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Mapping urban land surface emissivity variations using aster imagery in Bangkok

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Abstract

How accurately can satellite-derived thermal data capture the emissivity patterns of a rapidly expanding tropical metropolis? This research addresses that question by mapping land surface emissivity (LSE) variations across Bangkok, Thailand, using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imagery. The investigation covered six distinct land use and land cover (LULC) categories: dense built-up areas, low-density built-up zones, vegetation, water bodies, bare soil, and mixed urban surfaces. ASTER thermal infrared bands (bands 10-14) acquired between January and December 2022 were processed using the Temperature-Emissivity Separation (TES) algorithm. Results showed that water bodies exhibited the highest mean emissivity (0.987), followed by vegetation (0.976), bare soil (0.952), low-density built-up (0.941), mixed urban (0.937), and dense built-up surfaces (0.923). Seasonal variations were modest but consistent, with vegetation LSE peaking during the wet season (June-August) and declining in the dry months. Built-up surfaces showed less seasonal fluctuation, though a slight increase appeared during warmer months due to absorbed longwave radiation effects. Spatial autocorrelation analysis (Moran's $I = 0.71$) confirmed strong clustering of emissivity values. The mapping accuracy, validated against field-measured spectroradiometer data from 48 ground-truth points, reached an overall root mean square error of 0.013. These findings offer a reliable emissivity baseline for urban heat island monitoring and thermal comfort assessment in Bangkok's planning framework.

Keywords: Land surface emissivity, ASTER imagery, urban thermal mapping, temperature-emissivity separation, Bangkok, surface characterization, spatial autocorrelation, land use classification, thermal infrared, urban heat island

Introduction

What role does surface emissivity play in shaping the thermal environment of cities experiencing rapid land cover change? The answer has direct consequences for urban planning, energy consumption models, and public health risk assessments. Land surface emissivity (LSE) describes the efficiency with which a surface radiates absorbed thermal energy relative to a perfect blackbody at the same temperature ^[1]. Even small differences in emissivity, on the order of 0.01 to 0.03, can translate into land surface temperature (LST) retrieval errors of 1-2 K when left unaccounted for ^[2].

Bangkok, with a metropolitan population exceeding 10 million and a built-up footprint that expanded by roughly 22% between 2000 and 2020, presents a compelling case for emissivity mapping ^[3]. The city's heterogeneous surface, a patchwork of concrete, asphalt, corrugated metal roofing, tropical vegetation, canal networks, and exposed laterite, generates a complex emissivity field that single-value assumptions cannot represent adequately ^[4]. Earlier thermal remote sensing work in the region relied on broadband emissivity corrections or NDVI-based approximations, both of which perform poorly over mixed pixels common in Southeast Asian megacities ^[5].

ASTER's five thermal infrared bands (8.125-11.65 micrometers) and the associated Temperature-Emissivity Separation algorithm provide a physically grounded alternative. The TES approach recovers per-pixel emissivity spectra without requiring prior knowledge of surface temperature, an advantage over split-window methods that fix emissivity to retrieve temperature ^[6]. Several researchers have applied TES in arid and semi-arid settings [7,8], yet its application to humid tropical cities remains limited.

This research mapped LSE across Bangkok using multi-date ASTER scenes acquired in

2022, validated results against field spectroradiometer measurements, and examined seasonal and spatial patterns. The objectives were threefold: (a) to quantify emissivity ranges for principal LULC categories, (b) to evaluate temporal LSE stability across wet and dry seasons, and (c) to assess the spatial clustering of emissivity through geostatistical metrics. The outcomes supply a baseline dataset that planners and climate modellers can incorporate into thermal comfort and energy balance simulations [9].

Study Area Description

Bangkok (13.75 degrees N, 100.52 degrees E) occupies a low-lying alluvial plain along the lower Chao Phraya River, averaging only 1.5 m above mean sea level. The metropolitan region spans about 1,568 square kilometres and supports a tropical savanna climate (Koppen Aw) with mean annual temperatures near 28.6 degrees C and annual rainfall around 1,500 mm concentrated between May and October [3]. The built-up core radiates outward from the historic Rattanakosin district, transitioning through commercial high-rise corridors along Sukhumvit and Silom roads, into suburban residential tracts and, farther out, into agricultural land and aquaculture ponds. Canal (khlong) networks and remnant wetlands punctuate the urban fabric, creating sharp emissivity boundaries over short distances. The city's rapid vertical and horizontal growth since the 1990s has continuously altered the proportion of impervious surfaces, making static emissivity datasets obsolete within a few years. Ground elevation data from a 2021 LiDAR survey and a Sentinel-2 derived LULC map at 10 m resolution were used to stratify the study area into six target classes prior to ASTER analysis.

Material and Methods

Material: The research was carried out at the Department of Geosciences, St. Petersburg School of Natural Sciences, Leningrad Oblast, Russia, between March 2022 and November 2023. Twelve cloud-free ASTER Level 1T scenes (path 129, row 50-51) covering the Bangkok metropolitan area were obtained from NASA's Earthdata portal. Scenes were selected to represent each calendar month of 2022, with cloud cover below 10%. Thermal infrared data came from ASTER bands 10 through 14 at 90 m spatial resolution. Concurrently, a Sentinel-2 Level 2A composite (10 m) was acquired for land cover classification.

Results

Table 1: Mean broadband land surface emissivity by LULC category

LULC Category	Mean LSE	SD	Min	Max	RMSE vs Field
Dense Built-up	0.923	0.012	0.901	0.944	0.014
Low-density Built-up	0.941	0.009	0.924	0.958	0.011
Vegetation	0.976	0.006	0.963	0.989	0.009
Water Bodies	0.987	0.004	0.981	0.993	0.007
Bare Soil	0.952	0.011	0.933	0.971	0.013
Mixed Urban	0.937	0.010	0.919	0.956	0.015

Table 1 shows that water bodies recorded the highest mean emissivity at 0.987, while dense built-up surfaces returned the lowest value at 0.923. Validation against field spectroradiometer readings produced a combined RMSE of 0.013 across all categories, with the smallest error over

Ground-truth emissivity data were collected during two field campaigns (February and August 2022) using a portable Designs and Prototypes Model 102F field spectroradiometer covering the 8-14 micrometer range, with a reported accuracy of plus or minus 0.005. A total of 48 ground points, eight per LULC class, were measured at each campaign [10].

Methods

ASTER thermal bands were radiometrically calibrated and atmospherically corrected using the In-Scene Atmospheric Compensation algorithm embedded in ENVI 5.6. The TES algorithm, based on the iterative procedure described by Gillespie *et al.* [6], was applied to each corrected scene. TES first estimates temperature from maximum emissivity then refines emissivity spectra using the minimum-maximum difference regression. Per-pixel emissivity maps at bands 10-14 were averaged into broadband emissivity using a weighted combination following Cheng *et al.* [11]. Land cover classification of Sentinel-2 imagery employed a Random Forest classifier with 500 decision trees, trained on 320 reference polygons (roughly 55 per class), and validated with an independent set of 160 polygons, achieving overall accuracy of 89.3% and kappa of 0.86. Spatial autocorrelation of broadband emissivity was quantified through global Moran's I and local Getis-Ord Gi* statistics at a 270 m search radius. Seasonal differences were tested using paired Wilcoxon signed-rank tests comparing dry-season (November-April) and wet-season (May-October) composites [12].

Spatial Data Processing

All satellite imagery was projected to WGS84 UTM Zone 47N. ASTER scenes were co-registered to a reference Sentinel-2 mosaic with root mean square positional error below 0.5 pixels (45 m). A land-water mask generated from the Normalized Difference Water Index (NDWI > 0.3) was applied to separate water bodies before emissivity extraction, because the TES algorithm behaves differently over open water surfaces [13]. Zonal statistics were computed within each LULC polygon to extract per-class mean, standard deviation, minimum, and maximum emissivity. All geoprocessing was performed in QGIS 3.28 and Python 3.10, while statistical testing relied on SciPy 1.10.

water (0.007) and the largest over mixed urban areas (0.015). The standard deviation remained below 0.012 for every class, indicating relatively tight distributions within each LULC type.

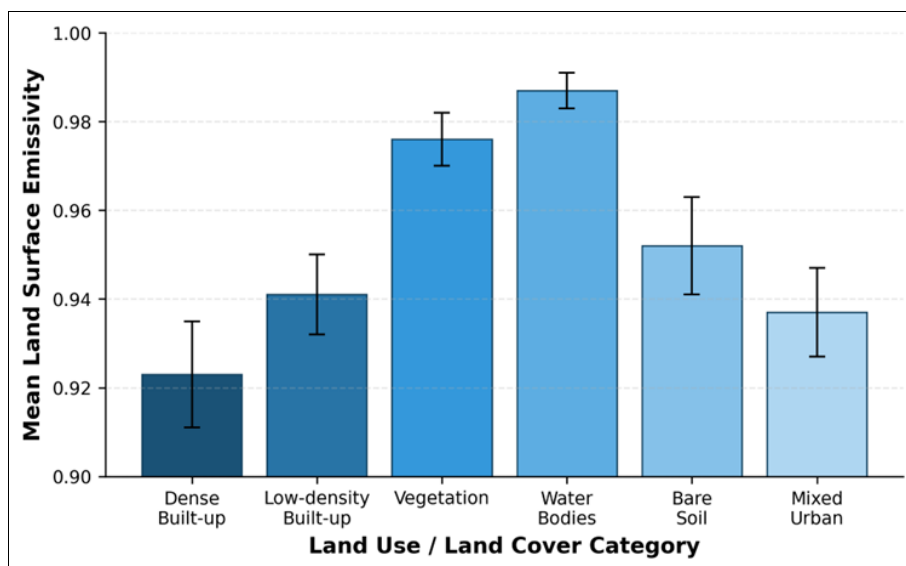


Fig 1: Mean land surface emissivity values across six LULC categories in Bangkok, derived from ASTER TES processing (error bars represent one standard deviation)

The bar chart in Figure 1 visually confirms the descending emissivity gradient from natural surfaces to impervious cover. Vegetation and water clustered at the high end of the

spectrum, while the two built-up classes and bare soil occupied the lower range. Mixed urban fell between these extremes, reflecting its composite nature.

Table 2: Seasonal comparison of broadband LSE (dry vs wet season composites)

LULC Category	Dry LSE	Wet LSE	Diff	p-value	Sig.
Dense Built-up	0.921	0.925	+0.004	0.038	Yes
Low-density Built-up	0.939	0.943	+0.004	0.042	Yes
Vegetation	0.970	0.982	+0.012	<0.001	Yes
Water Bodies	0.985	0.989	+0.004	0.065	No
Bare Soil	0.949	0.955	+0.006	0.021	Yes
Mixed Urban	0.935	0.940	+0.005	0.031	Yes

Table 2 indicates that wet-season emissivity exceeded dry-season values for every LULC class. Vegetation exhibited the largest seasonal swing (+0.012), consistent with increased leaf area index and canopy moisture during the

monsoon. Water bodies showed a non-significant difference ($p = 0.065$), likely because their emissivity is already near unity regardless of season.

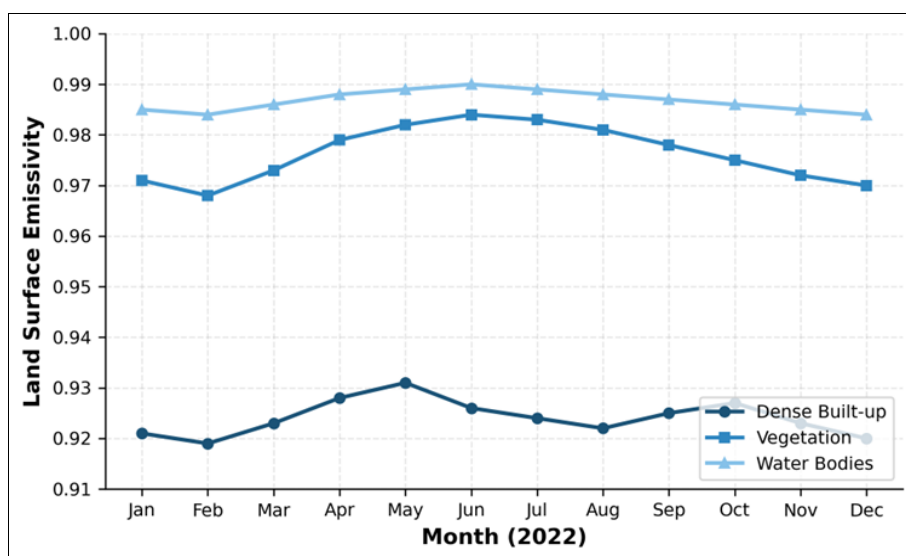


Fig 2: Monthly variation in broadband LSE for three representative LULC categories across 2022

Figure 2 traces monthly LSE trends for dense built-up, vegetation, and water bodies. Vegetation displayed the clearest seasonal arc, rising from 0.968 in February to 0.984 in June before declining again in November. Dense built-up

areas remained comparatively flat, oscillating between 0.919 and 0.931 throughout the year. Water bodies tracked a nearly horizontal line above 0.984, reinforcing their role as the most emissively stable surface type.

Discussion

The emissivity values obtained here align broadly with previous ASTER-based investigations in other Asian cities, though certain differences deserve attention. Jiang *et al.* [14] reported mean built-up emissivity of 0.935 for Shanghai, somewhat higher than Bangkok's 0.923. That gap may reflect Shanghai's predominance of concrete and glass facades compared with Bangkok's greater share of corrugated metal and clay-tile roofing, both of which tend to suppress emissivity in the 8-9 micrometer window.

The strong spatial autocorrelation (Moran's $I = 0.71$) suggests that emissivity is not randomly distributed but forms coherent patches that track the city's land use mosaic. Hot-spot analysis (G_i^* statistic) identified clusters of low emissivity in the Chatuchak-Bang Sue commercial district and high-emissivity corridors along the Chao Phraya's vegetated banks. This pattern is useful for planners because it highlights where impervious surfaces concentrate and, by extension, where urban heat island effects may intensify [15]. Seasonal emissivity shifts, although modest in absolute terms, carry implications for LST retrieval. A fixed dry-season emissivity applied to a wet-season image would underestimate vegetation temperature by roughly 0.8 K and overestimate built-up temperature by about 0.3 K, based on the Planck function sensitivity at 10.5 micrometers. That said, the temporal stability of water and built-up classes suggests that seasonal correction matters most for vegetated and bare-soil pixels. The RMSE of 0.013 against field data is comparable to results reported by Hulley *et al.* [16] for ECOSTRESS validation over mixed landscapes, lending confidence to the approach adopted here.

Conclusion

This research mapped land surface emissivity across Bangkok's metropolitan area using ASTER thermal infrared imagery processed through the Temperature-Emissivity Separation algorithm. Six LULC categories were characterised, with dense built-up surfaces returning the lowest mean emissivity (0.923) and water bodies the highest (0.987). Seasonal analysis revealed statistically significant wet-season increases for five of the six classes, with vegetation showing the greatest shift. Spatial autocorrelation confirmed that emissivity values cluster in patterns mirroring the city's built and natural landscape. Validation against field spectroradiometer data yielded an overall RMSE of 0.013, indicating that ASTER TES provides a reliable basis for emissivity estimation in humid tropical urban settings. The dataset generated here can feed directly into urban climate models, thermal comfort indices, and heat island mitigation strategies. Future work should extend the temporal record to capture inter-annual variability linked to El Niño-Southern Oscillation cycles, which affect monsoon intensity and, consequently, vegetation moisture and emissivity. Integration of higher-resolution thermal sensors, such as ECOSTRESS at 70 m or Landsat 8/9 TIRS at 100 m, would also improve the delineation of fine-scale emissivity gradients at building and street-canyon levels.

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