non-linear (hysteresis) relation between ΔQ_s and Q^* using three coefficients, with a_1 indicating the overall strength of dependence ΔQ_s on Q^* , a_2 describing the degree and direction of phase relation between ΔQ_s and Q^* (positive values indicate peak ΔQ_s prior to peak Q^*), and a_3 an intercept term in Equation 1.

$$\Delta Q_s = \sum_i f_i \left[a_{1i} Q^* + a_{2i} \frac{\partial Q^*}{\partial t} + a_{3i} \right] \quad (1)$$

where f is the surface cover fraction for each surface type (e.g., pavement, buildings, vegetation, bare soil and water). The time derivative of net all-wave radiation $\frac{\partial Q^*}{\partial t}$ can be approximated by $0.5(Q_{t+1}^* - Q_{t-1}^*)$ in $\text{W m}^{-2} \text{h}^{-1}$. While the OHM has been widely used due to its rapid computation (Crawford et al., 2018; Grimmond & Oke, 1999; Järvi et al., 2011; Roberts et al., 2006; Velasco et al., 2011; Ward et al., 2016), it remains limited by parameter availability. Parameters have been derived from simple surface observations (e.g., Grimmond & Oke, 1999; Omidvar et al., 2022), the observations of whole neighborhoods (Crawford et al., 2018; Roth & Oke, 1994) and from numerical modeling (Arnfield & Grimmond, 1998; Meyn & Oke, 2009; Offerle et al., 2005; Roberts et al., 2006; Sun et al., 2017).

Buildings play a central role in the storage and release of heat within complex urban systems. Previous studies have often used OHM coefficients derived from specific material (e.g., concrete) to represent the behavior of entire building (e.g. Hang et al., 2024; Ward et al., 2016). However, even within a single material type, such as concrete or brick, thermal properties (e.g., conductivity and volumetric heat capacity) can vary substantially. Such variability affect how these surfaces heat absorption, storage and release (Kawai & Kanda, 2010). Numerical modelling by Arnfield and Grimmond (1998) shows that heavyweight material (higher thermal admittance) will increase a_1 for building walls, indicating greater heat storage capacity, and more negative a_3 reflecting enhanced nocturnal heat release. Given the variability of material properties in urban structures, particularly for buildings, there is a need to determine OHM coefficients tailored to different materials to better estimate ΔQ_s in urban areas.

Additionally, meteorological conditions impact the OHM coefficients (Arnfield & Grimmond, 1998; Meyn & Oke, 2009). Urban surfaces absorb net-all wave radiation and distribute them into conductive and convective heat fluxes at urban surfaces. Theoretically, higher wind speeds (WS) enhance convective heat transfer from surfaces to the atmosphere, reducing the amount of heat stored within urban materials. Meyn and Oke (2009) found the exponential decrease in a_1 for gravel and shingle roofs with increasing WS , suggesting the increased convective heat fluxes results in less net radiation being stored because of cooler surface temperatures. Similarly, modelling work by Arnfield and Grimmond (1998) demonstrated a negative correlation, where doubling the WS decreased the magnitude of both a_1 and a_3 (making a_3 less negative). It indicates larger wind speed results in storing less heat during daytime (smaller a_1) and releasing less (less negative a_3) at night. Roberts et al. (2006) found when using fixed OHM coefficients there was greater bias compared to the measured ΔQ_s with high WS in Marseille. These findings highlight the importance of quantifying the impact of WS on OHM coefficients to enhance model accuracy under varying meteorological conditions.

Seasonal changes in earth–sun geometry alter the amount of solar radiation received, thereby impacting seasonal (or monthly) variation in OHM coefficients, particularly for a_3 (Anandakumar, 1999; Ward et al., 2016).

Generally, a_3 is more negative in summer and less negative or even positive in winter. This seasonal cycle linked to incoming solar radiation ($K_{\downarrow}$) variations with larger daytime $K_{\downarrow}$ in summer increasing the energy available for storage during the day, leading to greater heat release at night, and larger (more negative) a_3 value (Sun et al., 2017). Whereas the lower $K_{\downarrow}$ in winter results in less daytime heat storage and a smaller a_3 (less negative). Analysis by Sun et al. (2013) demonstrates that the net shortwave radiation ($K^* = K_{\downarrow} - K_{\uparrow}$) to outgoing longwave radiation ($L_{\uparrow}$) ratio is crucial to shaping the phase difference (a_2) between ground (soil) ΔQ_S and Q^* . Since both outgoing shortwave ($K_{\downarrow}$) and longwave ($L_{\uparrow}$) radiation depend on $K_{\downarrow}$ and surface thermal properties, the influence of $K_{\downarrow}$ on OHM coefficients needs further investigation.

Building energy modelling tools, such as EnergyPlus (US DOE, 2021), are widely used to evaluate the impacts of various building design elements (e.g., envelope materials, occupancy patterns, ventilation strategies) and climate conditions on building thermal performance. These tools solve the complex energy balance equations for both internal and external building surfaces and are able to accurately compute both ΔQ_S and Q^* at building scale. Compared to long-term, expensive field measurements, building energy modelling offers a faster and more cost-effective way to generate storage heat flux data for different construction materials and weather conditions to parameterize the OHM coefficients. Although it is well accepted that both material properties and meteorological factors influence OHM coefficients, the combined effects of these factors have not yet been fully quantified.

In this study, we enhance the OHM model by dynamically parameterizing its coefficients to reflect both building material properties and varying meteorological conditions. We use parametric building energy modelling of a simple “shoebox” building, systematically varying construction materials across four distinct climate types in China. This approach enables us to obtain OHM coefficients (a_1, a_2, a_3) tailored to the building material properties and to be responsive to varying meteorological conditions. We then develop a dynamic parameterization scheme (dyOHM) that maps material and meteorological predictors to these coefficients. In this sense, dyOHM complements analytical approaches such as Analytical Objective Hysteresis Model (AnOHM): whereas AnOHM provides a first-principles framework for deriving bulk OHM coefficients for land surface, dyOHM targets multilayer building envelopes in which insulation placement and exposed material properties control heat storage. Our new approach improves building-scale ΔQ_S estimate across diverse building material and enable to scaling up heat storage assessment to complex urban systems. Because the parameterization requires only readily available inputs, it enables rapid evaluation of urban heat storage for alternative building designs and future climate scenarios, thereby supporting evidence-based urban planning and heat mitigation strategies.

2. Materials and Methods

In this study, we enhance the OHM model by dynamically parameterizing its coefficients to reflect both building material properties and varying meteorological conditions. We use parametric building energy modeling of a simple “shoebox” building, systematically varying construction materials across four distinct climate types in China. This approach enables us to obtain OHM coefficients (a_1, a_2, a_3) tailored to the building material properties and to be responsive to varying meteorological conditions. We then develop a dynamic parameterization scheme (dyOHM) that maps material and meteorological predictors to these coefficients.

2.1. Parametric Building Energy Modeling

We use EnergyPlus (US DOE, 2021) as the building-physics solver to generate a controlled data set of heat-storage responses for an isolated shoebox building. The ASNI/ASHRAE standard-140 case 900 test model (ASHRAE, 2017) provides the shoebox geometry, consisting of one-story cuboid prism with a floor area of 48 m² and a height of 2.7 m. To establish a clear link between OHM coefficients and construction material properties, we make three simplifications to reduce the uncertainties: (a) windows are removed as glass has limited capacity to store heat, (b) all opaque components (external wall and roof) have the same material, and (c) the building is assumed to be unoccupied, with no internal heat gains or HVAC systems, to eliminate the influence of occupant behavior. Therefore the derived OHM coefficients represent the passive storage response of construction materials to external meteorological forcing. The storage perturbation caused by human activities and building operation is treated separately as part of the anthropogenic heat flux term in the urban surface energy balance (Liu et al., 2022).

The construction materials are a key aspect of this study, as we aim to determine which properties have the greatest influence on OHM coefficients. We consider a typical three-layer composition for wall and roof

Table 1
Parameter Types and Values in Simulations (6048 Cases After Removing Unrealistic κ)

Parameters	Units	Discrete values used
Thickness of thermal mass material (d)	m	0.02, 0.03, 0.04, 0.05, 0.06, 0.08, 0.10, 0.12, 0.14, 0.16, 0.18, 0.20, 0.25, 0.30, 0.35, 0.40
Conductivity of thermal mass material (k)	$\text{W m}^{-1} \text{K}^{-1}$	0.2, 0.6, 1.0, 1.4, 1.8, 2.2
Volumetric heat capacity of thermal mass material (C)	$\text{J m}^{-3} \text{K}^{-1}$	500000, 1000000, 1500000, 2000000, 2500000
Insulation layer thickness (d_{ins})	m	0.05, 0.1, 0.15
Insulation position	–	External, Internal
Solar absorptance (1-albedo) of external surfaces (sa)	–	0.5, 0.7, 0.9 (or albedo of 0.5, 0.3, 0.1)

construction: (a) a thermal mass layer, consisting of materials like concrete or brick, whose thickness, thermal conductivity, and volumetric heat capacity are varied to represent different levels of thermal mass; (b) an insulation layer, which provides the primary thermal resistance to minimize heat gain and loss through the envelope, with insulation thickness varied to represent different insulation levels; and (c) a plaster layer typical of that added for finishing.

Apart from material properties, the construction configuration (notably insulation position) is another critical factor influencing OHM coefficients. The insulation layer, characterized by low conductivity and heat capacity, effectively reduces heat conducted into the building interior. If insulation is internal to the thermal mass layer, high K_l can significantly heat the thermal mass material (e.g., exposed brick or concrete). Conversely, with external insulation less energy is conducted through the insulated layer, reducing heat conduction by the thermal mass material. Additionally, solar absorptance (defined as one minus the albedo) of K_l is impacted by external surface albedo.

Table 1 gives the parameters values used. To understand how these fundamental parameters affect OHM coefficients, all combinations of parameter values are initially considered to ensure comprehensive coverage of possible scenarios. However, some combinations are unrealistic (e.g., large conductivity (k) paired with small volumetric heat capacity (C) and small k paired with large C). Hence, we use a range of thermal diffusivity ($\kappa = k/C$) values restricted to that found in common building construction materials ($0.2 \times 10^{-6} - 1.5 \times 10^{-6} \text{ m s}^{-1}$).

For the building energy modeling, typical meteorological year (TMY) data (hourly resolution) are used from four cities across a wide latitudinal range (China Meteorological Bureau, 2005), with distinct climates (MOHURD, 2015): very cold (Harbin), cold (Beijing), cold winter and hot summer (Shanghai), warm winter hot summer (Guangzhou). This selection captures the effects of diverse climates on OHM coefficients, helping to generalize the findings across various climatic scenarios. Overall, the simulated data set has 6048 (building cases (Table 1)) * 8760 (hours (i.e., 1 year)) * 4 (cities) hourly data pairs of ΔQ_s and Q^* per building footprint area.

2.2. Classification and Data Fitting

The temporal resolution and duration of ΔQ_s and Q^* is fair critical to determine the response of OHM coefficients to weather variability. One approach is to first classify the weather conditions, prior to deriving the OHM coefficients (i.e., fitting ΔQ_s and Q^* by Equation 1) per weather class. For example, Meyn and Oke (2009) classify the weather based on measured surface wetness (i.e., dry, wet or mixed) and wind speed ranges. Hang et al. (2024) categorize by date into seasons (summer and winter) and sky condition (rainy, cloudy and clear sky).

Here, we classify the daily WS and K_l data from the four cities TMY data sets by clustering. The wind speed data used is at the half building height, as it is directly involved in calculating the wall's convective heat transfer coefficient in EnergyPlus, and this height could better reflect the influence of urban morphology than WS at a fixed height (e.g., 10 m). The K-mean clustering algorithm is selected for its stable performance (e.g., Park et al., 2019; Rhodes et al., 2014; Sala et al., 2021) and ensures that the OHM coefficients for each building case are derived from similar weather conditions, allowing the coefficients to reflect weather variations.

To classify daily weather conditions, we first normalize the variables (K_l and WS) to a common scale between 0 and 1 using the maximum daily mean of the full data set (all cities) to ensure consistency across sites and variable scales. Second, the appropriate number of clusters (K) is determined by assessing the intra-cluster

variance. The goal is to ensure that the variance within each cluster is minimized, thereby representing similar weather conditions. To determine the optimal number of clusters we use the elbow method, with K identified as the point when increasing the number of clusters no longer considerably reduces the criterion (within-cluster sum-of-squares, WCSS). Thirdly, using the determined ($K = 18$), the daily weather data (365×4 days (4 cities)) are classified into 18 regimes using K-means clustering. Fourth, for each building scenario, the ΔQ_s and Q^* within each cluster are used to derive the 6048 *18 sets (a_1, a_2, a_3) of OHM coefficient by Equation 1. Finally, the relation between derived coefficients (a_1, a_2, a_3) and material (e.g., thermal mass material thickness) and meteorological states (K_1 and WS cluster means) is determined. Analysis is undertaken for each of three coefficients (Section 3.1 and 3.2) to determine the appropriate mathematical functions to best describe the dependencies. Both linear and nonlinear regression fits are assessed, while ensuring the physical trends exhibited by each coefficient are accurately captured. These fitted relations (dyOHM v1) are used to generalize OHM coefficients and to evaluate the performance with outdoor observations (Section 2.3).

2.3. Verification Against Outdoor Observations

To evaluate the developed parameterization scheme for OHM coefficients, we use the measurements undertaken at the Scaled Outdoor Measurement of Urban Climate and Health (SOMUCH) platform (Hang et al., 2022, 2024; Wang et al., 2021) located in Guangzhou, China.

The scale model consists of dense buildings (height, H of 0.5 m) and canyons (width, $W = 0.25$ m) with an aspect ratio (H/W) of 2, covering an area of 37.8 m by 33.5 m (canyon length, Figure S1 in Supporting Information S1). The hollow concrete blocks buildings have a plan area fraction of 0.667, with the remainder being pavement (0.333). The material thermal properties are given in Hang et al.'s (2022) Table 3. The scale model has building material homogeneity and has no anthropogenic heat flux (Q_F) sources.

A Campbell Scientific IRGASON eddy covariance system is installed 1 m above the canyon (i.e., $2H$, within inertia sub-layer) consisting of a CSAT3 sonic anemometer and an EC150 H₂O/CO₂ analyser, are used to obtain sensible (Q_H) and latent heat fluxes (Q_E) in 2020. Net all-wave radiation (Q^*) and its components are observed with a Kipp and Zonen CNR4 net radiometer at 5 s intervals. Both external and internal facets surface and air temperatures are measured at multiple heights at 1-s interval (Figure S1d in Supporting Information S1) (instrument details see Table 1 in Hang et al. (2022)). The hourly-average temperatures are used to determine an observation-based ΔQ_s through element surface temperature method (ESTM, Offerle et al., 2005):

$$\Delta Q_s = \sum_{i=1}^n \frac{\Delta T_i}{\Delta t_i} C_i \Delta x_i \lambda_{pi} \quad (2)$$

where $\frac{\Delta T_i}{\Delta t_i}$ is the rate of temperature change over a given period ($K s^{-1}$), C_i is the volumetric heat capacity ($MJ m^{-3} K^{-1}$), Δx is the element thickness (m) and λ_p is the plan area fraction (%). The i represents the basic elements in urban volume. In this study, we focus on the building element to remove the uncertainty of other land covers (e.g., pavement, bare soil and vegetation).

The parameterized OHM coefficients are assessed by comparing the modeled (Section 3.1 and 3.2) and ESTM-derived observed ΔQ_s for four weather conditions (i.e., summer-rainy, summer-cloudy, winter-clear, winter-cloudy) identified in Hang et al. (2024)'s Table 1. As dyOHM v1 parameterization of coefficients are only for building ΔQ_s , we ignore the canyon "road." To quantify the agreement between dyOHM and observations we use the following metrics: root mean square error (RMSE), mean absolute error (MAE), mean bias error (MBE) and index of agreement (d-index).

2.4. Use of the New Scheme Within a Land Surface Model

We integrate the OHM coefficient parameterization (Sections 3.1 and 3.2) into Surface Urban Energy and Water Balance Scheme (SUEWS) (Järvi et al., 2011; Sun & Grimmond, 2019; Ward et al., 2016), using the Storageheatmethod = 6 (dyOHM) option in the SUEWS version used in this study (2025.10.15) (Grimmond et al., 2025). The equivalent configuration in the latest SUEWS release (after 2026.07.13) can be found in Table S2 in Supporting Information S1 (Grimmond et al., 2026). This allows systematic assessment of how different building materials influence the building heat storage flux ΔQ_s and subsequently affect neighborhood-scale

Table 2

Thermal Properties of Three Building Construction Material (Bold Indicates Is the Layer External to Insulation) Used to Derive OHM Coefficients (Sections 3.1 and 3.2)

Wall type	Layers	d (m)	k (W m ⁻¹ K ⁻¹)	ρ (kg m ⁻³)	c _p (J kg ⁻¹ K ⁻¹)
B1	Brick	0.22	0.77	1,750	1,000
	Insulation	0.05	0.042	12	1,030
	Plasterboard	0.012	0.21	700	1,000
B2	Brick	0.105	0.77	1,750	1,000
	Insulation	0.05	0.042	12	1,030
	brick	0.105	0.77	1,750	1,000
	Dense plaster	0.013	0.57	1,300	1,000
B3	Render	0.019	0.8	1,600	1,000
	Insulation	0.05	0.042	12	1,030
	Brick	0.22	0.77	1,750	1,000
	Dense plaster	0.013	0.57	1,300	1,000

meteorological variables (e.g., 2-m outdoor air temperature, RSLmethod = 2). At the same time, SUEWS provides the local metrological variables required by dyOHM, including Q^* , wind speed, and air temperature, allowing the OHM coefficients to respond to the evolving urban environment. Here, we choose a typical UK residential neighborhood with 1–2 storey houses in Swindon (Ward et al., 2016) as a case study. A prior evaluation of SUEWS using local-scale radiation and eddy covariance (EC) flux observations shows good agreement, confirming its ability to capture the local surface energy thermodynamics (Ward et al., 2016).

In this neighborhood application, the wall assemblies are tested as controlled sensitivity experiments rather than as a representation of heterogeneous building stock. In each SUEWS simulation, one wall assembly is assigned uniformly to the building surfaces of the Swindon neighborhood, while the land-cover fractions, urban morphology and meteorological forcing are kept unchanged. Here we examine three typical brick wall assemblies with different insulation positions (Table 2; CIBSE, 2018), because the material external to the insulation layer primarily controls the OHM coefficients. For wall B1, with internal insulation, the full 220 mm brick layer is exposed to outdoor forcing and acts as the effective external thermal mass. For wall B2, with cavity insulation, the effective external brick thickness is reduced to 105 mm. For wall B3, with external insulation, only a thin 19 mm render layer is exposed, while the main brick layer is thermally separated from the outdoor environment. Comparing these three wall types therefore allows us to quantify how insulation placement and exposed thermal mass influence building ΔQ_s and the surrounding urban climate.

3. Results and Discussion

For the K-means clustering of daily typical meteorological year (TMY) data for the four cities, using the within-cluster sum of squares (WCSS), 18 clusters has been chosen as it balances minimizing intra-cluster variance and avoiding overfitting (Figure S2a in Supporting Information S1). The resulting 18 clusters have distinct weather regimes based on daily mean (24 hr average) wind speed (WS) and incoming shortwave radiation (K_1) (Figure S2b in Supporting Information S1).

3.1. Parameterization and Evaluation of OHM Coefficients a_1 and a_2

The derived OHM coefficients from the EnergyPlus simulation vary with material properties, with material thickness of the thermal mass and insulation position being primary factors influencing the magnitude of the OHM coefficients. The influence of thermal mass thickness is more pronounced when the insulation is located internally (Figures 1a and 1c) rather than externally (Figures 1b and 1d).

With an internal insulation configuration (Figure 1a) a_1 increases rapidly with increasing thermal mass thickness, particularly in the lower range (typically <0.1 m). The initial increase in a_1 suggests that thicker thermal mass material exposed to outdoor conditions enhances the ability to store heat during the day, leading to higher a_1

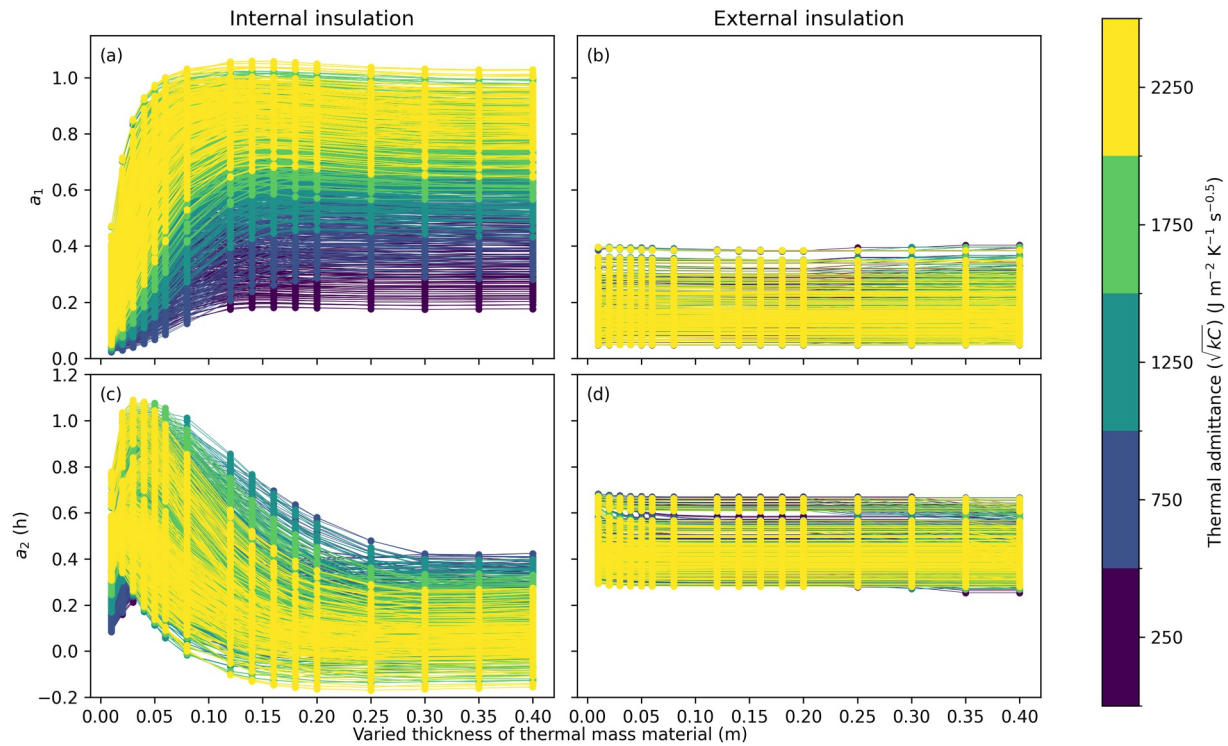


Figure 1. Thickness of the thermal mass material (dot), thermal admittance ($\mu_s = \sqrt{kC}$) (color) and derived OHM coefficients: (a, b) a_1 and (c, d) a_2 , with insulation located (a, c) internally, and (b, d) externally with plaster the outer most layer. Variations in material properties or meteorological conditions are shown by different curves.

values. However, as the thickness continues to increase, a_1 begins to slightly decrease. This decrease can be attributed incomplete release of stored heat during nighttime, especially in thicker thermal mass materials. As the thermal mass thickness increases, the deeper layers retain heat that cannot dissipate within the 24-hr cycle. This incomplete heat release warms the fabric, reducing its capacity to store more energy the next day and facilitating transfer of heat into inner building. This explanation is also consistent with the decreasing trend in a_2 when thickness exceeds 0.04 m (Figure 1c). A smaller a_2 suggest the peak ΔQ_S is gradually shifting closer to, or even after, the peak in Q^* .

The strong influence of thermal admittance ($\mu_s = \sqrt{kC}$) on a_1 is consistent with the importance of material thermal properties. μ_s is a measure the extent to which heat is stored within or withdrawn from urban materials (Arnfield & Grimmond, 1998; Oke et al., 2017). With higher thermal admittance being correlated with increased heat storage capacity, the central role of material properties in shaping the diurnal pattern of heat storage is evident.

The meteorological influence on a_1 and a_2 is easier to explore using one construction case (Figure 2). As demonstrated in prior studies (e.g., Sun et al., 2013; Sun et al., 2017), WS is negatively correlated with a_1 (Figure 2b). K_1 is important in shaping a_2 the phase differences, with clear larger values during periods of greater K_1 (e.g., summer) than when less (Figure 2c). a_1 is generally smaller when K_1 is larger but the role of WS is more important (Figures 2a and 2b).

Increases of thermal mass thickness (<0.04 m, Figure 1c) are initially linked to a_2 increases when there are very small heat capacities. This results in ΔQ_S reaching its peak very early (e.g., 8–9 a.m.). However, Q^* continues to increase (positive $\frac{\partial Q^*}{\partial t}$) until midday to early afternoon (typically 1–2 p.m.). This extremely large phase difference between ΔQ_S and Q^* results in a situation where the OHM model must fit a large positive a_2 (and small a_1) to fit the diurnal pattern of ΔQ_S . Once the thermal mass is ~ 0.04 m, a_2 begins to decrease to more expected values. The increased thickness with higher heat capacity, allows the building fabric to store more heat through conduction, thereby reducing the phase difference between the peak ΔQ_S and Q^* .

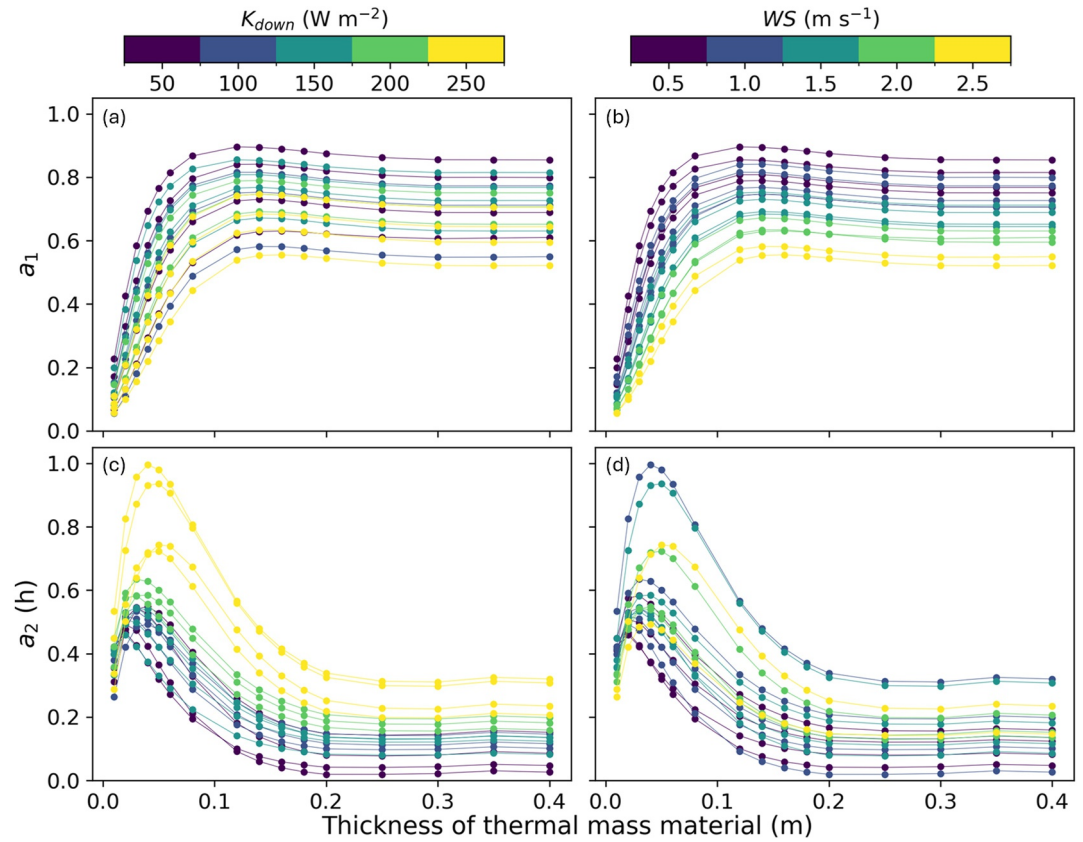


Figure 2. As Figure 1, but showing one construction configuration with thermal conductivity $k = 1.0 \text{ W m}^{-1} \text{ K}^{-1}$, volumetric heat capacity $C = 1,000,000 \text{ J m}^{-3} \text{ K}^{-1}$, solar absorptance = 0.7 (i.e., albedo = 0.3), with internal insulation that is 0.1 m thick and the varying (color) cluster-mean meteorology (a, c) K_1 and (b) WS . All meteorological variables have their actual values.

Contrastingly, if insulation is installed external to the thermal mass material (Figures 1b and 1d), both a_1 and a_2 remain relatively low and stable across different thermal mass thicknesses, with minimal variation. This stability can be attributed to the external insulation layer acting as a strong thermal barrier, which limits heat conduction into the thermal mass layer and minimizes the amount of heat absorbed and stored during the day, as well as the heat released during the night. Consequently, both coefficients exhibit only slight changes, showing that the thickness of the thermal mass has a limited role in influencing heat storage when the insulation is positioned externally. Therefore, the position of insulation is crucial when estimating heat storage in building construction.

For the external insulation scenario, variations in a_1 and a_2 are attributed to meteorological factors. These impact the amount of heat stored and released by the plaster layer that is directly exposed to the external environment. Note in these simulations the albedo (solar absorptance) varies independent of material configuration (Table 1). The negligible change in a_1 and a_2 indicates material internal to the insulation layer contributes minimally to the urban heat storage. Whilst, the external surface properties and meteorological conditions are more important.

Hence to parameterize a_1 , we first consider the insulation location. For internal insulation cases we can establish a clear relation between a_1 and thermal mass thickness, as well as other material and meteorological properties. To capture the observed complex relation with increasing thermal mass thickness (Figure 1a) of a_1 , we select the following mathematical function:

$$a_1 = S + (y_0 - S)(e^{-\varphi d} \cos(\omega d)) \quad (3)$$

where d is the thermal mass material thickness external to insulation layer, y_0 is the initial a_1 when d is minimal (i.e., 0). The exponential term $e^{-\varphi d}$ describes the initial rapid increase followed by a leveling off as the thickness grows. The cosine component $\cos(\omega d)$ accounts for the slight decrease observed at larger thicknesses, such as

insufficient heat dissipation at greater depths. The S parameter is the value a_1 asymptotes toward. The following equations should be interpreted as physically informed reduced-order parameterizations, rather than universal analytical laws. Their functional forms are selected to reproduce the dominant responses observed in the EnergyPlus-derived OHM coefficients, including the rapid increase and subsequent saturation of storage with exposed thermal-mass thickness, the phase response between ΔQ_S and Q^* , and the weak sensitivity to material located behind external insulation. The numerical constants are calibrated (Figure 3) within the simulated material and meteorological domain defined by Table 1 and the 18 weather clusters.

Second, we extend this approach for the external insulation case. Given the thermal mass material properties are neglected when insulation is external, we assume the external plaster layer as the effective thermal mass.

The parameters of S , φ , ω , y_0 are obtained by fitting the a_1 with thickness (d) for each curve (Figure 1) for each building material and meteorological cluster combination. These material—meteorological combinations are used to determine the most influential factors, which are used to develop linear regression models for each parameter, parameterized as:

$$S_{a_1} = \left(0.296 - 0.00270 \frac{Q^*}{\lambda_c}\right) \log(\sqrt{kC}) - 0.116WS - 1.194 \quad (4)$$

$$\omega_{a_1} = (-14.8 + 2.25WS) \log\left(\frac{\sqrt{k}}{C}\right) + 29.7WS - 190 \quad (5)$$

$$\varphi_{a_1} = (16.1 + 4.48WS) * 10^{-6}C - 3.32k - 0.106 \frac{Q^*}{\lambda_c} + 10.7 \quad (6)$$

$$y_{0,a_1} = 0.01 \quad (7)$$

Where WS is the wind speed at half building height. Q^* is the net all-wave radiation for the building per building footprint area. λ_c is the ratio of building external surface area to footprint area.

Similarly, a_2 is parametrized considering with thermal mass thickness, using:

$$a_2 = S + \left((y_0 - S) + n \left(\frac{\varphi^2 + \omega^2}{\omega} \sin(\omega d)\right)\right) e^{(-\varphi d)} \quad (8)$$

With linear regression used to capture other influences:

$$S_{a_2} = -7.81 \times 10^{-5}kC + 0.00348 \frac{Q^*}{\lambda_c} + 0.0131WS + 0.123 \quad (9)$$

$$\omega_{a_2} = (-9.44) \log\left(\sqrt{\frac{k}{C}}\right) + 1.68WS - 126 \quad (10)$$

$$\varphi_{a_2} = 1.05 * 10^{-5}C - 6.67k - 0.120 \frac{Q^*}{\lambda_c} - 3.48WS + 28.0 \quad (11)$$

$$y_{0,a_2} = 1.29 * 10^{-7}C + 0.0603k - 0.0008 \frac{Q^*}{\lambda_c} - 0.146WS + 0.0910 \quad (12)$$

Parameter n captures the amplitude adjustment linked to the observed initial oscillation (Figure 2c):

$$n_{a_2} = 3340\sqrt{\frac{k}{C}} + 507 \frac{Q^*}{\lambda_c} \sqrt{\frac{k}{C}} - \frac{1.54 * 10^4 \sqrt{\frac{k}{C}}}{WS} + 0.0161 \quad (13)$$

To evaluate the parameterizations (Equations 3–13) of a_1 and a_2 , the originally derived OHM parameters from the EnergyPlus simulation data are used (Figure 3). For internal insulation cases (Figures 3a and 3c) there is strong

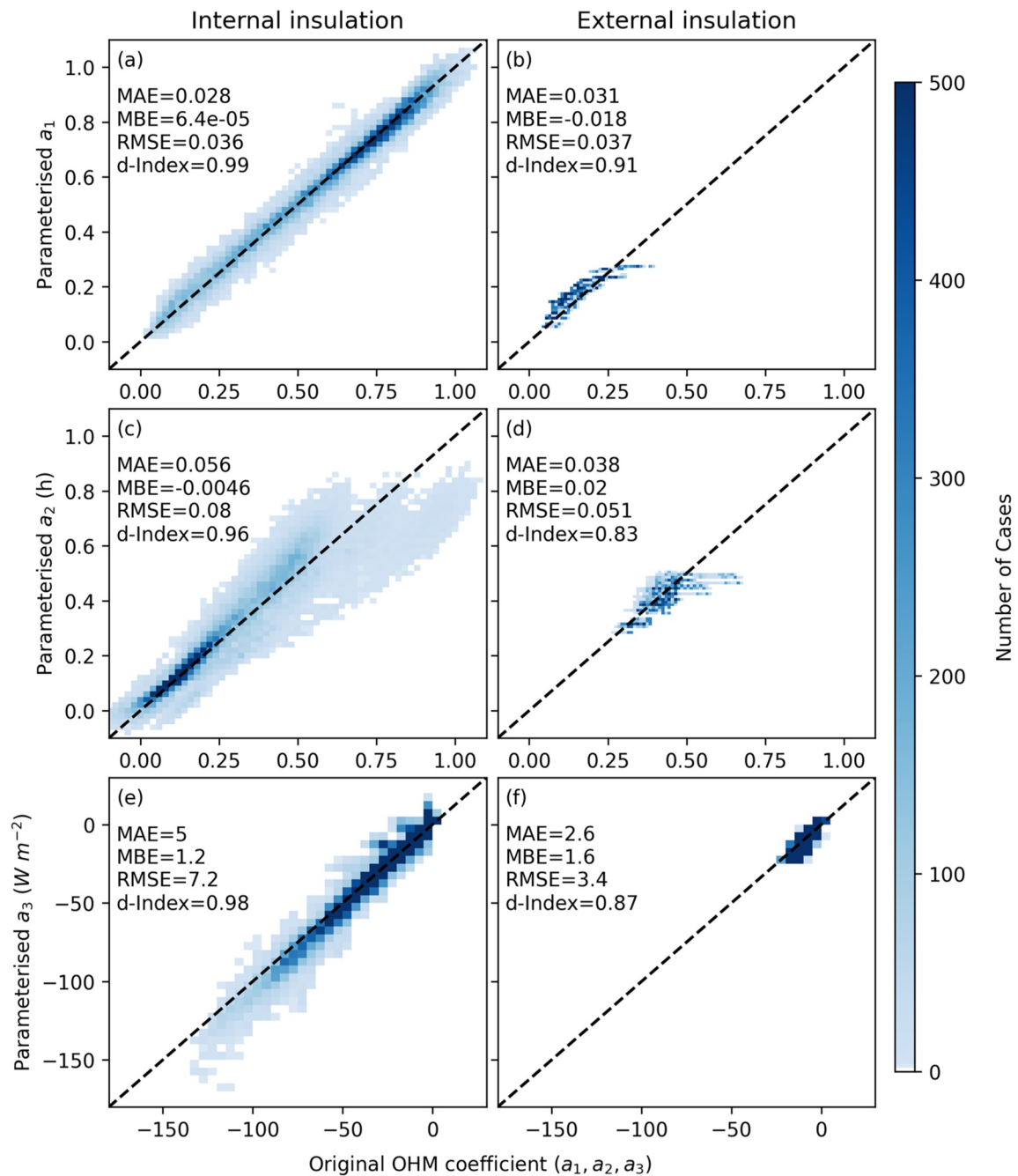


Figure 3. Evaluation of the parameterized (Equations 3–16) OHM coefficients with the originally derived OHM for (a, b) a_1 and (c, d) a_2 , (e, f) a_3 for (a, c, e) internal and (b, d, f) external insulation with a plaster layer at the exterior. The mean absolute error (MAE), mean bias error (MBE), root mean square error (RMSE) and index of agreement (d-index) with units the same as each coefficient, with data density (color).

agreement between the original and parameterized OHM values (MAE = 0.028 and d-index = 0.99 in Figure 3a). Surprisingly, the bias and agreement for external insulation configuration is also acceptable by using the thermal properties of the external plaster layer (Figures 3b and 3d). This highlights the minimal influence of the material internal to the insulation layer, while emphasizing the properties of the material external to the insulation play a crucial role in shaping building heat storage.

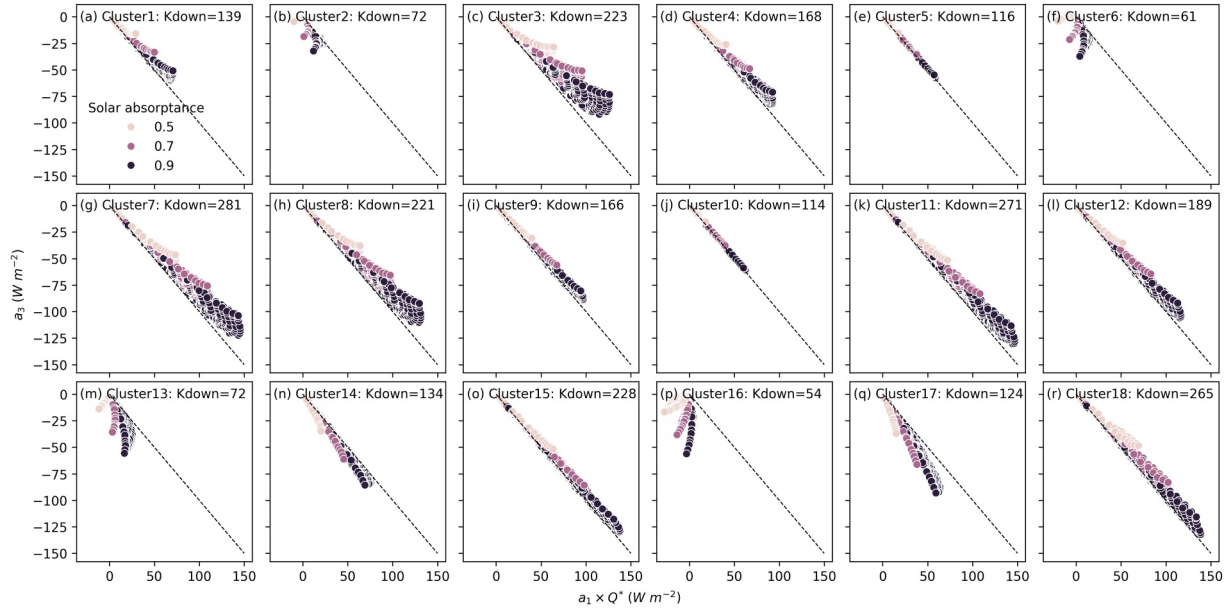


Figure 4. Relation between a_3 and $a_1 Q^*$ for the 18 weather clusters, with variability linked to the building material properties, with solar absorptance (1-albedo) indicated (color).

3.2. Parameterization and Evaluation of OHM Coefficient a_3

With a_1 parameterized based on meteorological and material factors, over 24 hr the hysteresis term for the building approaches zero ($\sum_{j=1}^{24} \frac{\partial Q^*}{\partial t} \approx 0$), allowing the a_3 to be estimated using a_1 with the following simplifications:

$$\Delta Q_{s,daily} = a_1 Q_{daily}^* + a_3 \quad (14)$$

$$a_3 = a_1 \times Q_{daily}^* \left(-1 + \frac{\Delta Q_{s,daily}}{a_1 \times Q_{daily}^*} \right) \quad (15)$$

The relation between a_3 and daily mean $a_1 Q^*$ differs for most meteorological clusters (Figure 4). It has a slope approaching -1 , indicating the net all wave radiation is the dominant energy source determining a_3 , particularly for Clusters 7, 11, 15, and 18 with large K_1 (Figures 4g, 4k, 4o, and 4r). However, clusters with low K_1 , the slope deviates from -1 , indicating reduced influence of Q^* . In these weather condition, a_3 is more reliant on daily heat storage ΔQ_s (Equation 15), which is directly influenced by day-to-day surface temperature changes (Kawai & Kanda, 2010).

Given that change in surface temperature influenced by both material properties and atmospheric conditions, we utilize outdoor air temperature to represent day-to-day variations. The role of materials on the slope between a_3 and $a_1 Q^*$ is small (Figure 4), with evidence of the external surface solar absorptance (sa) most distinct. Using these weather clusters with sa to further investigate how the slope varies with daily changes in air temperature (ΔT_{air} , midnight to midnight) we observe a linear relation (Figure 5) which allows us to parameterize a_3 as:

$$a_3 = a_1 \times Q_{daily}^* \left(-1 + \frac{5.2 \lambda_c \Delta T_{air}}{Q_{daily}^*} \right) \quad (16)$$

To evaluate this a_3 parameterization (Equation 16) we consider internal and external insulation cases separately because of a_1 (Equations 3–7). Figures 3e and 3f show a strong agreement between the parameterized and fitted values for all building cases under 18 weather clusters (d-index ≥ 0.87 for both internal and external insulation). However, a_3 is generally too large (more negative) for internal insulation cases, particularly the largest negative

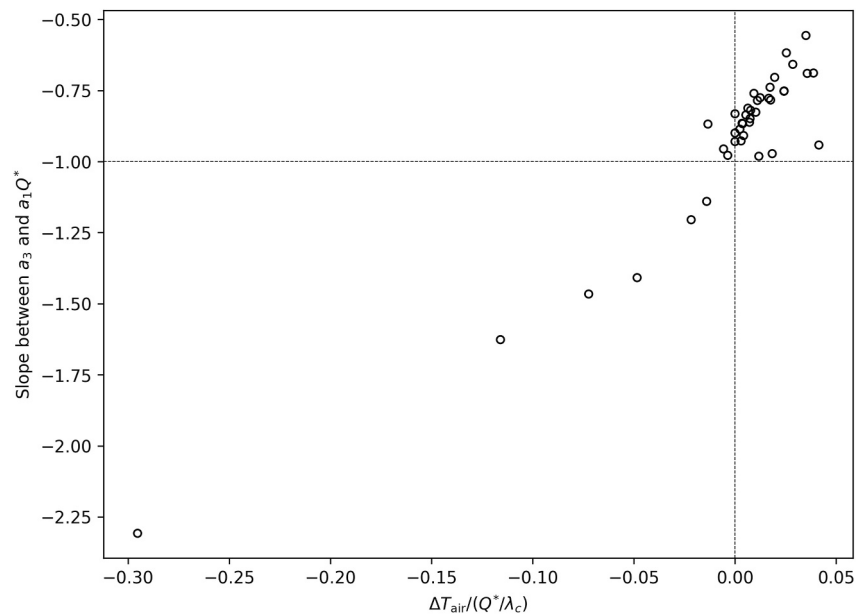


Figure 5. Relation between slope of a_3 and a_1Q^* to the ratio between air temperature change (midnight to midnight) to daily mean net all wave radiation. Each point shows the average values of cases grouped by weather cluster (subplots) and sa (color-codes) as in Figure 4.

values. This overestimation may be attributed to bias from overestimation in a_1 . Despite this bias, the effects may potentially compensate each other when evaluating the net storage heat flux.

3.3. Verification Against the Observations

Here we apply new OHM coefficient parameterization (Equations 3–16), accounting for both building material properties and varying meteorological conditions into the SOMUCH site described in Section 2.3 and verify against the observations. The daily OHM coefficients capture the meteorological variability using observed daily mean WS and Q^* , together with the midnight-to-midnight air-temperature change, ΔT_{air} .

The assessment metrics are better (lower MAE, MBE RMSE and higher d-index) using the new dynamic parameterization (Figures 6e–6h) than the fixed values selected by Hang et al. (2022, 2024) (Figures 6a–6d), which have been widely used in prior research. For all four weather conditions. Especially during hours (e.g., 10:00–15:00 dark colors) with high solar radiation, our new parametrization shows much higher agreement with observations compared the traditional parameterization. The hysteresis bias is also removed in winter clear-sky conditions (Figure 6c cf. Figure 6g).

The dyOHM-v1 coefficients are derived from dry EnergyPlus simulations; therefore, the summer-rainy case partly falls outside the training assumptions (Figure 6e). Rainfall and surface wetness can reduce conductive heat storage by redirecting available energy to evaporation, while rainfall and runoff can also cool surfaces directly through sensible heat exchange with water. These processes are not represented in dry OHM coefficients, so dyOHM-v1 may overestimate positive storage during or immediately after rainfall and may not fully capture rapid negative storage caused by surface cooling (Figure 6e). Nevertheless, the overall error remains moderate in the summer-rainy case because Q^* is generally small under rainy conditions, limiting the absolute magnitude of ΔQ_S . The improved performance relative to fixed OHM coefficients indicates that material properties and meteorological variability remain important even under these conditions.

3.4. Impacts of Building Materials on Building Heat Storage and Urban Air Temperature

The diurnal variation of ΔQ_S differs among houses in the neighborhood with three different wall types (Table 2). For B1 and B2 walls the diurnal range in ΔQ_S is similar, with the 220 mm external brick layer (B1) being the largest (Figure 7). This similarity, despite the cavity insulation wall (B2) external brick thickness (105 mm) being

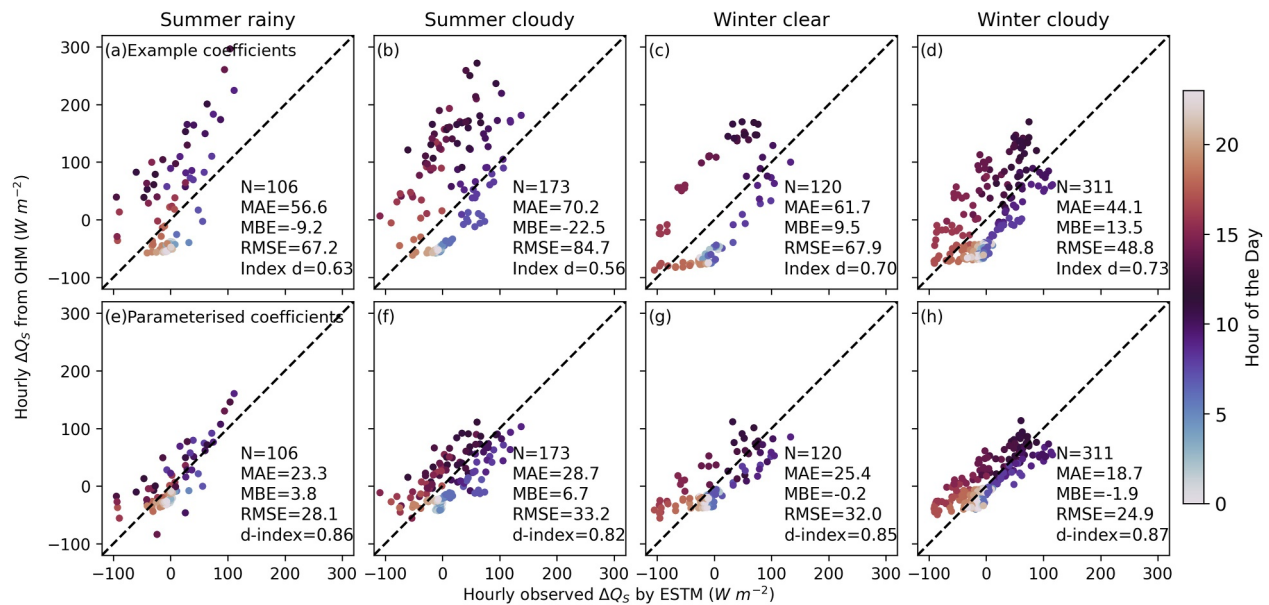


Figure 6. Comparison between observed and modeled ΔQ_s for (a–d) Hang selected parameters and (e–h) new dynamic OHM coefficients for different meteorological conditions (a, e) summer rainy, (b, f) summer cloudy, (c, g) winter clear, and (d, h) winter cloudy. The assessment metric is based on the number (N) hours indicate in each case.

less than half, is explained by the non-linear scaling of a_1 OHM coefficient with material thickness (Section 3.1). The external insulation case (B3), has the smallest diurnal variation in ΔQ_s , associated with the much lower heat capacity of the thin (19 mm) external render material.

Given this small difference between B1 and B2, we focus on comparison between wall types B1 and B3 (Figure 8) below. The daytime temperature change ΔT_2 are negligible across all seasons (median ≤ 0.03 , Figures 8e–8h) despite larger change of storage heat flux. This is because heat fluxes are mixed into a deeper atmospheric boundary layer at daytime than night (Anand & Sailor, 2023). At night more pronounced differences are observed. This occurs primarily when atmospheric stability changes are more likely to be neutral and stable than unstable (Figures 8e and 8h). This is particularly evident during spring (MAM) and winter (DJF), when the $\Delta_{B1-B3}[T_2]$ differences are linked to stability changes when having internal insulation (B1) versus external insulation (B3).

Figure 9 illustrates how the choice of building wall material (B1: thick external brick, B3: external insulation in Table 2) influences atmospheric stability and resulting temperature changes. The large temperature increase (red) is observed during transitions where the scenario with external insulation (B3) maintains stable atmospheric conditions, while the thick brick wall scenario (B1) shifts to neutral stability. This occurs because the exposed

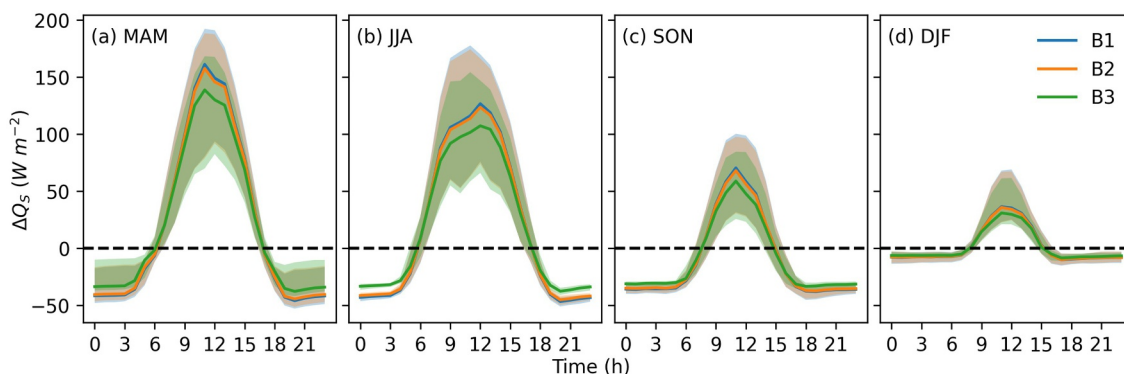


Figure 7. Seasonal diurnal profile (median: line, interquartile range: shading) of ΔQ_s for three brick walls (Table 2).

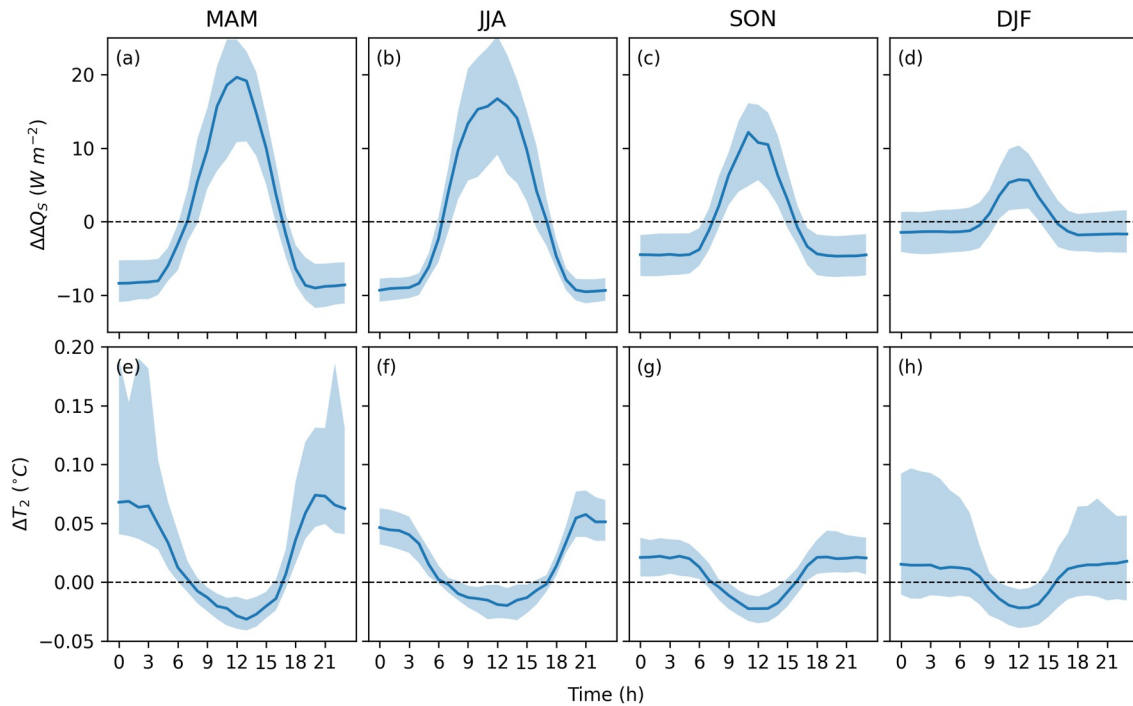


Figure 8. As Figure 7, but for B1–B3 differences (Table 2) of (a–d) $\Delta_{B1-B3}[\Delta Q_s]$ and (e–h) $\Delta_{B1-B3}[T_2]$ 2 m outdoor air temperature.

thick brick in B1 releases substantial stored heat at night, thereby enhancing the sensible heat flux. Interestingly, there are also instances of notable temperature decreases (indicated in blue) when B3 exhibits neutral stability while B1 becomes stable. This phenomenon only occurs at winter night coinciding with increased ΔQ_s in

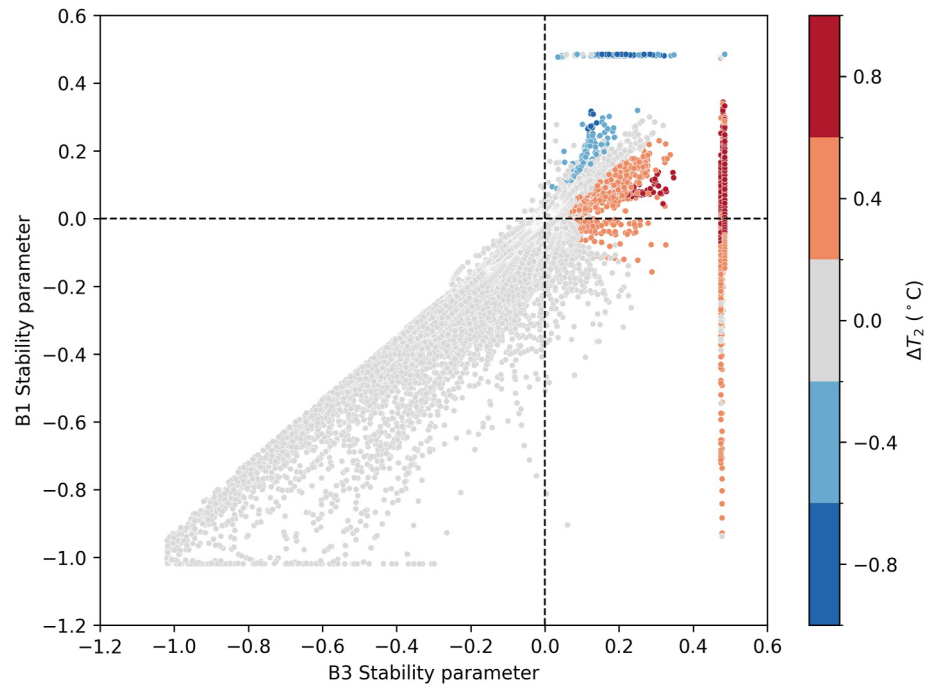


Figure 9. Difference of modeled 5-min atmospheric stability parameter ($[z_{\text{forcing}} - z_d]/L$) and 2 m air temperature (ΔT_2 , color) between two types of brick wall (B1, B3, Table 1), where z_{forcing} is forcing height, z_d is displacement height (derived from RSLscheme, (Grimmond et al., 2025)) and L is Obukhov length.

Figure 7d. These conditions are characterized by low incoming shortwave radiation (K_i) and elevated outdoor air temperatures relative to preceding days. The reduced daytime heat storage, combined with higher nighttime air temperatures, promotes heat uptake by the brick at night. As a result, the heat storage term (a_3) becomes positive for B1, as discussed in Section 3.2.

This implies that the spatial variability of the urban heat island (UHI) can occur between neighborhoods when material properties and insulation position are different. Representing building construction solely through wall thickness or uniform thermal properties will oversimplify its role. The position of insulation layers substantially alters how building thermal mass interacts with urban meteorological conditions, directly influencing the estimates of ΔQ_S and therefore many other urban climate variables (e.g., air temperature and wind speed). Recognizing the position of insulation is crucial for capturing neighborhood-scale variability in urban climate modeling.

From a building physics perspective, thermal mass internal to insulation is conventionally prioritized for controlling indoor thermal conditions. While appropriate at the individual-building scale, this may overlook the implications at neighborhood or city scales, where thermal mass external to insulation notably impacts the outdoor environment. Change in outdoor environment subsequently feedback to building thermal performance through ventilation and convective heat transfer mechanisms. Therefore, urban designers and planners should explicitly consider insulation placement and external thermal mass exposure in neighborhood planning strategies to balance indoor and outdoor environment.

4. Conclusions

In this paper, a new dynamic parameterization scheme (dyOHM) for obtaining coefficients (a_1 , a_2 , a_3) for Objective Hysteresis Model is proposed, to improve the accuracy for estimating building heat storage flux (ΔQ_S) in urban climate models. By conducting parametric building energy simulations using EnergyPlus, we analysed how building construction properties (thermal mass material thickness, position and thermal properties) and meteorological conditions influence the OHM coefficients, quantifying their relations.

Our findings indicate that, apart from material properties and meteorological factors, the insulation position within the building envelope is critical but rarely discussed control on building heat storage. The building materials external to the insulation layer are the dominant contributors to heat storage and release from net radiation. When insulation is placed external to the massive material, the latter has negligible impact on heat storage. In contrast, with internal insulation the massive material both thickness and thermal properties (e.g., conductivity, heat capacity, and solar absorptance) play an important role in affecting heat storage. Therefore, practical applications of dyOHM should prioritize accurate information on insulation position and the material properties of layers external to the insulation.

The developed dynamic parameterization is assessed using observations made at the Scaled Outdoor Measurement of Urban Climate and Health (SOMUCH) platform. There is good agreement between the modeled ΔQ_S and observed values obtained from the Element Surface Temperature Method (ESTM). The new approach provides a more accurate estimation of urban heat storage fluxes by accounting for variations in building material properties and weather conditions. This has indicated to be important before—but not systematically dealt with until this time.

Furthermore, integrating this scheme (dyOHM-v1) into the Surface Urban Energy and Water Balance Scheme (SUEWS) enabled the assessment of how different building constructions influence ΔQ_S and urban air temperature. The results clearly emphasize the necessity of considering insulation positioning and exposed material property in urban climate modeling, highlighting an opportunity to actively modulate urban climate through informed building design choices.

However, limitations remain that future work could improve. First, the data set used to derive dyOHM-v1 defines the applicability range of the parameterization. The current EnergyPlus simulations are based on dry, opaque, multilayer building envelopes with typical conductive materials. Rainfall, evaporation and moisture-related changes in material thermal properties are therefore not explicitly represented. The exclusion of windows also means that dyOHM-v1 is most directly applicable to opaque envelope storage and should be used cautiously for buildings with high window-to-wall ratios. Further testing is also required for novel materials or envelope systems whose storage behavior is not governed by typical conductive heat transfer, such as phase-change materials and ventilated facades.

Second, dyOHM-v1 is developed from an unoccupied reference building without internal heat gains or HVAC systems. It therefore parameterizes the passive storage response of construction materials to external meteorological forcing. In real buildings and neighborhoods, human-induced changes in storage heat flux should be represented consistently with anthropogenic heat parameterizations (Liu et al., 2022).

Third, the Swindon demonstration assumes homogeneous building construction within each wall-assembly scenario. Future applications should therefore assign OHM coefficients to distinct building construction types and aggregate them to better represent the heterogeneity of urban heat storage.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The data and code to reproduce the all figures are archived in Liu et al. (2026). The SUEWS simulation are produced by supy (version 2025.10.15 in Grimmond et al., 2025). The observation data in SOMUCH is available at <https://doi.iium.cn/home/index/view/id/21.html>.

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