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Linking urban growth and surface temperature change in capital and secondary cities of Southeast Asia



Ronghua Xu¹, Shankar Acharya Kamarajugedda¹, Raffaele Laforzezza²,
Shaikh Fairul Edros Ahmad Shaikh^{1,3} & Perrine Hamel^{1,3} ✉

Rapid urbanization exacerbates heat-related environmental issues. Yet urban expansion patterns and associated heat risks in developing countries remain poorly understood. We selected eight capital and eight secondary cities in Southeast Asia and characterized urban growth and heat hazards in their fringes using three spectral indices: built-up percentage of landscape (PLAND), Normalized Difference Vegetation Index (NDVI), and Land Surface Temperature (LST). From 2000 to 2020, PLAND and LST in the fringes increased by 11.93% and 1.39 °C, respectively. LST in the fringes of capital cities was 1.70 °C higher than in secondary cities. LST increases exceeded those in urban cores, particularly in secondary cities (+0.35 °C). Highly populated and wealthier cities showed marked PLAND increases and NDVI declines, but not necessarily elevated LST. We identify priority areas for land cover management and urban heat mitigation by city type and geographic location to inform sustainable regional planning.

Climate change threatens sustainable development by increasing urban heat risks and raising environmental justice concerns, particularly in rapidly developing countries^{1,2}. In 2023, extreme heat records peaked, with air temperatures reaching 39.2 °C in most areas^{3,4}. Rapid urbanization intensifies thermal environmental risks, contributing to rising temperatures and more frequent extreme weather events, jeopardizing both ecosystems and human survival^{5,6}. Changes in Land Cover and Land Use (LCLU) affect Land Surface Temperature (LST) and lead to the surface urban heat island (UHI) effect, in which urban areas are generally warmer than rural areas⁷.

Recent studies of the surface UHI have primarily examined the effect of land cover changes in temperate regions such as Europe, China, and North America, yet these insights may not be applicable to urban planning in other regions^{8–12}. Tropical cities of Southeast Asia display heightened sensitivity to global warming and rapid urban growth¹³. Despite the region's diverse development patterns, economic stages, and policy frameworks^{14,15}, UHI-related studies primarily focus on individual cities^{16,17}. Hence, region-wide analyses of urban expansion and temperature dynamics is needed to inform tailored urban heat mitigation strategies.

Surface UHI is driven by the expansion of built-up areas in urban fringes¹⁸, defined as the transitional zone between the urban core and surrounding rural areas¹⁹, which leads to an increase in impermeable surfaces and a reduction in blue-green spaces like vegetation and water bodies²⁰. These changes affect the microclimate, both ambient air temperature and

LST^{11,21}, depending on the urban form the spatial layout of landscape elements such as land cover²² and building pattern²³.

Urban form in Southeast Asian urban fringes are often considered unique, with patterns of density characterized by a mix of urban and rural landscapes, and megacities such as Bangkok or Jakarta following North American urban sprawl^{24,25}. Yet, very few studies document urban growth in Southeast Asian cities, let alone with quantitative indicators²⁶ or distinguishing between megacities and secondary cities. The definition of secondary cities vary across studies, can range between 50,000 and 3 million, but generally accepted to be significantly below the largest megacity in the region²⁴. They are expected to drive almost 40 percent of the region's economic growth through 2030 but receive much less attention than megacities, making them a policy blind spot²⁷.

High-resolution, multi-temporal spectral imagery (Landsat, MODIS, Sentinel-2) enables monitoring of impervious and vegetation surfaces affecting urban thermal environments^{28,29}. Air temperature and composite thermal indices are more direct indicators of thermal comfort, but their utility is often limited by the sparse distribution of weather stations^{30,31}. Although satellite-derived LST is not an ideal proxy for characterizing thermal comfort, it remains useful for capturing spatiotemporal patterns in studies of long-term trends and regional comparisons^{10,21,32}. MODIS provides LST data at 1 km resolution with high temporal frequency²⁸, whereas Landsat 8 offers finer spatial detail (30 m) but may introduce “false

¹Asian School of the Environment, Nanyang Technological University, Nanyang, Singapore. ²Department of Soil, Plant, and Food Sciences, University of Bari Aldo Moro, Bari, Italy. ³Earth Observatory of Singapore, Nanyang Technological University, Nanyang, Singapore. ✉e-mail: perrine.hamel@ntu.edu.sg

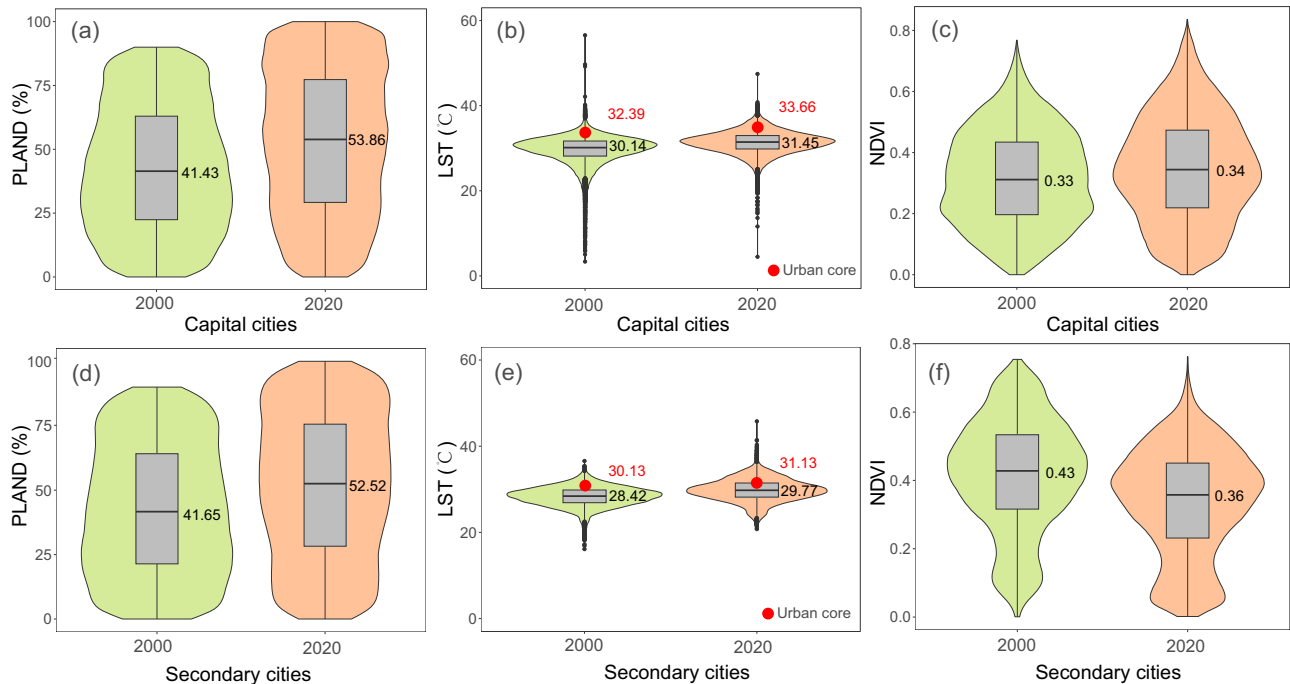


Fig. 1 | Distribution of urban form indicators and LST for capitals versus secondary cities in 2000 and 2020. Each violin plot depicts the full distribution of grid-cell values in the urban fringe areas, with the box spanning the 25th to 75th percentile and the horizontal black line marking the median. **a–c** present the distribution of PLAND, LST, and NDVI for capitals, while panels **(d–f)** show the corresponding

distributions for secondary cities. In **b, e**, red dots on the violin axis indicate the median LST of urban core area for 2000 and 2020, with their values annotated in red. Distributions of LST, PLAND, and NDVI across all urban cluster types are shown in Fig. S1. LST distribution in the urban core area is shown in Fig. S2. The distinction between urban core and fringe areas is shown in Fig. 5.

precision” due to resampling²⁹. To improve consistency across multi-source datasets, neighborhood resampling has frequently been applied in remote sensing studies on LST and urban thermal environments³³. Urban expansion is a major driver of land cover transformation and often produces concentrated hotspots of change at the urban fringe³⁴. However, its impacts on tropical urban heat dynamics, as well as the relative contributions of different drivers in Southeast Asia, remain insufficiently quantified¹³.

Built-up percentage of landscape (PLAND), is a widely used landscape pattern indicator³⁵ that quantifies impervious surface growth and urban activity intensity^{20,36}. PLAND is an aggregated percentage metric of urban land cover, distinct from continuous variables such as LST and Normalized Difference Vegetation Index (NDVI). In comparison with vegetation metrics derived from LCLU data³⁵, NDVI provides continuous measurements, higher temporal resolution, and enhanced sensitivity to vegetation dynamics⁹. While the increase in vegetation is effective in mitigating the UHI effect³⁷, urban growth resulting from the expansion of built-up areas tends to offset these benefits^{13,21}. Therefore, integrating indicators is essential for assessing trade-offs between urban expansion and greening strategies.

Urban land cover change impact on LST is scale-dependent^{18,21}. Local-scale studies employing high-resolution data capture intra-urban LST variation but lack broad applicability due to limited coverage^{8,20}. Regional and global-scale analyses provide valuable insights into climate modeling but miss local heterogeneity^{38,39}, leading to inefficiencies in climate-related policymaking^{15,40}. Investigating multi-scale perspectives is essential for understanding LST mechanisms and guiding effective heat mitigation strategies.

This study examines urban expansion and LST dynamics in Southeast Asia using remote sensing data from 2000 to 2020. The analysis focuses on eight capital and eight secondary cities that are most urgently in need of urban heat island effects mitigation. “Secondary” cities are here defined as independent urban areas located outside the capital metropolitan area, ranking after the capital in terms of both population size and economic significance^{24,27}, and their selection also considered national urban development context and representativeness. Detailed characteristics of the case cities and the corresponding selection criteria are provided in Table S1.

To our knowledge, this study represents the first systematic examination of urban forms and LST patterns in the expanding urban regions (i.e., urban fringes) of Southeast Asia, with particular attention to diverse urban growth types. The specific objectives of this study are to: (1) quantify changes in urban forms and land surface temperature for both capital and secondary cities between 2000 and 2020; (2) analyze the relationship between urban form metrics and LST change; and (3) assess how city type and socioeconomic factors influence changes in urban form metrics and LST.

To address these objectives, we focused on urban fringes where most of the land cover changes occur, outside the urban core areas already developed in 2000. By analyzing the distinct urban dynamics of recently developed areas in Southeast Asia, the findings offer context-specific insights and practical strategies that support sustainable urban development and inform effective climate adaptation.

Results

Differences in urban forms and temperature across Southeast Asian cities

Between 2000 and 2020, PLAND in the urban fringe areas generally increased, with a shift in the distribution towards higher values (Fig. 1a, d). Across all urban fringe grid cells in the 16 cities of Southeast Asia, the median PLAND increased 1.29-fold (from 41.5 to 53.4%) and LST increased by 1.39 °C (Fig. S1). In capital and secondary cities, PLAND increased by 12.4% and 10.9%, while LST increased by 1.31 °C and 1.35 °C, respectively (Fig. 1). While the distribution of NDVI values is relatively stable, with a slight increase of 0.01 in capital cities, the distribution shifted toward lower values in secondary cities, with median NDVI decreasing by 0.07 (Fig. 1c, f). LST in capital cities was consistently about 1.7 °C higher than that in secondary cities in both 2000 and 2020 (Fig. 1b, e). Within urban core areas, LST was higher than that in urban fringes, but the increase in LST was more substantial in urban fringes, with increases of 0.04 °C in capitals and 0.35 °C in secondary cities (Fig. 1b, e). This suggests an overall net increase in LST in Southeast Asian cities over the past 20 years, especially in secondary cities.

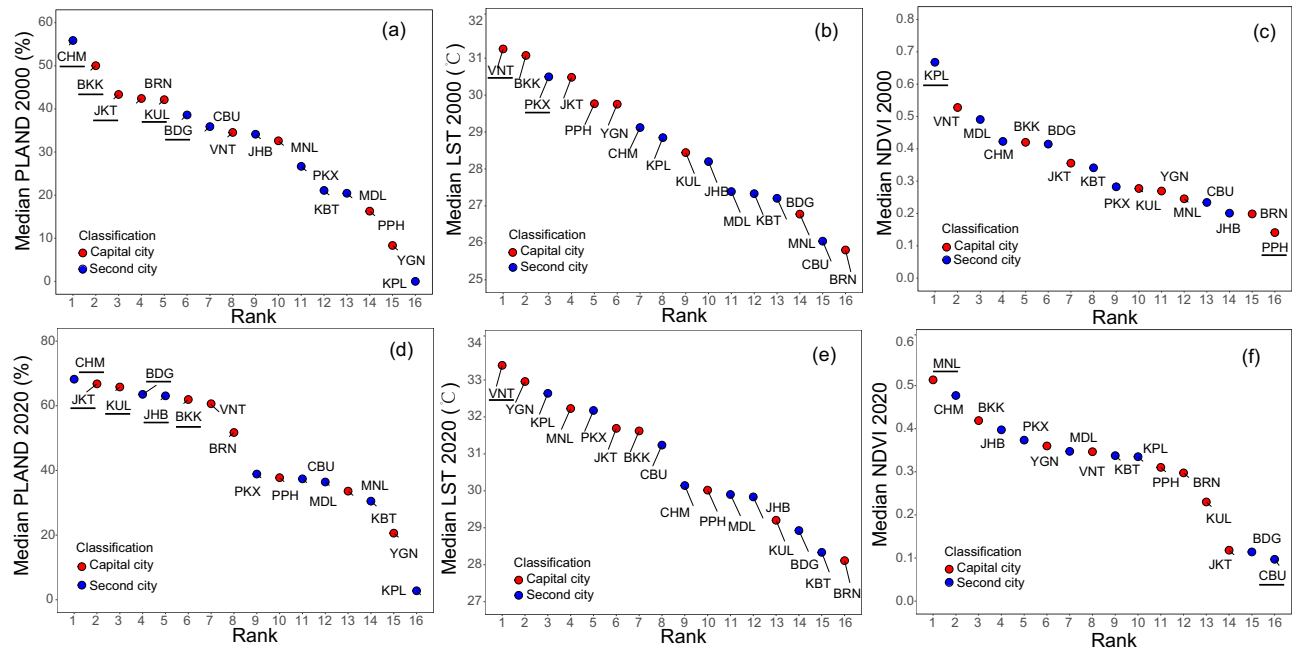


Fig. 2 | Ranking of urban clusters by urban form indicators and LST in 2000 and 2020. a–c present the rankings of median PLAND, LST, and NDVI values in 2000, while panels (d–f) show the corresponding rankings in 2020. Abbreviations of

urban clusters are listed in Table 1. Underlined clusters are highlighted. Density plots with medians for each urban cluster in 2000 and 2020 are shown in Fig. S3–S5. Ranking of changes in urban form indicators and LST is shown in Fig. S6.

Table 1 | Results of bivariate global Moran's I index analysis

Urban cluster			PLAND - LST		NDVI - LST	
Abbreviation	Cluster name	Country	2000	2020	2000	2020
JKT*	Jakarta	Indonesia	0.098	0.264	−0.136	0.083
BDG	Bandung	Indonesia	0.452	0.042	0.053	0.112
BKK*	Bangkok	Thailand	0.339	0.555	0.070	0.056
CHM	Chiang Mai	Thailand	−0.083	0.148	−0.162	−0.271
KUL*	Kuala Lumpur	Malaysia	0.151	0.255	−0.079	−0.097
JHB	Johor Bahru	Malaysia	0.322	0.342	−0.251	−0.196
PPH*	Phnom Penh	Cambodia	−0.014	0.404	−0.117	−0.076
KPL	Krong Pailin	Cambodia	0.230	−0.184	−0.341	−0.078
YGN*	Yangon	Myanmar	0.027	−0.132	0.309	−0.050
MDL	Mandalay	Myanmar	0.075	0.031	−0.090	−0.025
VNT*	Vientiane	Laos PDR	0.120	0.360	0.003	−0.067
PKX	Pakse	Laos PDR	0.085	0.213	0.409	0.395
MNL*	Manila	Philippines	0.068	0.489	0.121	−0.195
CBU	Cebu	Philippines	0.208	0.496	−0.269	−0.122
BRN*	Bandar Seri Begawah	Brunei	0.237	0.361	0.017	−0.068
KBT	Kuala Belait	Brunei	0.447	0.569	−0.389	−0.380

Asterisks (*) denote capital cities. All Moran's I values have corresponding p -values of 0.001 (i.e., $p < 0.05$), except for the bolded values, which are greater than 0.05.

However, analyses of urban form indicators within groups (capital and secondary cities) suggest that the overall distributions in Fig. 1 do not reflect consistent trends in either group. Rather, distributions vary significantly across all cities (Figs. S3–S5). When comparing the median values of indicators in the urban fringes, we find that both capital and secondary cities can exhibit high values, as well as substantial changes in these indicators (Fig. 2). Notable changes from 2000 to 2020 included a median PLAND increase of more than 25% in some cities (e.g., in Johor Bahru, Malaysia, and Vientiane, Lao PDR, respectively secondary and capital cities), and large LST increases of more than 5 °C in the fringe of two cities in the Philippines (capital and

secondary) (Fig. S6; the abbreviations are provided in Table 1). Largest NDVI changes were found in the fringes of Krong Pailin, Cambodia (−0.33), and Manila, Philippines (+0.27) (Fig. 2c, f; Fig. S6).

Trade-off of changes in urban forms and temperature from 2000 to 2020

A trade-off analysis of changes in PLAND, NDVI, and LST across urban clusters from 2000 to 2020 (Fig. 3) revealed that most urban clusters experienced substantial changes in PLAND. In most urban clusters, there is a positive spatial correlation between PLAND and LST, and a negative

Fig. 3 | Multi-variable changes in urban forms and LST from 2000 to 2020. The ternary plot in (a) shows the relative median changes in PLAND, LST, and NDVI for each urban cluster. Vertices represent a dominant role of that variable, while shifts along the edge reflect a reduced role. All values are normalized, and NDVI uses absolute values. Abbreviations of urban clusters are shown in Table 1, and asterisk (*) denotes capitals. Pairwise relationships among median changes are shown in Fig. S7. Red circles highlight the two urban clusters illustrated in (b): Cebu (CBU) and Kuala Lumpur (KUL), illustrating contrasting spatial patterns of changes in LST and PLAND (low LST change and high PLAND change for Kuala Lumpur; high LST change with low PLAND change for Cebu).

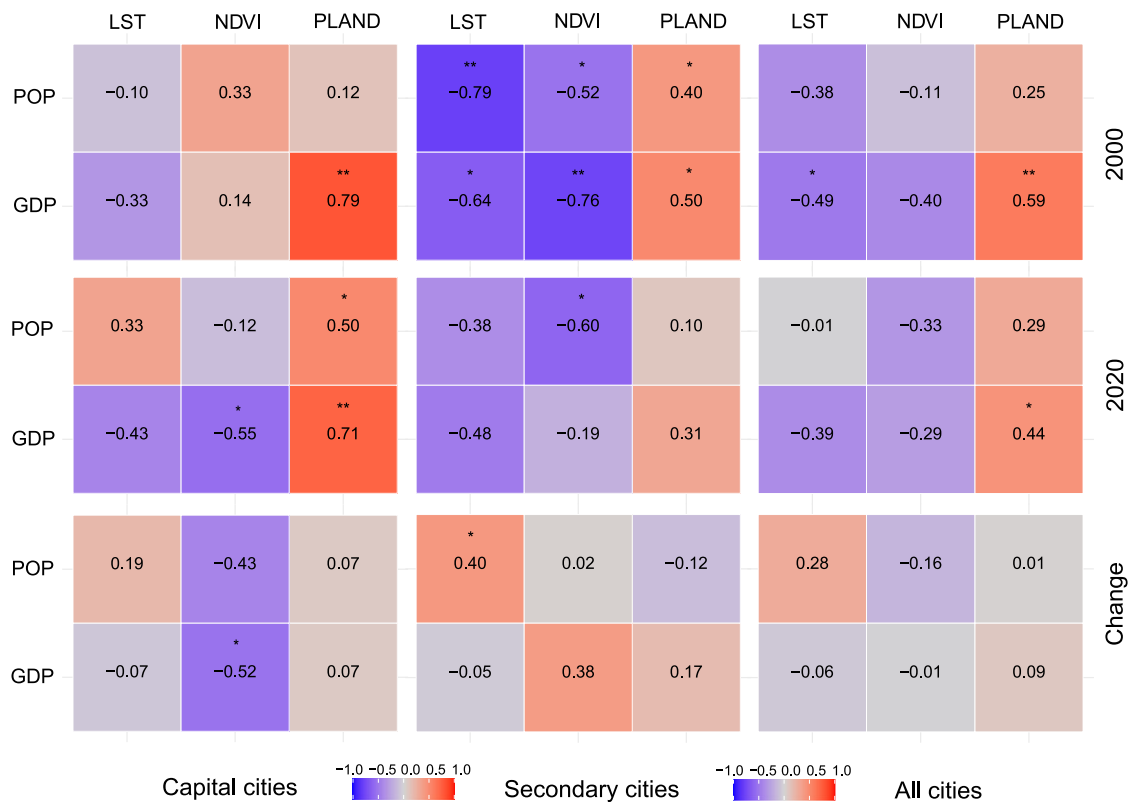
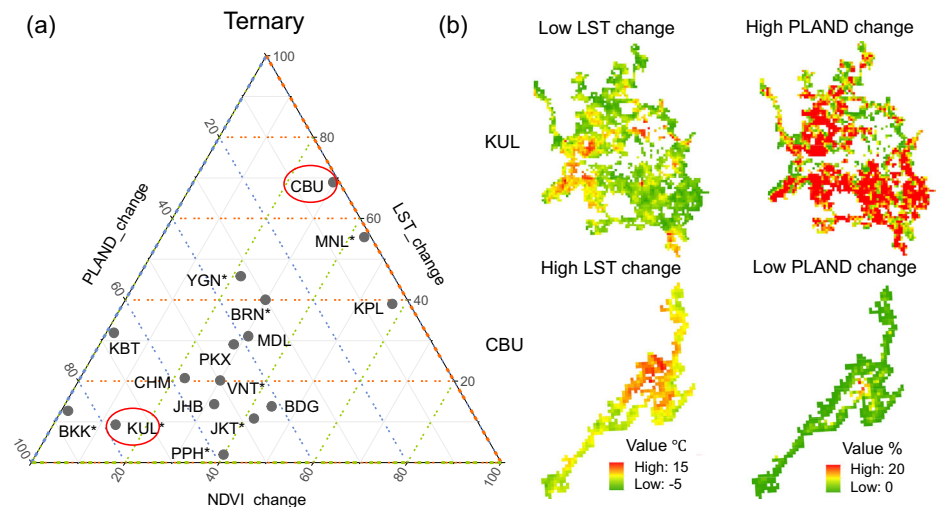


Fig. 4 | Spearman correlations analysis between spectral indices and socio-economic factors. Positive correlations are shown in red and negative correlations in blue. POP and GDP denote population density and gross domestic product (Table

S2), respectively. Correlations are based on median values for each urban cluster in 2000 and 2020. Pearson correlations, which include building attributes for 2020, are presented in Fig. S8. Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

spatial correlation between NDVI and LST (Table 1). However, some urban clusters, such as Manila, Cebu and Krong Pailin, showed a pronounced increase in LST, with values of 5.4 °C in Manila, 5.2 °C in Cebu, and 3.8 °C in Krong Pailin (Fig. S6). The corresponding PLAND changes were only 1.0%, 1.5%, and 2.8%, respectively. Their NDVI trends also differed, with Manila increasing by 0.27, while Cebu and Krong Pailin decreased by 0.14 and 0.33, respectively. Two contrasting spatial patterns of LST and PLAND are shown in Fig. 3b to illustrate extreme changes in these indicators. These exceptions suggest that complex dynamics, including other indicators of urban forms such as socioeconomic factors, influence urban temperatures.

The impact of socio-economic factors on urban forms and temperature

Spearman correlation analysis showed that urban clusters with higher gross domestic product (GDP) and population density in secondary cities were associated with relatively low LST in urban growth areas (Fig. 4). Multiple ordinary least squares (OLS) regression analysis further revealed distinct influencing patterns on LST across urban clusters (Table 2; Table 3). In capital cities, the influence strength generally decreased in the order of PLAND > GDP > NDVI > POP, while in secondary cities, the order was PLAND > NDVI > GDP > POP. LST showed significant positive

Table 2 | Results of multiple ordinary least squares regression for urban clusters in 2000

Urban cluster	PLAND		NDVI		GDP		POP	
	β	p	β	p	β	p	β	p
JKT*	0.15	NS	-0.51	***	1.23	***	-0.64	***
BKK*	0.67	***	-0.04	NS	-0.20	NS	0.26	NS
KUL*	1.20	***	-0.40	NS	-0.14	NS	0.33	NS
PPH*	0.14	NS	-0.23	*	-0.36	*	-0.70	***
YGN*	0.04	NS	0.28	**	-0.15	*	-0.18	NS
VNT*	0.51	***	0.07	NS	-0.34	**	-0.07	NS
MNL*	1.00	***	0.82	***	-0.10	NS	0.19	NS
BRN*	0.60	NS	-0.72	*	0.92	**	-0.03	NS
BDG	0.74	***	0.12	NS	1.45	***	0.27	NS
CHM	0.07	NS	-0.28	***	-0.71	***	0.28	NS
JHB	1.14	***	-0.41	*	-0.09	NS	0.16	NS
KPL	0.25	NS	-0.58	***	-0.03	NS	0.32	NS
MDL	0.13	NS	-0.21	NS	-0.23	NS	-0.53	**
PKX	0.81	***	0.94	***	0.87	*	-0.74	NS
CBU	2.08	***	-1.88	***	-1.92	***	0.28	NS
KBT	1.92	**	-0.71	*	-0.90	NS	-0.67	**

Asterisks (*) denote capital cities. Urban cluster abbreviations are listed in Table 1. POP population density, GDP gross domestic product. β denotes the standardized beta coefficients; effects are classified as weak ($|\beta| < 0.1$), moderate ($0.1 \leq |\beta| < 0.3$), and strong ($|\beta| \geq 0.3$). Significance levels: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$; NS not significant. Additional ordinary least squares (OLS) regression parameters, residual spatial autocorrelation (Moran's I), and Spatial Durbin Model (SDM) robustness checks are provided in Table S3–S5.

associations with PLAND, whereas its relationships with GDP and NDVI varied across urban clusters, being either positive or negative. Although population density showed a correlation with LST at the urban cluster level in secondary cities (Fig. 4), it was generally not significant in the pixel-based spatial regression (Table 2; Table 3). In addition, nearly all indicators demonstrated stronger explanatory capacity for LST in 2020, along with a higher number of cities showing statistically significant associations. Taken together, these results indicate a strengthening spatial signal of urban expansion and associated landscape changes in shaping LST patterns across cities.

Discussion

Global urban land expansion typically is generally characterized by a combination of outward suburban sprawl and vertical densification, accommodating population and economic growth along with their associated development demands^{41,42}. In the Southeast Asian cities examined here from 2000 to 2020, the median percentage of built-up areas (PLAND) increased by 12.4 points in capital cities and 10.9 points in secondary cities, indicating widespread urban growth (Fig. 1a, d). Urban growth was slightly stronger in capital cities, with PLAND increasing by 1.5 points more than in secondary cities. Importantly, our results suggest that it is difficult to generalize these statistics, as distributions and shifts of the urban form indicators from 2000 to 2020 are extremely varied, with no clear patterns for either group (Fig. 2; Figs. S3–S5). These urban expansions can be linked to general urbanization drivers such as population growth and economic activity^{18,19} (Fig. 4; Table 2), as well as the potential influence of local urban land use policies, such as urban growth boundary management^{11,18}.

Our findings indicate that land surface temperature (LST) changes do not show clear divergence between capital and secondary cities (Fig. 1; Fig. S2), likely reflecting the convergence of urban development pathways^{15,43}. LST change is driven by multiple factors, both related to land cover but also to socio-economic development (Fig. 4; Table 2; Table 3; Fig. S8). For example, both PLAND and GDP are strongly

Table 3 | Results of multiple ordinary least squares regression for urban clusters in 2020

Urban cluster	PLAND		NDVI		GDP		POP	
	β	p	β	p	β	p	β	p
JKT*	0.42	**	0.48	**	2.06	***	-0.05	NS
BKK*	0.90	***	-0.08	**	0.13	*	-0.23	**
KUL*	1.37	***	-0.32	***	0.38	***	0.24	*
PPH*	0.75	***	0.04	NS	0.25	***	0.12	NS
YGN*	-0.04	NS	-0.23	*	-0.95	***	0.14	NS
VNT*	0.31	**	0.02	NS	0.19	***	0.08	NS
MNL*	1.36	***	-0.06	NS	0.50	***	0.22	**
BRN*	1.58	***	-0.61	*	0.92	*	0.19	NS
BDG	0.06	NS	0.51	**	-1.23	***	2.94	***
CHM	0.17	*	-0.21	***	0.03	NS	0.09	NS
JHB	1.28	***	-0.31	***	0.42	**	0.17	NS
KPL	0.08	NS	-0.07	NS	-0.68	***	-0.38	NS
MDL	0.17	NS	0.20	***	-0.34	***	-0.02	NS
PKX	1.06	***	0.71	***	0.10	NS	-0.65	NS
CBU	2.32	***	-0.66	**	-0.18	NS	-0.41	*
KBT	2.30	***	-0.19	*	-0.33	NS	-0.26	NS

The meanings of all parameters refer to Table 2. Additional ordinary least squares (OLS) regression parameters, residual spatial autocorrelation (Moran's I), and Spatial Durbin Model (SDM) robustness checks are provided in Table S3–S5.

correlated with LST increases in many capital cities. Importantly, both urban form and socioeconomic indicators showed stronger explanatory capacity for LST in 2020 than in 2000 (Table 2; Table 3). These findings suggest that, with increasing urbanization, the spatial association between landscape metrics and urban heat patterns have become more pronounced. In addition, the number of cities exhibiting statistically significant relationships increased, with such patterns more frequently observed in capital cities (Table 2; Table 3; Tables S3–S5). Sustainable urban land development typically requires balancing high-density growth with greening policies¹⁷. Secondary cities, while following the expansion patterns of capital cities, often face resources constraints and greater challenges in implementing comparable green strategies^{44,45}. This disparity leads to greater NDVI loss in secondary cities (Fig. 1), and the influence of NDVI on LST is correspondingly stronger than in capital cities (Table 2; Table 3). As cities are projected to continue expanding beyond 2030^{42,46}, it is particularly essential for secondary cities to prioritize green space planning in order to achieve sustainable growth.

Urban areas experiencing rapid urbanization and economic growth tend to exhibit higher surface temperatures and stronger urban heat island effects^{7,13}. From 2000 to 2020, capital cities in Southeast Asia were, on average, 1.7 °C warmer than secondary cities, with core areas consistently hotter than fringes (Fig. 1; Fig. S2). Higher LST in urban cores is linked to dense built-up areas and limited green-blue spaces^{13,20}. However, LST increases were more pronounced in urban fringes, especially in secondary cities (Fig. 1), highlighting their climate sensitivity to vegetation loss from urban sprawl. Our analysis shows that changes in PLAND, building density, and volume significantly affect the increase in LST (Fig. 4; Table 2; Table 3; Fig. S8), confirming that urban form and human activities strongly influence the thermal environment^{12,47}. In Southeast Asia, Singapore exemplifies how urban form is linked to thermal stress and employs strategies such as ventilation corridors and green walls to maintain wind pathways and mitigate urban heat⁴⁸.

Socioeconomic factors drive urbanization by increasing housing demand and energy consumption, indirectly affecting urban climate^{18,20}. Our findings reveal a strong link between GDP and urban expansion in capital cities, with the influence of GDP on LST being more pronounced

than in secondary cities (Table 2; Table 3). Notably, urban clusters with higher population density, GDP, and even greater building density tend to exhibit low surface temperatures (Fig. 4; Fig. S8), possibly resulting from multiple interacting factors¹¹. However, we also found that population density exhibited relatively weak explanatory capacity for LST at the spatial pattern, and that some cities showing statistically significant relationships in 2000 became non-significant in 2020 (Table 2; Table 3). Wealthier urban clusters often benefit from greater investment in green infrastructure, modern building designs, and climate-adaptive planning, all of which help reduce local surface temperatures^{44,49}. By contrast, while population density shows limited direct influence on the spatial patterns of LST, continued population growth can still indirectly drive increases in PLAND, thereby weakening cooling effects over time, particularly in secondary cities (Fig. 4). Together, these dynamics underscore the complex long-term climatic implications of urban development.

Our study highlights Southeast Asian urban clusters with substantial land cover and surface temperature changes over the past two decades. In Johor Bahru, where PLAND increased by nearly 29.0% (Fig. 2), policy priorities should therefore place greater emphasis on controlling expansion, protecting natural land cover, and promoting mixed land use to ensure sustainable urban development^{15,50}. Although water bodies can provide strong cooling effects through lake influence and evaporative cooling^{35,48}, their proportion within our defined urban clusters was consistently below 5% and thus not considered in this study (Fig. S9). Studies have shown that coastal wetlands and mangroves in cities such as Bangkok and Jakarta have been severely impacted by urbanization and land reclamation for industry³². Relevant policy measures can draw on Singapore's strict reservoir and wetland protection policies^{32,48}. For urban clusters such as Krong Pailin and Bandung, which face severe land degradation, "greening and cooling" strategies can repurpose fragmented suburban land^{51,52}. In contrast, cities such as Manila, Cebu, and Yangon, despite relatively modest PLAND changes, have experienced substantial increases in surface temperature (Fig. 2), underscoring the critical role of local activities. Importantly, future planning should restrict energy-intensive industries to suburbs⁵³, integrate greening with low-carbon transport^{54,55}, and promote collaborative land use across ASEAN cities to ensure sustainable and balanced regional development¹⁵.

Land cover change plays a critical role in affecting climate change across various spatial scales, reinforcing the need to reshape urban form to meet Sustainable Development Goals (SDGs) 11 and 13^{56,57}. Many Southeast Asian cities, including Jakarta, Manila, and Bangkok, have incorporated "heat risk" into their climate adaptation policies^{25,32}, yet the priority strategies still vary depending on differentiated urban growth characteristics. In short, both capital and secondary cities should prioritize investments in green corridors, vertical greenery, and smart building materials to reduce surface heat and mitigate climate impacts^{51,58}. In addition, for some capital cities, promoting high-density, mixed-use developments in combination with ventilation corridors can help optimize the use of limited urban land and mitigate local thermal environments^{59,60}. For secondary cities, where urban fringe areas face substantial reductions in vegetation cover and the implementation of urban greening policies is relatively constrained, priority should be given to controlling urban growth boundaries and promoting sustainable land use to mitigate temperature increases in fringe areas¹⁶. In Southeast Asia, nature-based solutions beyond general strategies need to be adapted to the hot and humid climate^{61,62}. Policy priorities should emphasize balancing dense urban development with the integration of blue-green infrastructure and natural reserves, while also promoting vertical greenery to mitigate urban heat and enhance long-term resilience.

Our results should be interpreted in light of certain limitations. First, our analysis was conducted at 1 km to ensure consistency with urban form and economic data. Although we demonstrated that the 1 km LST analysis is broadly representative of the spatial patterns observed at 30 m, future work should employ higher-resolution data to improve accuracy³³. Second, LST provides an intuitive measure of surface temperature but does not fully reflect human thermal comfort, and resampling of Landsat 8 LST may

introduce false precision²⁹. Future research could integrate multi-source LST datasets with air temperature and indices such as the Wet Bulb Globe Temperature to better assess climate impacts and their links to urban growth^{30,31}. Third, although NDVI is widely applied to indicate vegetation cover⁹, spectral confusion such as from blue-roof factories may lead to artificially high values⁶³. Future studies could consider extracting vegetation cover from high-accuracy land cover products when feasible. Finally, we focused on the years 2000 and 2020 to represent long-term dynamics, but including more time points would provide a more detailed understanding of the evolution of urban form and LST. Future studies should also expand the geographical coverage, ensure cross-scale consistency, and apply advanced modeling approaches to better capture interactions between urban growth, climate, and ecosystems.

Methods

Study regions and data acquisition

We defined urban clusters for capital and secondary cities in Southeast Asia using 2020 WorldPop 1-km gridded population data (<https://hub.worldpop.org/>) and Global Administrative Areas (GADM) boundaries (<https://gadm.org/>). We selected urban clusters that meet the following criteria⁶⁴: (1) population density ≥ 300 people km^{-2} ; (2) total population ≥ 5000 ; (3) an area composed of contiguous grid cells; (4) availability of high-resolution remote sensing data; and (5) inclusion of both the capital and at least one qualifying secondary city from each country (Fig. 5a).

This study utilized Land Cover and Land Use (LCLU), Land Surface Temperature (LST), and the Normalized Difference Vegetation Index (NDVI) to characterize key landscape metrics, the surface temperature, and vegetation cover. The LCLU data was used to compute the percentage of built-up areas (PLAND)³⁵. The LST data were derived from Landsat-8 over Coimbra, and mean LST images were generated by compositing all available scenes for the years 2000 and 2020³⁹. The NDVI data were obtained from the MODIS Terra product (MOD13A2), and annual mean NDVI images were generated for the years 2000 and 2020. A detailed description of these remote-sensing datasets in GeoTIFF format is provided in Table S2. For population density, we employed the 1 km dataset rather than the 100 m product to maintain consistency with the gross domestic product (GDP) data.

Assessing spatiotemporal dynamics of urban forms and land surface temperature

We overlaid a 1 km grid within Southeast Asia's administrative boundaries and applied GIS-based (ArcGIS; version 10.4) density (≥ 300 ppl/ km^2) and population (≥ 5000) thresholds⁶⁴, following the selection criteria of urban clusters in the above, to delineate 16 urban clusters in eight countries. We then analyzed multiple spatial datasets to assess the changes in land cover (represented by urban form indicators) and surface temperature of urban clusters between 2000 and 2020^{18,65} (Fig. 5c). Detailed abbreviations and classification of urban clusters are provided in Table 1.

Using 2020 urban cluster boundaries, we computed PLAND, NDVI, and LST at 1 km resolution by applying 3×3 focal statistics to capture neighborhood averages for both 2000 and 2020. Although this aggregation reduces some of the detail of the 30 m product, it enhances the spatial consistency of multi-source data (e.g., urban form and socioeconomic parameters) and reduces scale mismatch³³. To further verify that the 1 km spatial pattern is representative of the 30 m analysis, we included a comparative density plot for Jakarta and Bandung (Fig. S10). Pixels with PLAND $> 90\%$ in 2000 were excluded to remove urban cores and isolate the urban fringe¹³, which then served as a mask for analyzing other remote sensing indicators (Fig. 5b). The 90% PLAND threshold was selected because pixels that had already reached such a high level of urban density in 2000 were likely to have become saturated by 2020, thereby limiting their potential for further urban growth^{29,66}. We then conducted pixel-level comparisons across urban clusters to evaluate land cover changes and increases in LST, while also assessing LST values in the urban core areas to consider the influence of broader regional climate change.

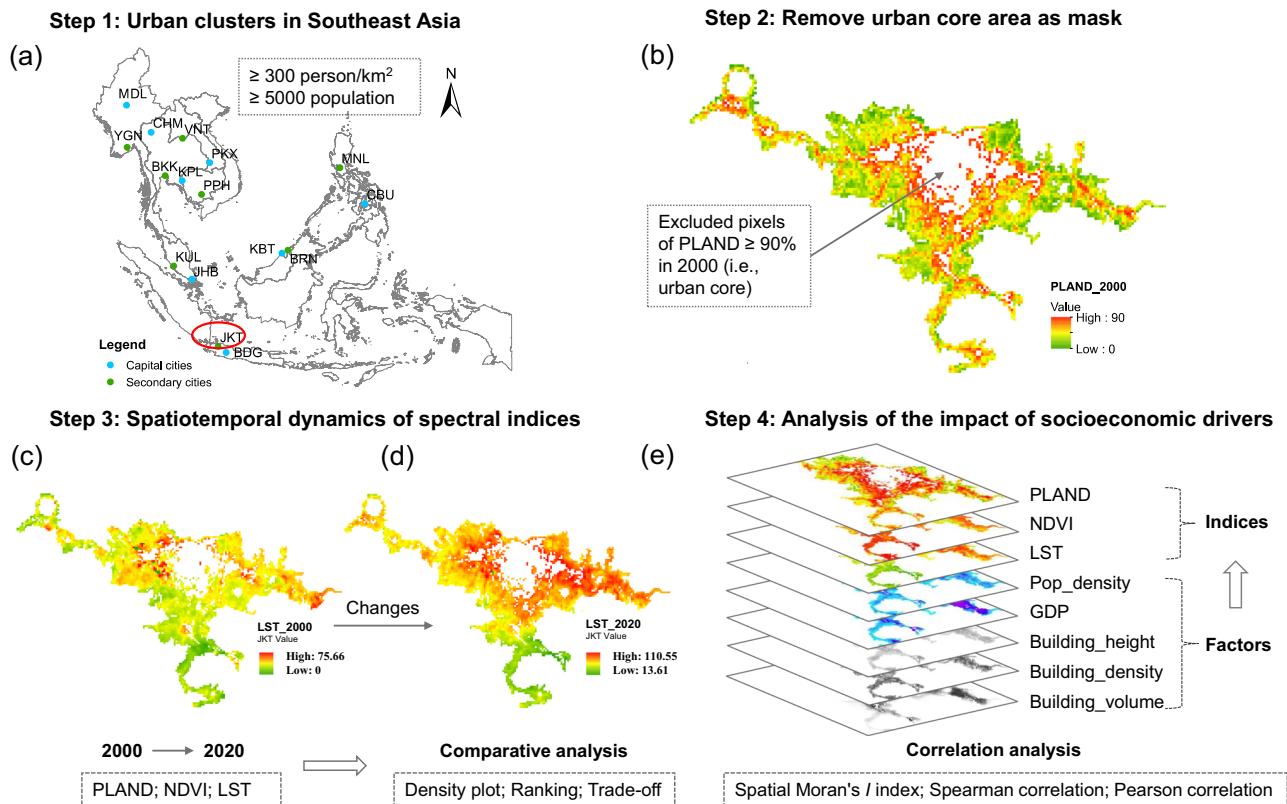


Fig. 5 | Research framework based on urban clusters in Southeast Asia. The framework comprises four steps: Step 1 presents the spatial distribution of urban clusters across Southeast Asia (a). Step 2, illustrated here for Jakarta, delineates urban core areas, defined as areas where PLAND in 2000 was higher than 90% (b). Step 3 derives relevant spectral indices for analyzing land cover and temperature

characteristics in 2000 (c) and 2020 (d). Step 4 conducts comparative analyses between capital and secondary cities through correlation and regression analyses. Abbreviations of urban clusters in (a) correspond to the full names listed in Table 1. Map visualizations were formed in QGIS (<http://qgis.osgeo.org>).

Using “raster” and “ggplot2” packages in the R software⁶⁷, we processed the raster to vectors, computed median density distributions of PLAND, NDVI, and LST for 2000 and 2020 per urban cluster.

Comparison of capital and secondary cities and analysis of influencing factors

We assessed urban form (PLAND, NDVI) and temperature (LST) changes across three perspectives: (1) comparing median density distributions across capital cities, secondary cities, and all urban clusters from 2000 to 2020; (2) calculating the LST for both urban core and fringe areas and analyzing their differences; and (3) ranking urban clusters by median PLAND, NDVI, and LST in 2000, 2020, and over the twenty-year period to identify urban expansion, vegetation loss, and temperature increases, followed by a ternary trade-off analysis. We applied the bivariate global Moran's I index to quantify spatial correlations between PLAND and LST and between NDVI and LST for 2000 and 2020.

To evaluate drivers of changes in urban land cover and temperature, we used Spearman correlation to link population density and GDP with PLAND, NDVI, and LST in 2000 and 2020, and Pearson correlations to examine relationships between 2020 building density (%), height (m), and volume (m³) from Google Earth Engine (GEE) Open Buildings dataset (Google/Search/open buildings temporal/v1) and spectral indices¹⁰ (Fig. 5d). Since building data are only available after 2016, the analysis of building related variables on LST was treated as supplementary support rather than a main explanatory component. Details of the data sources are provided in Table S2. It should be noted that the GDP data in Chen et al.⁶⁸ were estimated using calibrated nighttime light data as the main inputs, which are closely linked to population distribution and socioeconomic activities. We

also considered the proportion of water bodies in the analysis using the 30 m resolution Global Surface Water dataset (Table S2) but was not included as an explanatory variable due to their low proportions in our study areas (<5%) (Fig. S9).

To assess the combined effects of urban form and socioeconomic factors on LST, we constructed regression models with LST as the dependent variable and PLAND, NDVI, population density, and GDP as independent variables for each urban cluster in 2000 and 2020, using 1 km grid-level data. We first applied a multiple Ordinary Least Squares (OLS) regression⁶⁹ and reported standardized coefficients (indicating both direction and magnitude) along with their statistical significance (p-values). The presence of spatial autocorrelation in the model residuals was tested using Global Moran's I with a k-nearest neighbors spatial weights matrix⁶⁹. In cases of significant autocorrelation, a Spatial Durbin Model (SDM)⁵⁵ was subsequently implemented to capture spatial dependence and spillover effects. The entire analysis was performed in R⁶⁷.

Data availability

The datasets used in this study are publicly available (Table S2 for details).

Code availability

The code used for calculating and statistical results of this study is available from the authors upon reasonable request.

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Author contributions

P. Hamel, S. A. Kamarajugedda, R. Laforteza, and R. Xu conceived the ideas and designed methodology; S. A. Kamarajugedda and R. Xu collected and analyzed the data; R. Xu and P. Hamel led the writing of the manuscript; R. Xu, P. Hamel, and S. F. E. A. Shaikh revised and improved the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Perrine Hamel.

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