Unveiling Causality: Does Demolishing Informal Settlements Cause Urban Surface Cooling?

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Article

Keywords:

Posted Date: October 29th, 2025

DOI: https://doi.org/10.21203/rs.3.rs-7288639/v1

Additional Declarations: No competing interests reported.

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Abstract

Can demolishing informal settlements actually cool the urban surface? Despite widespread renewal efforts, the direct impact of these interventions on land surface temperatures (LST) remains unclear. Most prior research has been limited to identifying associations, lacking the methodological tools to distinguish cause from correlation. Conventional before-and-after or cross-sectional comparisons are unable to disentangle the specific impact of demolition from confounding influences like ongoing urbanization, climate variability, or overlapping policy shifts. Here we apply the difference-in-differences (DiD) approach—rarely used in this context—to rigorously decode the causal relationship between informal settlement demolition and LST dynamics. Drawing on a time series of Landsat satellite thermal images, we track 77 demolished informal settlements and 584 control sites across Beijing, Shanghai, and Guangzhou from 2002 to 2022. The DiD framework enabled us to filter out confounding factors and isolate the causal effect of urban renewal. Our findings reveal significant, city-specific cooling effects—3.04 ± 0.37 K in Beijing, 1.09 ± 0.27 K in Shanghai, and 1.23 ± 0.36 K in Guangzhou (all $p < 0.05$). This study provides robust causal evidence confirming that demolishing informal settlements can significantly mitigate urban heat in megacities. These findings underscore urban renewal's potential as an effective tool for thermal management, enhancing our understanding of its direct environmental impacts.

Introduction

Globally, over 1 billion people live in informal settlements—dense, unplanned neighborhoods that often emerge on the edges of rapidly growing cities[1]. This pattern is not unique to one region: for example, Brazil's loteamentos[2] and Indonesia's kampongs[3] reflect similar forms of informal urban growth. In China, this phenomenon is especially pronounced in major cities, where such areas—often referred to as "urban villages," a subtype of informal settlements—typically arise as rural land is absorbed by expanding urban boundaries. Residents in these informal settlements, many of whom are rural migrant workers, face a range of socioeconomic disadvantages: poor living conditions, ambiguous property rights, limited access to healthcare, and systemic barriers due to restrictive residence registration policies[4,5].

Informal settlements are often characterized by extreme density and precarious, makeshift housing: single-room dwellings constructed from scavenged wood, corrugated metal, or plastic, with multiple families crowding into tight spaces. Their dense, low-rise structures, absence of trees or vegetated areas, and narrow alleys that hinder airflow contribute to elevated land surface temperatures (LST)[6,7], creating persistent "thermal hotspots". To alleviate such heat burdens, diverse urban renewal strategies have been explored. One widely implemented approach is the use of cool roofs[8], where packaging materials ("white coats") enhance the reflectivity of tin roofs to send solar radiation back into the atmosphere—Ahmedabad's pilot showed cool roofs lowering indoor temperatures and even residents' heart rates. Another approach is informal settlement upgrading, which integrates essential infrastructure such as paved roads, drainage, water supply, and green buffers—a tactic successfully applied in cities like Salvador (Brazil)[9] and Zenata (Morocco)[10]. Meanwhile, demolition and redevelopment projects in cities like Mumbai or Guangzhou[11] are replacing dense informal housing with planned, higher-rise developments and public green spaces, improving ventilation and enabling nature-based cooling. Together, these interventions—cooler surfaces, enhanced shade, improved airflow—offer promising solutions to mitigate heat stress and improve thermal comfort in vulnerable urban communities.

However, previous research on the temperature effects of such interventions has produced mixed and sometimes contradictory results. For instance, Jiang et al. (2024)[12] documented a substantial cooling effect—about a 5 K decrease in land surface temperature—when commercial buildings in Beijing's Jingzhuang area were replaced with urban parks. Similarly, Wu et al. (2022)[13] found notable LST reductions in central Guangzhou, particularly in the Pazhou and Yangji neighborhoods following renewal. In contrast, Wu et al. (2018)[14] reported that, in the core area of the Guangzhou-Foshan region, informal settlements actually exhibited lower LST than adjacent formal urban lands by 2–3 K, challenging the assumption that renewal always leads to cooling. Further complicating the picture, a longitudinal study in Guangzhou[15] found that between 2007 and 2017, urban renewal led to LST reductions in only half of the city's districts, while the other half experienced increases.

Most existing studies assess the relationship between informal settlement demolition and LST through simple before-and-after snapshots[12,13,15] or cross-sectional analyses[14,16], yielding correlations rather than causal insights. These methods were unable to separate the specific impact of demolition from broader trends such as ongoing urbanization or climate change. For example, if a city is undergoing rapid urbanization, the expansion of built-up areas and reduction of green space can intensify the urban heat island effect across the entire city, raising LST everywhere—including both areas undergoing renewal and those that are not. Similarly, if the region is experiencing climate change, rising background temperatures can mask the local cooling effects of demolition. In such cases, a straightforward before-and-after comparison might misleadingly show an increase in LST after demolition, even if the intervention itself actually caused a local cooling effect. Without a method that isolates the effect of demolition from these overlapping influences, it becomes difficult to attribute any observed changes in LST directly to the demolition of informal settlements, leading to inconsistent or even contradictory results across studies. This causal inference challenge is compounded by systemic selection bias–demolition sites are not randomly chosen but are selected based on location, land value, and political factors that themselves correlate with temperature. Simple comparisons between demolished and non-demolished areas confound pre-existing differences with treatment effects, while purely temporal comparisons cannot distinguish demolition impacts from city-wide climate trends that affect all areas simultaneously[17].

To address these challenges, this paper applies a difference-in-differences (DiD) approach[18–20] to rigorously isolate and quantify the impact of demolishing informal settlements on land surface temperature in three major Chinese cities: Beijing, Shanghai, and Guangzhou. Unlike conventional methods, the DiD framework allows us to control for confounding time trends and unobservable factors by comparing temperature changes in demolished settlements (treatment group) with those in comparable settlements that were not demolished (control group) over the same period. This quasi-experimental design has established precedent in urban environmental research: DiD analysis has been applied to analyze health and safety effects of vacant lot greening programs[21], climate-resilient city policies[22], and carbon market effects on urban greening[23]. The method's key advantage lies in its two-stage differencing strategy: the first difference (before-after within each group) eliminates time-invariant confounders including unobserved site characteristics, while the second difference (comparing changes between treatment and control groups) removes common time trends such as regional climate change. This approach requires only that demolished and control settlements would have followed parallel temperature trajectories absent the intervention–a weaker and more testable assumption than the random assignment required by experimental design. By leveraging over two decades of consistent satellite thermal data, a quasi-experimental design, and a suite of robustness tests, our analysis provides a clearer, more causal understanding of how urban renewal affects the urban thermal environment. Throughout this paper, we use the term “informal settlement” as an umbrella category encompassing *urban villages* in China and equivalent forms such as *slums, kampongs,* or *loteamentos* elsewhere, to maintain terminological consistency across global contexts.

Results

Quasi-Experimental Design and Data Organization

To rigorously investigate the causal impact of demolishing informal settlements on land surface temperature (LST), we designed a quasi-natural experiment using a difference-in-differences (DiD) framework. We assembled a time series panel dataset of 661 informal settlements across three major Chinese cities — Beijing, Shanghai, and Guangzhou — from 2002 to 2022 (Table 1). Among these, 77 settlements underwent demolition (the treatment group) at different years, while 584 remained intact (the control group). We tracked each settlement’s annual average LST in summer-time (June, July, and August) using satellite-derived data for multiple years before and after demolition and realigned each settlement’s time series so that “year 0” corresponds to the demolition yearThis synchronization enables direct comparison between treated and control groups while controlling for broader temporal effects such as global warming or urban growth.

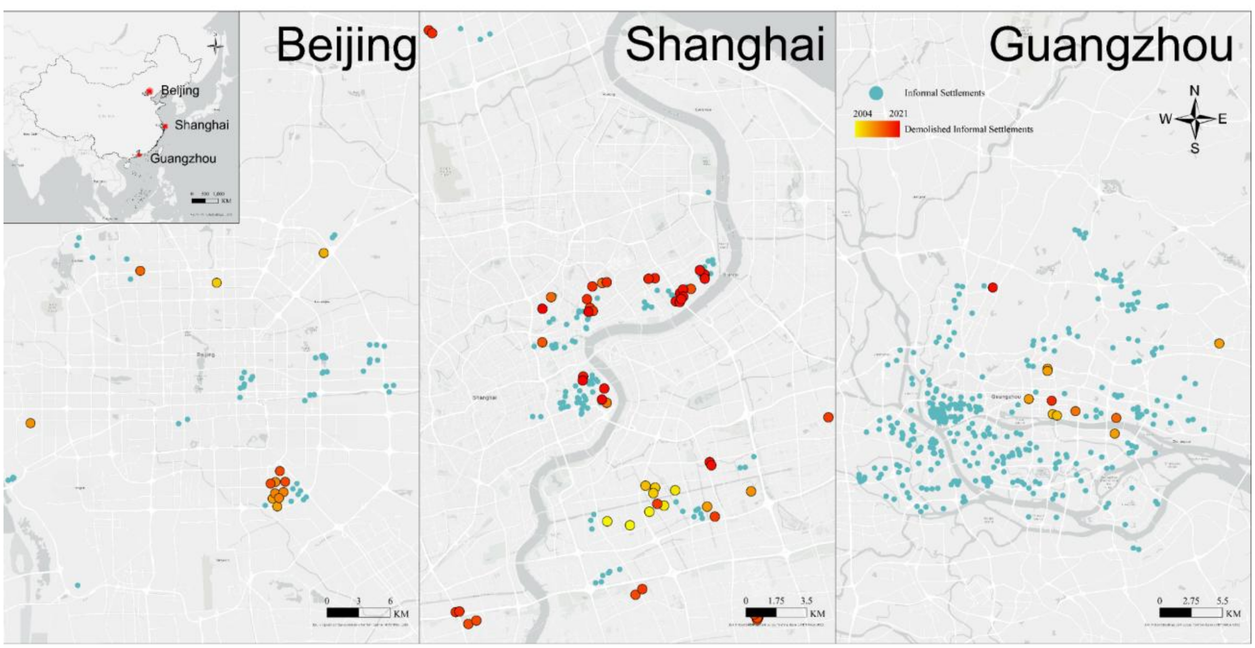


Figure 1| Locations of informal settlements. Dots with colors from red to yellow show the demolished informal settlements. Blue dots show the un-demolished settlements.

Table 1| Descriptive Statistics for the Samples of Informal Settlements

City	Types	Sample Size	Area (km^2)		Distance to CBD (km)		LST[K]		Air Temperature[K]		Reference Sources
			Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
All	Demolished	77	0.11	0.16	7.57	4.84	312.74	4.92	299.95	0.87	
	Not-demolished	584	0.06	0.09	8.32	5.51	311.56	4.10	300.81	0.91	
Beijing	Demolished	14	0.29	0.28	10.26	4.56	309.60	3.18	299.19	0.59	(Liu and Jia, 2021)[24]; ("Beijing Municipal People's Government," n.d.)[25]
	Not-demolished	58	0.05	0.07	11.64	11.19	310.82	3.46	299.09	0.83	
Shanghai	Demolished	52	0.06	0.08	7.48	4.60	314.11	4.93	299.89	0.72	(Peng et al., 2023)[26]
	Not-demolished	102	0.02	0.04	6.56	7.46	314.63	4.99	299.87	0.72	
Guangzhou	Demolished	11	0.12	0.10	4.53	4.35	309.66	3.05	301.19	0.36	("Guangzhou Municipal People's Government," n.d.)[27]
	Not-demolished	424	0.08	0.10	8.29	3.0	310.81	3.46	301.27	0.36	

Cooling Effects and the Role of Confounding Factors

Our difference-in-differences (DiD) analysis provides strong evidence that demolishing informal settlements significantly reduces local land surface temperature (LST) within the settlement areas themselves. Across all three cities studied, demolition led to an average LST decrease of 1.47 K (± 0.25 K) at the settlement level, with strong statistical significance ($p < 0.01$, $R^2 = 0.40$). Beijing exhibited the most pronounced cooling, with an average settlement-level LST reduction of 3.04 K (± 0.37 K, $p < 0.01$, $R^2 = 0.87$), while Shanghai and Guangzhou showed smaller but still significant effects of 1.09 K and 1.23 K, respectively (with R^2 values of 0.75 and 0.61). These results suggest that transforming dense, mid-rise informal settlements in these cities can substantially lower local surface temperatures. In Beijing, the stronger cooling effect observed following the demolition may be partly attributed to the city's semi-arid climate. This climate enhances evapotranspiration (ET) cooling, particularly in newly developed formal neighborhoods that have well irrigated greenspaces like parks (Supplementary Table 2). In contrast, cities like Shanghai and Guangzhou, which have more humid climates, exhibit more modest cooling effects. This difference may be due to the higher moisture content in the air, which limits the effectiveness of ET as a cooling mechanism[28].
Furthermore, Beijing's higher latitude plays a role in the cooling dynamics. National planning regulations mandate at least one hour of sunlight during the winter solstice, which encourages the

design of larger spaces between buildings in formal settlements[29]. This, in turn, creates more room for vegetation, further enhancing the cooling effect.

Table 2| Estimated Effects of Urban Renewal on Land Surface Temperature [K].

City	Effect of Urban Renewal	St. Err.	p-value	95% Conf. Interval	R^2
All	-1.47	0.25	<0.01***	[-1.97, -0.97]	0.40
Beijing	-3.04	0.37	<0.01***	[-3.77, -2.30]	0.87
Shanghai	-1.09	0.27	<0.01***	[-1.62, -0.56]	0.75
Guangzhou	-1.23	0.36	<0.05**	[-1.95, -0.52]	0.61

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Year and informal settlement individual fixed effects included.

To characterize post-demolition outcomes, we audited land uses by scraping Points-of-Interests (POIs) from AMap (gaode.com) within each polygon of demolished settlement. The tally shows that most cleared sites were redeveloped as formal residential or commercial neighborhoods, with a smaller share converted to parks (Supplementary Table 2). So the estimated cooling largely reflects regulated redevelopment rather than wholesale park conversion.

However, the observed cooling effects could potentially be confounded by broader trends such as ongoing urbanization, regional climate change, or shifts in economic activity—factors that influence settlement temperatures regardless of whether demolition occurred. To ensure that our estimated effects truly reflect the causal impact of demolition—rather than these external influences—we conducted a series of robustness checks, including parallel trends testing, placebo experiments, and alternative model specifications.

Robustness Checks: Validating the Causality of Cooling Effects

First, begin by testing the parallel-trends assumption. A difference-in-differences (DiD) design can only deliver credible causal estimates when the treated and control units would have followed the *same* trajectory in the absence of the intervention. To test this assumption, we conducted a visual inspection[30–32] by plotting the yearly temperature gap between demolished and non-demolished settlements from 7 years before through 7 years after demolition (Fig. 2).

For the pooled sample (Fig. 2a) the pre-intervention coefficients (years –7 to –1) are tightly centred on zero and statistically indistinguishable from it; all 90 % confidence bands overlap the horizontal reference line. This flat pre-trend indicates that, absent demolition, the two groups were on identical thermal paths. Year –1 serves as the reference period, so every plotted coefficient represents a deviation from that baseline. Immediately after demolition the series bends sharply downward, with the LST gap reaching –2.19 K in year +1 and stabilizing around –2 K by year +7. Because the pre-period is flat, this divergence can be attributed to demolition rather than to pre-existing differences or coincident shocks.

City-specific estimates tell a consistent story while revealing local nuances (Fig. 2b–d). Beijing shows the cleanest pattern: a level pre-trend followed by a monotonic fall that bottoms out near –4 K by year +6, suggesting that the city's dry continental climate amplifies the cooling benefit. Shanghai exhibits a similar, though gentler, response: post-demolition cooling settles between –1 K and –2 K, and the wider confidence bands reflect greater year-to-year humidity and cloud-cover variability. Guangzhou displays the largest confidence intervals and a brief rebound in years +2 to +5, yet the post-demolition average remains below zero, implying that local hydrometeorological dynamics modulate but do not overturn the treatment effect.

Taken together, the absence of any statistically detectable gap in the years preceding demolition, combined with a clear and sustained divergence afterwards, satisfies the parallel-trends requirement and strengthens the causal interpretation of the estimated cooling effect.

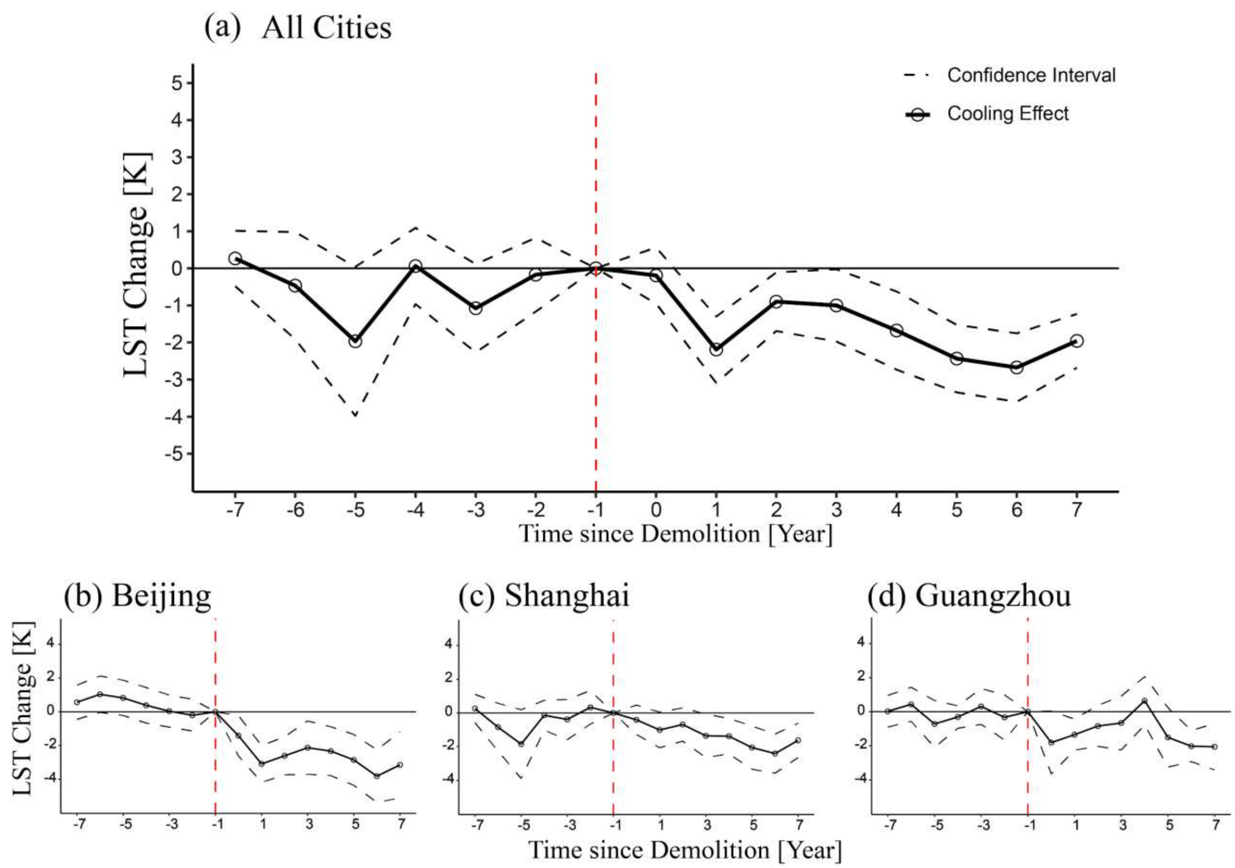


Figure 2| Changes in surface temperatures in informal settlements in All Cities (a), Beijing (b), Shanghai (c), and Guangzhou (d). The time series of each settlement has been shifted so that the years of being demolished are aligned. Dashed lines show the 90% confidence intervals.

Second, to further verify the reliability and consistency of our results, we conducted a series of **model specification tests** using stepwise regression (Table 3).

Besides urban renewal, Model 1 adds only urban population as a basic control and yields a significant cooling effect of –1.42 K ($p < 0.01$). Model 2 further adds air temperature to account for broader climatic influences[33], and the estimated effect remains nearly unchanged at –1.43 K ($p < 0.01$), indicating that the result is robust to the inclusion of climate factors. Model 3 further incorporates urban construction land area[34], which slightly reduces the effect to –1.25 K ($p < 0.01$), suggesting that land-use factors help explain part of the variation. Finally, Model 4 adds nighttime light intensity as a proxy for economic activity[35] and it includes all covariates together—urban population, air temperature, urban construction land area, and nighttime light data—resulting in the strongest estimated effect of -1.47 K ($p < 0.01$) and the highest explanatory power ($R^2 = 0.40$). This consistency across models indicates the cooling effect is robust to omitted variable bias.

Table 3| Model specification test results

	Model-1	Model-2	Model-3	Model-4
Effect of Urban Renewal	-1.419***	-1.429***	-1.248***	-1.467***
	(0.226)	(0.229)	(0.240)	(0.254)
Urban population	0.003***	0.003***	0.003***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Air temperature		0.637***	0.653***	0.586***
		(0.063)	(0.070)	(0.069)
Urban construction land area			0.001***	0.001***
			(0.000)	(0.000)
Nighttime light data				1.52e-5***
				(0.000)
Observation	11827	11827	10714	10714
R^2	0.361	0.365	0.391	0.402

Note: Standard errors for the informal settlement cluster are reported in parentheses. The constant term is omitted for brevity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Third, to confirm that our estimated cooling effects were not spurious, we conducted a placebo test, randomly assigning demolition years 500 times and comparing actual DiD estimates against the null distribution. If the actual DiD estimate falls within the range of the placebo distribution, it suggests that the observed effect may be attributable to random variation. Conversely, if the actual estimate lies far outside the placebo distribution, this indicates that the effect is statistically significant and robust.

As shown in Figure 3, the distribution of placebo effects (red curves) is centered near zero and concentrated on the right side of the actual DiD estimates (blue vertical lines), which fall far in the left tail—indicating that the observed cooling effects are unusually large and unlikely to occur by chance. For the pooled sample (Figure 3a), the distribution peaks near zero, while the observed effect of -1.47 K lies far in the left tail of the distribution, indicating it is a strong outlier. Similar patterns are observed in each individual city: in Beijing (Figure 3b), the actual DiD coefficient of -3.04 K is well outside the range of placebo values, nearly all of which lie above -1.0 K; in Shanghai (Figure 3c), the true estimate of -1.09 K falls on the extreme left of a distribution centered above zero; and in Guangzhou (Figure 3d), the actual effect of -1.23 K is also well separated from the bulk of placebo estimates, which are almost symmetrically distributed around zero.

These results provide strong validation of our causal inference: the true DiD estimates consistently appear as extreme outliers, underscoring that the cooling effects are highly unlikely to be artifacts of random timing or model noise.

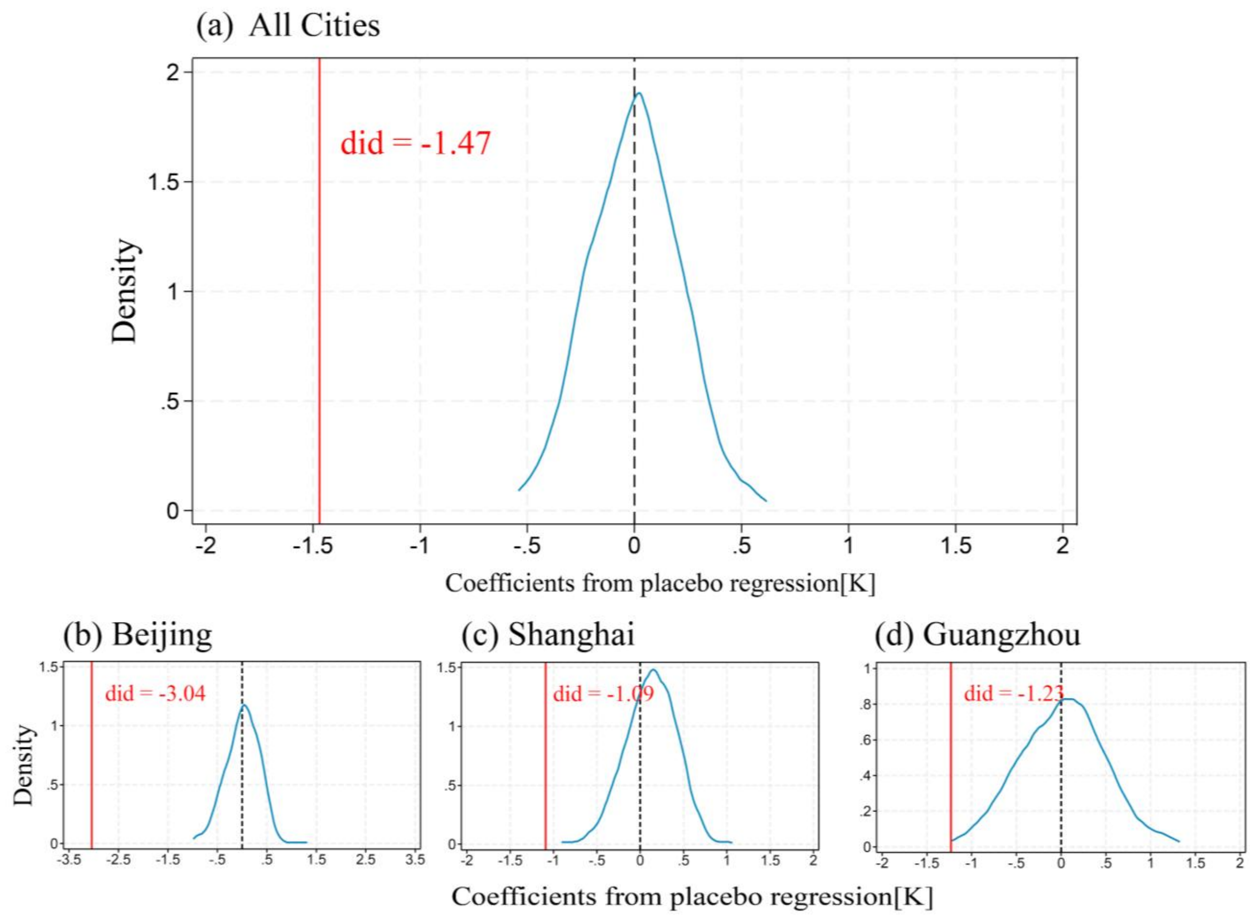
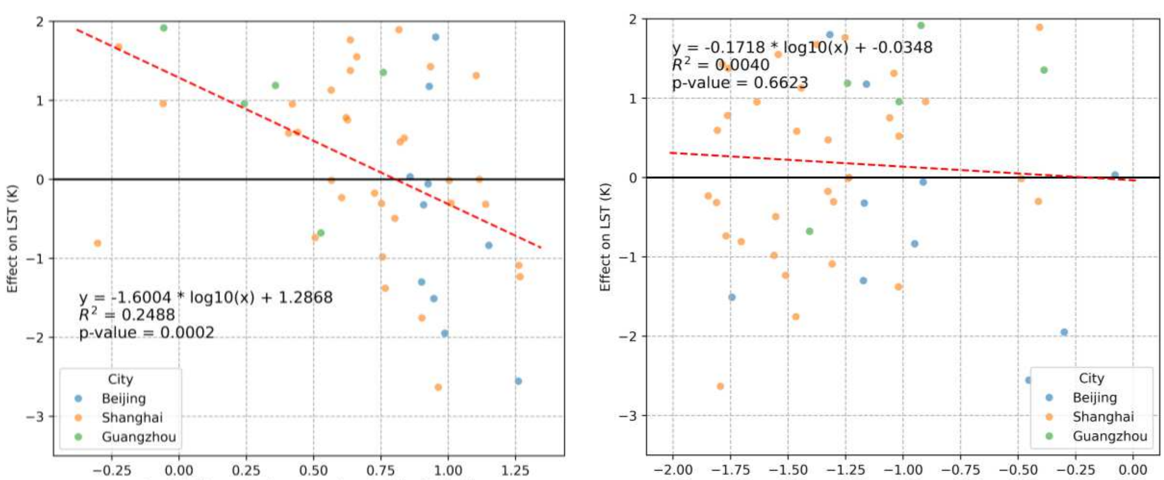


Figure 3| Placebo test results for samples in all cities (a), Beijing (b), Shanghai (c), and Guangzhou (d). The vertical red lines are the coefficients from the difference-in-difference (DiD) analysis. The curves are the probability density functions of the coefficients from the placebo test with randomly assigned treatment years.

Finally, we examined spatial heterogeneity by testing whether settlement location and size influence cooling magnitude. As shown in Figure 4a, we find a statistically significant negative correlation between distance and LST reduction ($R^2 = 0.25$, $p < 0.01$; slope = –1.60), indicating stronger cooling effects on urban peripheries where redevelopment may accommodate more vegetation and open space. This distance-dependent pattern reflects systematic differences in post-demolition redevelopment outcomes shaped by land economics[37]. Lower peripheral land prices enable developers to reduce building coverage ratios—in contrast to central redevelopments prioritizing higher density to extract maximum value from expensive land[38].

We also tested whether the size of demolished settlements influences the magnitude of temperature change. However, as shown in Figure 4b, the relationship between settlement area and cooling effect is both weaker ($R^2 = 0.004$) and statistically insignificant ($p > 0.1$). This indicates that, unlike spatial location, settlement size does not meaningfully modulate the thermal response to demolition. This result reflects the scale-independent nature of local surface cooling mechanisms. The primary thermal effects of demolition—increased sky view factor enabling radiative cooling, reduced aerodynamic roughness enhancing atmospheric mixing, elimination of thermal mass from structures, and potential evapotranspiration from replacement vegetation—operate universally within the urban canopy layer regardless of site extent[39,40].

Taken together, these findings suggest that while urban geography can shape the intensity of surface cooling, particularly through proximity to city centers, the core causal relationship remains consistent: demolishing informal settlements leads to measurable and often substantial reductions in local land surface temperatures. The spatial heterogeneity observed reflects where and how post-demolition sites are redeveloped (distance-dependent), not whether local thermal environments respond to physical property changes (scale-independent).



a **b**

Figure 4| The relationship between the effects of demolition on LST and (a) the log-scale distances to the nearest city center, and (b) the log-scale areas of the informal settlements. There is a relatively weak (R^2=0.25) but statistically significant (p<0.01) negative correlation between the effects on LST and the log-scale distances to the nearest city center. The relationship between temperature effects and the log-scale areas is weaker (R^2=0.004) and not statistically significant (p>0.1).

Discussion

Urban informal settlements, while providing crucial low-cost housing and economic footholds for rural migrants, are also among the hottest micro-environments in the city: cramped buildings, scant vegetation, and narrow airless streets amplify the urban heat island effect and leave residents especially vulnerable to extreme heat. Despite decades of demolition and renewal programs, the true thermal impact of these interventions has remained uncertain, due largely to the limitations of before-and-after or cross-sectional designs that cannot disentangle demolition effects from city-wide warming trends. This study addresses that gap by applying a quasi-experimental difference-in-differences design to 77 demolished settlements and 584 matched controls in Beijing, Shanghai, and Guangzhou (2002–2022), revealing a clear causal cooling signal: demolition lowers settlement-level LST by an average of 1.47 K, with city-specific reductions reaching 3.04 K in drier Beijing and approximately 1.1 K to 1.2 K in more humid megacities. But these cooling effects are mostly local: the total demolished area is only ~7.7 km^2 and represents <1% of the city land – far below the ~15-30% land-cover change thresholds that previous studies suggest are needed to shift the temperature of whole cities[41,42], unless redevelopment is orchestrated as part of a coherent city-wide greening and ventilation corridor strategy.

This study advances urban climate research by addressing a widely recognized challenge: establishing causation rather than correlation in observational studies of urban interventions. Environmental and Earth system scientists increasingly recognize that moving from descriptive associations to causal understanding requires explicitly accounting for confounding factors and constructing counterfactual scenarios[43,44]. For urban heat research specifically, the dominance of space-for-time substitution and cross-sectional comparisons has limited our ability to evaluate whether interventions actually cause temperature changes or merely correlate with them[45]. Our quasi-experimental approach demonstrates that natural variation in demolition timing across settlements enables rigorous causal inference while accounting for spatial dependencies and temporal confounding. This framework can extend beyond informal settlements to other urban climate interventions where treatment assignment is non-random and background trends must be separated from intervention efforts.

Our findings suggest that informal settlement renewal—when it replaces dense, thermally inefficient structures with open space, vegetation, or planned development—can be reframed not just as a tool for land management or aesthetic improvement, but as a concrete strategy for climate adaptation. Although our analysis does not directly measure post-demolition regulatory compliance, the pattern of temperature reduction is consistent with the institutional logic of Chinese regulations. Formal redevelopment projects are typically required to follow national and municipal codes[46] that mandate minimum greenspace ratios (25-35%), building spacing for sunlight and ventilation, and upper limits on building density. These requirements, once applied to former informal settlements, plausibly contribute to the observed cooling by enforcing greener, more ventilated urban forms. Thus, the cooling we detect likely reflects both physical and regulatory effects.

Cooling effects are especially pronounced in peripheral urban areas, where redevelopment may more often include green space or open land. In these zones, planning codes tend to specify higher greening standards and lower floor-area ratios, reinforcing the potential for temperature reduction. While we cannot disentangle these institutional influences from physical ones within our dataset, they provide a plausible explanation for the consistent cooling patterns observed across cities. As such, cities facing growing heat stress should consider integrating informal settlement renewal into their broader climate resilience strategies, particularly when prioritizing interventions in urban heat hotspots.

However, the thermal benefits of demolition are not automatic nor universally equitable. Without supportive policy frameworks, demolition risks displacing the very populations most vulnerable to heat, pushing them toward peripheral areas with worse access to jobs, infrastructure, and often more extreme environmental exposure. For instance, in Hangzhou, urban village demolition has driven nearly a third (29.2%) of migrant workers to spend over 30% of their income on rent, with 14.1% planning to return to rural areas due to housing pressures[48]. Moreover, such demolitions force relocation to more remote suburbs, significantly increasing commute distances and durations for affected workers[47]. These findings underscore a critical paradox: a city may become cooler overall, while its poorest residents are pushed further into marginality. These findings underscore a critical paradox: a city may become cooler overall, while its poorest residents are pushed further into marginality. Addressing this requires a deliberate shift toward inclusive planning frameworks that combine thermal mitigation with social equity goals[49]—for example, inclusionary zoning, on-site affordable housing, or tenant protections that ensure displaced residents can return or remain nearby[50].

While this study centers on China's past experience with large-scale demolition, the findings carry broader relevance for the Global South, where cities such as Nairobi, Mumbai, and São Paulo face similar trade-offs between cooling dense settlements and protecting vulnerable populations. The cooling effect demonstrated here provides quantitative evidence that reducing built density and increasing surface permeability can alleviate local heat stress—a result consistent with prior experimental and modeling studies showing the cooling benefits of surface greening and reflective materials[8,12,13]. These insights remain valuable even as China and other countries shift from demolition toward incremental, in-situ upgrading[51], in line with evolving policy priorities that discourage large-scale clearance and emphasize micro-renewal and climate adaptation. The difference-in-differences framework developed here offers a transferable tool for evaluating the causal thermal impacts of diverse interventions, from cool roofs and tree planting to ventilation corridors and micro-greening. Applying this quasi-experimental approach to upgrading efforts can help identify which strategies yield the greatest thermal relief with the least social disruption, advancing evidence-based, climate-resilient urban policy across the Global South[49,50].

This equity challenge also highlights a broader methodological gap: while our findings show that demolition reduces surface temperatures, they leave open the question of how such changes translate into actual human experience. Although our analysis uses satellite-derived LST as a proxy for urban heat, it does not directly capture residents' lived experiences of thermal discomfort. A 1.5 K LST reduction could translate to vastly different lived experiences depending on building materials, ventilation, and household cooling capacity—factors systematically correlated with socioeconomic status. Without ground-truth validation linking LST changes to physiological heat exposure (core body temperature, heat-related morbidity) or behavioral adaptation (cooling expenditure, time-activity patterns), we cannot claim these surface cooling effects translate into health benefits for displaced or remaining residents. Future work should triangulate these findings with ground-level data on air temperature, humidity, indoor heat, and health outcomes. For instance, integrating wearable temperature sensors or surveying residents about heat-related health symptoms could clarify how much cooling is necessary to produce tangible well-being benefits[52].

This study also opens methodological and geographic frontiers. The difference-in-differences framework[18,20], rarely used in urban climate research, can be extended to assess the causal impacts of other interventions—such as tree planting, cool roof programs, or green infrastructure. Moreover, testing whether similar thermal outcomes occur in smaller, less-resourced cities or across different climate zones (e.g., tropical or semi-arid regions) will be key to understanding the external validity of our results. Initial evidence suggests that cooling effects may be stronger in drier cities like Beijing, and more modest in humid cities—a hypothesis future multi-city comparisons could explore.

The broader relevance of our findings is considerable. Informal settlements in many Global South cities—from Nairobi's Kibera to Mumbai's Dharavi—exhibit similar characteristics: extreme density, poor ventilation, impervious materials, and high thermal exposure. These parallels suggest that renewal or upgrading efforts in such settings could yield meaningful thermal benefits. However, because our analysis is limited to three Chinese megacities, the generalizability of these findings should be interpreted with caution. Unlike the Chinese megacities in our sample, many cities elsewhere lack the governance capacity or resources to support resettlement, compensation, or service upgrades post-demolition. In these cases, in-situ upgrading—through green buffers, cool roofs, or ventilation corridors—may be more feasible and socially sustainable[8].

In summary, our results provide the first robust causal evidence that demolishing dense informal settlements leads to significant reductions in land surface temperatures. Yet, for this cooling to translate into broader urban resilience, demolition must be accompanied by policies that mitigate social displacement and ensure that vulnerable populations share in the environmental gains. Urban climate adaptation strategies should treat informal settlements not just as risks to be managed, but as opportunities for transformative, inclusive change.

Methods

Delineation of informal settlements

Informal settlements, characterized by high density, low-rise construction, and substandard living conditions, are a persistent feature in rapidly urbanizing regions. In this study, informal settlements are defined not only by their physical form but also by tenure arrangements, where land is extra-legally occupied and exchanged, rather than outright illegally seized. The built environment in these areas typically exhibits high land coverage and limited building height, a spatial logic driven by land scarcity and constrained resources.

To delineate these settlements, we synthesized multiple data sources. Spatial extents were initially identified from published maps in peer-reviewed articles and policy documents, and further refined using city redevelopment policy materials (see Table 1). All delineations were independently performed by two researchers and cross-validated using high-resolution optical imagery (WorldView and Google Earth Pro) to ensure spatial accuracy. Any discrepancies were jointly reviewed and resolved through consensus. These candidate boundaries were verified against official policy publications to ensure that the delineated boundaries align with recognized urban development areas. The validated boundaries were digitized as regions of interest (ROIs) in shapefile format, suitable for subsequent spatial analysis.

To minimize potential selection bias, non-demolished (control) settlements were selected from the same administrative districts as demolished ones, ensuring comparable socioeconomic and environmental contexts. The final dataset comprises 661 informal settlement polygons across Beijing, Shanghai, and Guangzhou, including 77 demolished and 584 non-demolished settlements. The mean areas of demolished and non-demolished settlements were 0.112 km² and 0.064 km², respectively. Descriptive statistics, including mean LST, mean air temperature, are provided in Table 1 to demonstrate the baseline comparability between demolished and non-demolished groups.

Retrieval of Land Surface Temperature (LST)

Land surface temperature (LST) is a key indicator of urban surface energy balance, and is especially relevant in the context of densely built informal settlements. Standard air temperature measurements are too sparse and coarse for this application, so we employed high-resolution LST retrieval using Landsat satellite data within the Google Earth Engine platform. The retrieval algorithm is based on top-of-atmosphere (TOA) radiance and surface reflectance, integrating auxiliary data on atmospheric water vapor and surface emissivity.

The workflow begins with calculation of the normalized difference vegetation index (NDVI) using surface reflectance, which is then converted to fractional vegetation cover (FVC) following:

$$FVC = \left(\frac{\mathrm{NDVI} - \mathrm{NDVI}_{\mathrm{bare}}}{\mathrm{NDVI}_{\mathrm{veg}} - \mathrm{NDVI}_{\mathrm{bare}}}\right)^2$$

where ($\mathrm{NDVI}_{\mathrm{bare}}$) and ($\mathrm{NDVI}_{\mathrm{veg}}$) represent the NDVI values of bare soil and fully vegetated pixels, respectively, as established in prior literature. Surface emissivity for mixed pixels is estimated using the vegetation cover method:

$$\epsilon_b = \epsilon_{b,\mathrm{veg}} \cdot \mathrm{FVC} + \epsilon_{b,\mathrm{bare}} \cdot (1 - \mathrm{FVC})$$

where ($\epsilon_{b,\mathrm{veg}}$) and ($\epsilon_{b,\mathrm{bare}}$) are the emissivities of vegetation and bare soil for a given thermal band. The LST is then retrieved via the Statistical Mono-Window (SMW) algorithm, which models LST as a linear function of TOA brightness temperature and surface emissivity:

$$\mathrm{LST} = A_i \frac{T_b}{\epsilon} + B_i \frac{1}{\epsilon} + C_i$$

Here, (T_b) is the TOA brightness temperature, (ϵ) is the surface emissivity, and (A_i), (B_i), and (C_i) are regression coefficients calibrated using atmospheric profile datasets. This approach yields LST at high spatial resolution, providing fine-grained temperature fields suitable for informal settlement analysis.

The approach follows established methods for NDVI-to-FVC conversion, surface emissivity estimation, and the Statistical Mono-Window (SMW) algorithm, as detailed in Ermida et al. (2020)[53], Caselles et al. (1997)[54], Rubio et al. (1997)[55], Li et al. (2013)[56], Sun et al. (2004)[57], and Martins et al. (2016)[58].

Control variables

We include four city-level time-varying covariates to isolate the demolition effect from confounding urban dynamics (Supplementary Table 1):

- **Urban population**: Captures agglomeration intensity and anthropogenic heat flux from human activities. This controls for the fact that more populous cities generate more waste heat regardless of demolition.
- **Air temperature**: Represents background climatic conditions. Year-to-year climate variability (e.g. El Niño events, heat waves) affect LST independently of land use changes. Omitting this would conflate demolition effects with natural climate fluctuations.
- **Urban construction land area**: Proxy for impervious surface expansion–the primary driver of urban heat island (UHI) intensification. This separates the local impact of demolition from citywide sprawl dynamics.
- **Nighttime light intensity**: Proxy for economic activity and energy consumption, which correlates with heat emission from industry, commerce, and buildings. This is independent of population size–a wealthy low-population district emits more heat than a poor high-population one.

Climate variables, including air temperature were obtained from the C3S Climate Data Store[33]. Urban form and socioeconomic variables were sourced from the China Stock Market & Accounting Research Database (CSMAR)[34] and included urban construction area, urban population, and nighttime light intensity, the latter of which was used as a proxy for economic activity[35]. These variables were included in the statistical models to account for background climate, urbanization, and economic trends that could otherwise confound the relationship between demolition and surface temperature.

Baseline Difference-in-Differences model

We assessed the causal impact of informal settlement demolition on LST using a difference-in-differences (DiD) framework. This quasi-experimental approach compares LST changes in demolished settlements (treatment group) to those in non-demolished settlements (control group) before and after the intervention, controlling for time-invariant unobserved heterogeneity and observed time-varying covariates.

The model specification is:

$$LST_{it} = \beta_0 + \beta_1 DiD_{it} + \gamma X_{it} + \delta_i + \delta_t + \epsilon_{it}$$

where $DiD_{it} = group_i * time_t$

Where (LST_{it}) is the land surface temperature for settlement (i) in year (t); $group_i$ indicates whether i is an informal settlement that was demolished or not; $time_t$ is a time dummy variable that takes a value of 1 for the year the settlement was demolished and for the subsequent years, and 0 otherwise. (X_{it}) is a vector of control variables, (δ_i) and (δ_t) denote the informal settlement and year fixed effects respectively,, and (ε_{it}) is the error term. The coefficient (β_1) represents the average treatment effect of demolition on LST. For the baseline model, control variables include urban population, air temperature, urban construction land area, and nighttime light intensity. To further analyze the contribution of these controls, we also conducted model specification tests using stepwise regression, as discussed in the Model specification test section.

Parallel trends test

The validity of the DiD estimator relies on the parallel trends assumption: in the absence of intervention, the treatment and control groups would have followed similar LST trajectories. We tested this assumption by aligning all settlements by their respective demolition years and estimating pre- and post-intervention LST differences between groups using the baseline model. If pre-intervention differences are statistically indistinguishable from zero, and post-intervention differences diverge, the parallel trends assumption is supported.

Model specification test

We employed forward stepwise regression to test the robustness of the core DiD coefficient, sequentially adding city-level covariates and retaining variables that minimized the Akaike Information Criterion (AIC).
The four model specifications are as follows:

- Model 1: Includes only basic demographic control, using urban population to account for city growth trends.
- Model 2: Builds on Model 1 by adding air temperature to capture broader climatic variation across cities and years.
- Model 3: Extends Model 2 by introducing urban construction land area as a proxy for land-use intensity.
- Model 4: Adds nighttime light data presenting economic activity and combines all covariates to provide the most comprehensive specification.

This stepwise approach, akin to adding variables in a classic regression setting to test for omitted variable bias, ensures that each additional covariate contributes meaningfully to explaining variation in LST. The consistency of the estimated effect of informal settlement demolition across all model specifications confirms the robustness of our results and indicates that the findings are not driven by omitted variable bias or model instability.

Placebo test

To rule out spurious correlations, we conducted a placebo test by randomly assigning demolition years to treatment settlements and re-estimating the DiD model. This process was repeated 500 times to generate a null distribution of placebo coefficients. The observed treatment effect was compared against this distribution to assess its statistical rarity under a null hypothesis of no effect.

Heterogeneity analysis

To explore spatial heterogeneity, we extended the DiD model with interaction terms for:

1. Log-distance to city center (measured from polygon centroids to the nearest historic/economic core)
2. Log-transformed settlement area (in km^2)

Distance to the city center serves as a key spatial variable because thermal responses to demolition likely vary along the urban-rural gradient. Core urban areas typically have higher baseline LST, denser surrounding development, and stricter land constraints that limit green space incorporation during redevelopment—factors that may dampen post-demolition cooling. In contrast, peripheral settlements often have more flexibility for lower-density redevelopment and vegetation integration, potentially amplifying cooling effects. By testing whether distance modulates the treatment effect, we assess whether location systematically influences the magnitude of thermal mitigation.

These interaction terms allowed us to assess whether larger or more peripheral settlements exhibited differential thermal responses to demolition.

Acknowledgment

This study was supported by the Google Award for Inclusion Research and the Shanghai Pujiang Program (23PJ1410100 STCSM).

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