

Urban Land-Use Change and the Surface Urban Heat Island in Greater London

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Abstract

Urban development and vegetation change can affect surface temperature, but observed differences also depend on weather and local conditions. This dissertation examined how mapped land-cover change related to summer land-surface temperature in Greater London in 2018, 2022 and 2025. Annual Sentinel-2 classifications identified 269 urbanisation and 93 greening candidate patches after area screening. Greater London Authority green-cover mapping and the National Trees Outside Woodland Map provided additional information on vegetation. Three sites from each category were paired with manually selected comparison areas. Temperatures were extracted from Landsat June–August composites, using the spatial mean of pixel-wise seasonal medians as the main measure. All three urbanisation pairs showed positive relative temperature changes from 2018 to 2025, with an average of $+1.96^{\circ}\text{C}$. The greening average was -0.53°C , although two pairs warmed relative to their comparisons and only G73 cooled. A supplementary analysis using summer-mean composites gave group changes of $+1.00^{\circ}\text{C}$ for urbanisation and $+1.10^{\circ}\text{C}$ for greening. The average greening result therefore changed sign, while every greening site remained cooler than its Built comparison in all years under both measures. The study found consistent group-level relative warming at the selected urbanisation sites, but no common additional cooling across the greening sites. Interpretation is limited by the small purposive sample, differences in initial temperatures and vegetation-product dates, and small thermal interiors; G55 retained only one 30 m output cell. The results suggest that site assessments should distinguish existing cool surfaces from changes in temperature over time, and examine individual sites alongside group averages.

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Abbreviations

BNG	British National Grid
C2	Collection 2
EROS	Earth Resources Observation and Science Center
GIS	Geographic Information System
GLA	Greater London Authority
LCZ	Local Climate Zone
LST	Land-Surface Temperature
LULC	Land Use and Land Cover
NDVI	Normalised Difference Vegetation Index
QA	Quality Assessment
SUHI	Surface Urban Heat Island
TIRS	Thermal Infrared Sensor
TOW	Trees Outside Woodland
UGF	Urban Greening Factor
UHI	Urban Heat Island
USGS	United States Geological Survey

1 Introduction

1.1 Urban Change and the Thermal Environment

Urban development changes the surfaces through which energy and water move. Vegetation and exposed soil have been replaced by buildings and sealed ground; thus, evaporation, solar absorption and heat storage have changed, and the arrangement of buildings also affects shade and ventilation. The above processes create temperature variations in the city and between the urban area and the surrounding region (Oke, 1982; Arnfield, 2003). The above differences are relevant to urban adaptation because redevelopment and vegetation management change the exposed surfaces of summer heat. Comparing land-cover maps with temperature data can help assess how development is associated with surface-temperature change.

Greater London has many areas of development, suburbs and large green spaces. New construction and vegetation growth can occur in different areas of this mixed landscape, including on the former development site. The effects of heat will not be distributed evenly. Built cover will reduce evaporation; however, the temperature will still be affected by the materials and other surfaces in the shade. Vegetation can lower the surface temperature by shading and evapotranspiration; however, both processes are limited by the structure of the vegetation and water supply (Gunawardena et al., 2017; Wong et al., 2021).

The planning relevance is not limited to areas already recognised as heat hotspots. London Plan Policy G5 incorporates urban greening in the development process and links the design of individual sites to broader environmental goals (Greater London Authority, 2021). The type and extent of the vegetation need to be considered in the assessment. Research in European cities has shown that tree-covered and treeless green surfaces have different temperatures (Schwaab et al., 2021). London field studies have also shown differences in cooling with greenspace size and surrounding conditions (Doick et al., 2014; Vaz Monteiro et

al., 2016). Therefore, the analysis selects a set of patches and maps their changes in vegetation.

1.2 Research Problem

A further challenge is to separate land-cover change from weather-related variation in thermal imagery. A hot image taken after a dry period and a cooler image taken in different weather may have a large temperature difference even if the land cover is the same. Therefore, the three satellite dates provide weak evidence of a long-term temperature trend. Seasonal composites have more observations than single images, and by comparing them with nearby areas, one can determine whether the temperature at a particular site has risen or fallen relative to its surroundings (Zhou et al., 2019).

The land-cover record also has a problem. The annual divisions are relatively uniform over a large area; otherwise, changes in the maps would also show classification uncertainty or physical conversion. Published accuracy describes the assessed product and sample, rather than certifying every subsequent transition in London. Established classifications are nevertheless valuable where equivalent historical training and validation observations are unavailable. Here, they are used to identify candidate changes for closer examination. Independent green-cover and tree-canopy layers can be used to describe the vegetation in the candidate areas if their observation periods and definitions are met (Karra et al., 2021; Impact Observatory, 2022).

The study therefore examines whether sites with mapped built-up or vegetation gains also show changes in summer surface temperature compared to the surrounding areas. Existing evidence that vegetation is often cooler than built surfaces does not establish how a particular site has changed. The analysis therefore considers both the temperature difference within each site pair and the change in that difference across the selected summers.

1.3 Research Aim and Questions

The purpose of this dissertation is to explore the connection between mapped urban land-cover change and summer land-surface temperature in Greater London using 2018, 2022 and 2025 as comparison years. The two categories of research are urbanisation, shown by the conversion to built-up area, and greening, shown by the conversion to vegetated area. Annual classifications identify candidate changes, vegetation products describe their cover, and Landsat seasonal rasters provide the temperature observations. The detailed analysis comprises three urbanisation sites and three greening sites, each examined alongside a selected comparison area.

The first research question asks which changes towards built or vegetated cover are identified in the land-cover series, and what their extent and patch characteristics are. Metropolitan Screening is used to address this problem, and then individual patches are selected. The second is how independent green-cover and tree-canopy measurements compare to the annual classifications at the selected sites. It considers both agreement and disagreement of the products, and distinguishes between total vegetation and tree canopy.

The third question asks how summer surface temperature differs between each change site and its comparison area in 2018, 2022 and 2025, and whether changes in these differences depend on the seasonal summary used. The main indicators are summer-median rasters, and summer-mean rasters are employed for sensitivity analysis. The analysis compares absolute temperatures and changes from the 2018 baseline across all six pairs. It concerns the selected cases rather than a representative sample of redevelopment or greening across London.

1.4 Scope and Contribution

The thermal variable is remotely sensed land-surface temperature, which is the radiometric temperature of the surface as seen by the sensor. It is not the same as near-surface

air temperature or the conditions inside buildings and under a tree canopy (Voogt and Oke, 2003; Weng, 2009). The surface urban heat island provides the general context, and the following studies investigate temperature variations in Greater London. An urban-rural reference pair was not established, so the study does not calculate metropolitan surface urban heat-island intensity. The focus is on temperature differences within the city and their relationship to mapped cover change.

The three study years provide a retrospective comparison of selected summers. Their temperature rasters summarise available clear-sky observations during June, July and August rather than continuous measurements of every summer day. The investigation therefore concerns seasonal surface conditions observed by Landsat. The Sites and comparison Areas were selected purposefully, and differences in their initial conditions remain relevant to the interpretation. Green-cover and tree-canopy layers provide complementary evidence for composition; they do not offer repeated historical observations of all three thermal years.

The above datasets can be combined to study the same sites for mapped changes, vegetation composition and summer temperatures. Reporting individual pairs as well as group averages also shows whether an average warming or cooling value is shared across the cases or driven by one site. This is relevant to site assessment, where a metropolitan average may conceal substantial local differences.

1.5 Dissertation Structure

Chapter 2 introduces urban heat processes, vegetation cooling and the application of remote sensing, and then identifies a research gap that this paper addresses. Chapter 3 introduces Greater London and the spatial and temporal basis for the comparison. Chapter 4 shows the datasets and site selection and processing methods. Chapter 5 shows the land-cover and temperature results, as well as sensitivity analysis. Chapter 6 discusses the results in relation to previous studies. Chapter 7 answers the research questions.

2 Literature Review

2.1 Urban Heat, Climate Adaptation and London Policy

Urban heat links changes in the physical city to the broader problem of climate adaptation. Buildings and roads have replaced permeable surfaces, altering the local exchange of energy and water, and a warmer background climate has increased the temperature at which these exchanges occur. These processes work together but are different types of changes. A city can become hotter during an unusually warm summer without any redevelopment, and a redeveloped site can become warmer relative to its surroundings even when metropolitan temperatures fall. Urban heat research consequently concerns both the climatic conditions affecting the city and the spatial organisation of surfaces within it (Oke, 1982; Arnfield, 2003).

The urban heat island encompasses several related phenomena. Canopy-layer heat island refers to a near-surface air-temperature difference in the layer over buildings and people. The urban boundary-layer heat island concerns the atmosphere above this layer, whereas the surface urban heat island concerns radiometric land-surface temperature, including roofs, vegetation, exposed soil and paved ground. Thermal satellites observe the latter through emitted thermal radiation. Surface temperature affects the exchange of surface and air, but this relationship is not the same under all conditions of moisture, shading, wind and time of day (Voogt and Oke, 2003). Therefore, a daytime surface-temperature map only shows a part of the urban heat and not the full thermal environment for residents.

This distinction is also important when interpreting health evidence. Iungman et al. (2023) assessed 93 European cities during summer 2015 and estimated 6,700 premature deaths attributable to urban heat-island effects. Their scenario increasing tree cover to 30% suggested that 2,644 deaths could potentially be prevented. These estimates combined temperature, population and mortality relationships; they were not direct observations of a

tree-planting intervention. For London, Simpson et al. (2024) estimated 370 heat-attributable deaths during 10–25 July 2022, with 38% attributable to the urban heat island. Both studies show that urban heat reduction is required for public health. However, the mortality estimates cannot be derived from land-cover and daytime-surface-temperature data alone; they also require population exposure and temperature-health relationships.

The effects of urban heat are also unevenly distributed because exposure and the capacity to adapt differ among residents. Housing conditions, age, underlying health, occupation and access to cooler spaces affect how similar outdoor conditions translate into harm. The London Climate Resilience Review identifies extreme heat as a risk to residents and interconnected systems, including healthcare, transport and energy, and calls for coordinated adaptation across institutions (Greater London Authority, 2024a). Temperature and vegetation maps help to identify areas with high suitability for adaptation and cooling resources. To identify vulnerable residents, demographic and exposure data need to be added; the hottest mapped surface is not necessarily where people are most at risk.

London planning policy connects these concerns to development decisions. Policy G5 of the London Plan requires urban greening to form a fundamental part of major development and recommends an Urban Greening Factor of 0.4 for predominantly residential development and 0.3 for predominantly commercial development (excluding B2 and B8 uses) where local targets have not been established (Greater London Authority, 2021). The associated guidance evaluates the quantity and quality of greening through weighted surface areas divided by total site area (Greater London Authority, 2023). These values are dimensionless planning scores, not percentages of tree cover or predicted temperature reductions. Different combinations of planting, roofs and water may have the same score but different effects on shade and heat absorption.

The long-term benefit of greening is not a single thermal index. Vegetation offers habitats, drainage, amenities and temperature regulation; however, it is only effective if it is well-developed and well-maintained in an urban area. Remote Sensing can offer planning support by observing changes in surface composition and spatial thermal variations after development. It is particularly useful for areas with large-scale changes in a city and cannot be observed everywhere on the ground. Therefore, the thermal effects of development need to be assessed in light of the resulting surface and its environment. A relatively high plan score may not indicate a longer cooling-off period (Wong et al., 2021).

2.2 Land Cover, Urban Form and the Surface Energy Balance

The surface energy balance provides the physical basis for interpreting these observations. Incoming short-wave and long-wave radiation, together with heat released by human activities, is partitioned among reflected radiation, emitted long-wave radiation, sensible heat, latent heat and storage. Urbanisation changes several terms simultaneously. Impervious surfaces reduce opportunities for evaporation, construction materials alter heat storage, and buildings change radiative exchange and airflow. Oke (1982) therefore explains urban warming through a combination of processes rather than one characteristic shared by all urban land. The same mapped increase in built cover may produce different thermal responses where water availability, materials or urban geometry differ.

Vegetated surfaces with adequate moisture can sustain evapotranspiration during warm periods. Vegetated soils dissipate energy through evaporation and transpiration, and generally, sealed surfaces direct a larger proportion of this as sensible heat and storage. It is different in the two cases. Dry grass or bare soil will be very hot in the presence of strong sunlight, and irrigated plants can still use latent heat. Antecedent rainfall will change the above relationships over several days, and drought will alter them in the summer. Arnfield (2003) believes that water and energy exchange in a heterogeneous urban area occur concurrently.

Areas assigned to the same land-cover class can therefore differ in temperature because weather and management alter the availability of water for cooling.

Urban materials affect both daytime heating and subsequent cooling. Albedo controls the proportion of incident solar radiation reflected, while emissivity, thermal conductivity and heat capacity influence radiative emission and storage. Dark exposed paving can heat rapidly during sunny conditions, but temperature cannot be inferred from colour alone. A surface may have a relatively low daytime temperature because it is shaded, yet belong to an environment that retains heat overnight. The different times for surface and atmospheric heat islands are due to these exchanges and to the movement of heat into the lower atmosphere (Voogt and Oke, 2003; Weng, 2009). Therefore, the daytime thermal observation is more sensitive to the surface exposed and illuminated by the overpass.

The three-dimensional city modifies this radiative environment. Building height, spacing and street orientation control solar access and the portion of sky visible from the ground. Street canyons can offer shade at certain times of the day, but long-wave cooling after sunset is unavailable. Roughness and ventilation affect the speed of heat and moisture loss from surfaces. Stewart and Oke's (2012) Local Climate Zone framework has formally divided these differences into 17 classes according to surface structure, cover and human activities. The division of areas is based on their actual conditions and not on urban-rural divisions. Building structure, surface cover and human activities are still relevant when selecting comparison areas, even if a full Local Climate Zone classification is not carried out.

Land-use categories do not necessarily describe the surfaces responsible for these thermal differences. Land use describes activities such as housing, transport, industry or recreation; land cover describes observable physical components such as trees, grass, roofs and water. Optical classifications generally map cover more directly. A residential area will have many trees, but an open recreational area will be relatively bare. Therefore, a change

referred to as urbanisation or greening is a mapped conversion, and its thermal response is determined by the mixture of surfaces within and around the polygon. Weng (2009) thus supports quantitative surface descriptors that represent sub-pixel composition and does not rely solely on broad land-use categories.

Relatively high temperatures may also be influenced by heat transported from surrounding areas. Brousse and others (2022) analysed hourly observations from 1,560 suitable citizen weather stations in South-East England and Greater London between 2015 and 2020. They have identified horizontal transport of urban heat, such as redistribution to downwind suburban areas and reduced cooling effects in some green spaces. Therefore, a place's temperature may be affected by heat from elsewhere. Nearby comparison areas can also share some of the thermal influence caused by the change in site. Deilami et al. (2018) also consider the Design of space and time for UHI analysis. Therefore, in comparing the sites, the surrounding cover and urban form, as well as the transition map within each boundary, should also be considered.

2.3 Vegetation, Patch Scale and Evidence of Cooling

Vegetation reduces the temperature in an urban area by shading and evapotranspiration. Tree crowns reduce solar radiation reaching the ground and buildings, and through transpiration, available energy can be converted into latent heat if water is available. Vegetated soils are not the same as sealed surfaces in terms of water retention and heat conduction. These mechanisms explain why tree cover and green spaces are often located in the cooler areas of the city, as well as differences in vegetation types. Canopy density, tree size, rooting conditions and water stress all affect thermal performance; therefore, equal areas of grass and mature trees may not provide the same cooling effect (Gunawardena et al., 2017; Wong et al., 2021).

Evidence shows a relatively small and unstable cooling effect. Wong and others (2021) have shown that ground-level greenery can reduce the peak surface temperature by about 2-9 °C, and the actual effect varies according to the area and planting structure of the vegetation. Gunawardena et al. (2017) have separated cooling in the urban canopy layer from its effect on the upper boundary layer. Therefore, the distribution and shape of green and blue spaces affect both the amount and transport of cooling. Water can reduce daytime temperatures and is relatively cool at night. A single cooling coefficient would not reflect this. Reported temperature reductions should be compared at the same spatial scale and observation period, and it should be checked whether the green or blue space is the same.

European Satellite data show the specific functions of trees. Schwaab et al. (2021) Used high-resolution land-cover data and Landsat temperature observations for 293 cities. Urban trees generally had a lower surface temperature than continuous urban fabric, and the cooling effect of treeless green spaces was about one-quarter to one-half that of trees. The differences in Europe and during different seasons were due to varying evapotranspiration and climate. The study links established tree cover with lower daytime surface temperature but does not follow the maturation of newly planted sites. The difference between tree-covered and treeless green spaces is suitable for interpreting mapped greening, but it cannot predict the size of the cooling response after conversion.

Marando et al. (2022) studied green infrastructure in an ecosystem-service model for 601 European Functional Urban Areas. The average cooling was about 1.07°C, the maximum was 2.9°C, and it was related to the extent of vegetation and water-exchange. They estimated the cooling coverage of urban areas, and Schwaab et al. (2021) have used satellite observations to compare the surface temperatures of different cover types. Both link vegetation with cooling, but their estimations refer to different results, reference scenarios

and spatial units. The numerical magnitudes are consequently not interchangeable measures of surface-temperature reduction or local air-temperature cooling.

Field observations show how surrounding cover shapes local temperature. Ziter and others (2019) measured the summer air temperature along bicycle transects in Madison, Wisconsin, and investigated canopy and impervious fractions in several neighbourhood radii. Canopy effects were non-linear and strongest at the scale of a city block, especially where cover exceeded about 40% within 60-90 m. Impervious cover also remained an important predictor of local temperature. The results linked local air temperature to neighbourhood-scale canopy and impervious cover, and do not use only the vegetation near a measurement point. The numerical threshold is in the study environment and is not a general standard for London Parks.

Field research in London will be more directly comparable. Doick and others (2014) observed a large green space in central London and a nearby street for five months. Estimated cooling extended about 20-440m beyond the greenspace, and the mean reduction over those distances in summer was 1.1°C, with some differences reaching 4°C on certain nights. A smaller range of cooling shows that the mapped boundary does not cover the whole area affected by vegetation. There is also a sampling problem: an urban reference area near a large green space may be relatively cool itself, thus reducing the perceived difference between urban and non-urban areas.

Vaz Monteiro and others (2016) reported on eight London green spaces ranging from 0.2 to 12.1 ha. On calm, warm nights, cooling distance increased with an increase in greenspace, canopy and grass area, and the magnitude of cooling was non-linearly related to these attributes. Very small Areas of less than 0.5 ha provided little cooling to the surrounding environment. The authors put forward that areas of 3-5 ha and about 100-150m apart can distribute nocturnal cooling in cities with similar conditions. These field

measurements link greenspace size and composition to air-temperature cooling, but do not set a lower limit for patch size in satellite analysis. The upper limit is also set by the spatial resolution of the thermal sensor and how much it is mixed with other surfaces.

London modelling also shows that the apparent cooling effect of an intervention varies with temperature and time of day. Brousse et al. (2024) compared interventions during two hot days in July 2018 and found different metropolitan 2 m air-temperature responses for cool roofs, green roofs, solar panels and vegetation. Green roofs cooled during hot daytime hours but provided little reduction in the two-day mean because night-time effects differed. These modelled metropolitan air-temperature scenarios do not quantify observed responses at individual changed sites. The contrast between daytime cooling and the two-day average nevertheless shows why an assessment must specify both its temperature measure and its observation period.

2.4 Measuring Urban Heat and Designing Thermal Comparisons

Urban heat is known at some fixed stations, measured by mobile devices, and also modelled or remotely sensed. The three ways have different trade-offs in terms of space, time and physical reality. Fixed stations collect several air-temperature measurements and observe changes in daily life and seasons, but they may not be representative of the entire area. A sparse network will be unable to distinguish between parks, industrial areas and residential streets. Mobile surveys expand the area covered but collect data at different times and need to consider changing circumstances. The above field studies have shown that they are effective in measuring vegetation cooling, but their limited geographical and historical coverage restrict retrospective analysis of redevelopment (Voogt and Oke, 2003; Deilami et al., 2018).

Citizen Weather Stations can expand the coverage area for air-temperature observation. Brousse and others (2022) have shown that a quality-controlled network can reveal both metropolitan differences and local effects of heat transport. Such observations nevertheless

depend on the availability, siting and continuity of privately maintained instruments. For historical land-cover analysis, their usefulness also depends on whether suitable stations operated near the relevant sites before and after change. Satellite archives offer a complementary advantage by observing many locations through a common acquisition and processing system. They can provide retrospective spatial evidence even where no ground instrument was present, although the measured quantity remains surface temperature.

Thermal retrieval is an inference from radiance rather than a direct thermometer reading. Atmospheric transmission, atmospheric emission and surface emissivity affect the signal at the sensor. Li and others (2013) have put forward some algorithms and verification methods for this problem, and have also pointed out that separating temperature and emissivity from limited spectral data is difficult. Heterogeneous urban pixels are difficult to interpret because roofs, vegetation and exposed ground have different emissivity and temperatures. The resulting estimate represents the radiometric contribution of the observed surfaces. Changes in viewing geometry and shadow can therefore affect comparability even where the geographical pixel boundary remains unchanged.

Operational temperature products improve consistency by applying documented retrieval and quality procedures across the archive. Malakar et al. (2018) developed and validated an operational Landsat surface-temperature approach, and the Landsat 8–9 Collection 2 Level-2 dataset provides an established source for retrospective analysis (Earth Resources Observation and Science (EROS) Center, 2020). Ermida et al. (2020) provide a separate, reproducible Landsat retrieval workflow, with validation against 12 stations yielding overall root mean square errors around 2 K. Their reported performance is specific to that algorithm and validation sample; it should not be treated as a universal error estimate for every Landsat product or London pixel. Using such products therefore requires attention

to their processing methods and quality information, as well as to the availability of images for the study period.

The spatial resolution of the thermal measurement limits the size of interpretable features. Landsat 8 and 9 thermal observations have a native resolution of 100 m, although products are distributed on a 30 m grid (U.S. Geological Survey, 2024). Resampling can align with the optical band, but it will not generate new 30m thermal details. A small hectare-sized patch is about 100m wide, and it may have little thermal information that has been affected by adjacent surfaces. Narrow, fragmented or irregular polygons have an even worse mixing problem. The number of 30 m cells inside a boundary therefore describes raster support, not the number of independent native thermal measurements.

Sensor choice also involves temporal trade-offs. Landsat provides useful spatial discrimination but relatively infrequent observations, with additional losses from cloud. MODIS has more frequent day-and-night observations at a coarser resolution and is more suitable for regional context studies than small-site analysis. Zhou and others (2019) have shown that the reported SUHI pattern is affected by sensor, acquisition time, spatial scale and reference definition. For an individual redevelopment site, the sensor needs to cover the changed area and provide sufficient usable observations during the desired time. A larger sensor may be more suitable for urban area comparisons where frequent coverage is required over high spatial resolution of small areas.

Temporal Sampling is required for the fluctuating summer weather in London. Cloud, wind, rainfall, soil moisture and heatwave timing alter surface temperature without requiring land-cover change. Bassett et al. (2021) reconstructed 70 years of London's climate-driven nocturnal UHI variability using a generalised additive model. Their series exhibited substantial seasonal and annual variability, with no significant central-London trend between 1950 and 2019 under the model's treatment of urban form. No trend was identified in the

modelled series; thus, regional warming or redevelopment may have still taken place. The considerable year-to-year fluctuations are also too large; therefore, a few satellite dates cannot reliably distinguish persistent local thermal anomalies from the environment in those years.

Seasonal composites reduce the dependence on a single overpass by aggregating valid observations in a common window. Means are the arithmetic means of the retained samples, and medians are less affected by isolated extremes or residual contamination. Neither is a continuous all-weather seasonal temperature: cloud screening may leave different observation dates at neighbouring pixels and different numbers of acquisitions among years. Observation counts and consistent quality rules are therefore part of the evidence supporting the composite. Aggregation improves temporal representation but does not eliminate sampling bias, and a seasonal surface-temperature difference is not automatically a climate trend (Ermida et al., 2020; Zhou et al., 2019).

2.5 Land-Cover Products and the Reliability of Change Evidence

Land-cover evidence has different uncertainties from thermal retrieval. Single-date classification assigns a label to the observed surface; a change analysis compares labels at different times. Errors in either map can lead to false transitions, and the accuracy of the common stable class may outweigh the total score even if rare changes are not well identified. Mixed pixels, shadows, vegetation conditions and different acquisition times can shift boundaries or class assignments without physical conversion. The above errors must be addressed in conjunction with land-cover maps and temperature data. Heterogeneous urban sites can be difficult to classify and can also contain mixed thermal pixels, so uncertainty may affect both the mapped transition and its temperature estimate (Karra et al., 2021; Weng, 2009).

The Esri and Impact Observatory series supplies annual Sentinel-2 land-cover maps at 10 m, with the current series extending from 2017 to 2025 (Esri and Impact Observatory, 2026). At the same time, several observations are grouped to create annual maps, and no new historical training data need to be added (Karra et al., 2021). Annual mapping can help identify coherent built-up area gain and vegetation gain across London, but the classes are too general. Rangeland can be divided into different low-vegetation areas, and built-up areas may be mixed-use. The general label for that year is a mapped condition, not a specific event date or a full description of urban morphology.

Interpret the published accuracy data cautiously. Impact Observatory's July 2022 assessment report reported an accuracy of at least 91% through strict expert consensus and a majority consensus of 76% or more for the 2017-2021 annual maps. Strict consensus keeps pixels that all three annotators agree on; majority consensus includes more ambiguous areas. The higher strict-consensus score therefore applies to a less ambiguous set of reference pixels. The assessment does not independently validate London transitions in 2022 or 2025. Its scores describe performance for an earlier period and depend partly on how reference labels were selected. Local change claims require additional spatial and temporal evidence even when a product has strong global performance (Impact Observatory, 2022).

The Greater London Authority provides a complementary source at finer spatial detail. Its 2024 tree-canopy and green-cover assessment draws mainly on 2022 aerial imagery and height information. The published estimates are 19.6% tree-canopy cover and 51.7% green cover across London, with stated uncertainties, and green-cover mapping is supplemented by other land-use information where image classification struggles with bare or worn surfaces (Greater London Authority, 2024b). The distinction between total green cover and canopy matters thermally because grass and trees contribute different shading and moisture processes.

These layers can describe whether candidate polygons contain vegetation during the principal observation period, but they do not constitute annual measurements of the same sites.

The National Trees Outside Woodland Map adds information about canopy outside the National Forest Inventory woodland boundary. Version 1 was published by the Forestry Commission in April 2025 and produced by Forest Research. It identifies canopy over 3 m high and 5 m² in area, categorised as lone trees, groups and small woodlands, using LiDAR-derived vegetation information, Sentinel-2 and spatial mapping (Forestry Commission, 2025). Its metadata cover inputs from 2017–2024, so publication year cannot be interpreted as a common acquisition date. A low TOW fraction may reflect the exclusion of inventoried woodland as well as genuinely limited canopy. It is therefore a measure of a defined tree resource rather than total vegetation.

The three products can be combined to examine different aspects of candidate change. The annual Sentinel-2 series supports temporal screening; the GLA layers describe detailed cover around their principal 2022 observation period; and TOW describes qualifying canopy outside mapped woodland. Agreement among them increases confidence in surface composition, but it cannot automatically prove the direction or timing of change. The reasons may include different class definitions, acquisition times, minimum feature sizes or exclusions. For example, significant green cover with a small TOW canopy may be grass, young trees or inventoried woodland outside the TOW, and not a disagreement over the presence of vegetation.

Spatial persistence and patch geometry are feasible tests of change plausibility. Require an endpoint class to recur in more than one annual map to reduce sensitivity to isolated label changes, and contiguous-area thresholds remove scattered pixels that are unlikely to be significant interventions. The above rules improve the uniformity of candidate selection but are not independent verifications; persistent classification errors may still occur. Historical

aerial photographs, development records or other relevant reference observations would provide strong support for the conversion. Existing products can therefore identify candidate changes and describe cover during the mapped observation periods, provided their sources and observation dates are recorded. Agreement on cover in those periods, however, is not equivalent to verification of historical conversion.

2.6 Greater London Evidence and the Analytical Gap

The literature supports a physical expectation that increased impervious cover can intensify surface heating and that vegetation can moderate it, while repeatedly identifying the importance of scale, water availability and urban form. London studies demonstrate greenspace cooling in near-surface air, European satellite studies show canopy-related surface contrasts, and recent London modelling distinguishes local interventions from metropolitan air-temperature responses. In short, the studies above have shown that vegetation and built-up areas have different thermal environments; however, they focus on different temperature parameters and scales. Retrospective GIS analysis can be performed to study the surface response at altered sites by combining land-cover evidence with comparable summer observations, provided that the patches are large enough to be resolved by a thermal sensor.

Semudara et al. (2024) provide a directly relevant Greater London case using Landsat observations for 2000, 2013 and 2022, supervised land-cover classification, NDVI and surface-temperature analysis. The chapter reports expanded developed land and warmer conditions in the latest image. As shown in the workflow, optical and thermal data can be used for London, and each selected date corresponds to a particular season and weather. Comparison will also include Landsat sensors. Therefore, the observed differences may be due to land-cover changes or variations in observation time and circumstances, and a prolonged warming trend cannot be confirmed. The study offers a London case for

combining land-cover and temperature analysis. Seasonal composites can also be used to reduce the impact of conditions at a single overpass.

A further issue is that spatial temperature differences do not necessarily indicate temporal change. A mature tree-covered area is likely to be cooler than a new construction site in all the summers, but this spatial difference does not indicate whether the tree cover has changed. Conversely, a site that warms relative to its own baseline may remain cooler than a consistently hot reference. Canopy and LST cross-sectional comparisons are used to investigate the thermal characteristics of different surfaces, and repeated observations monitor alterations in these features over time. Both are required to distinguish between a persistently cold area and a place that has become colder compared to before. Therefore, vegetation-cover studies and temporal UHI research have provided support for reporting absolute temperatures and changes from a common baseline (Schwaab et al., 2021; Bassett et al., 2021).

Stable comparison areas can help separate shared annual conditions from site-specific differences. If a candidate and its control are observed through the same seasonal thermal product, subtracting their baseline changes provides a measure of relative thermal divergence. The interpretation depends on comparability: initial cover, urban form, distance to water and local development history can influence how each area responds to weather. A control that is stable in a broad land-cover classification may still undergo changes in irrigation, surface materials or building form. Urban-form differences and heat advection can also affect a site and its comparison area differently (Stewart and Oke, 2012; Brousse et al., 2022). Pairing helps identify relative thermal change, but it does not by itself isolate the causal effect of land-cover conversion.

The gap addressed here concerns the link between sustained mapped land-cover transitions and seasonally aggregated surface temperature in Greater London. The reviewed

studies establish expected differences between impervious and vegetated surfaces, but their cross-sectional comparisons, field measurements and modelled scenarios do not directly describe the selected London transitions. Annual cover maps, along with separate canopy and green-cover layers, can be used to show the changes in candidates before comparing their summer temperatures with those in reference areas. Determine whether the mapped transitions are relatively warmer or cooler, and how consistently this pattern occurs at different sites and in different summers. It offers site-level evidence relevant to redevelopment and greening, and keeps the difference between observed surface-temperature change and metropolitan air-temperature effects.

3 Study Area and Analytical Framework

3.1 Greater London as a Case Study

Greater London was selected because built and vegetated surfaces can be compared within one metropolitan area. Including suburban and open areas as well as the central districts allowed both built-cover gain and vegetation gain to be examined. The availability of an annual Sentinel-2 classification, London-specific green-cover mapping and a national canopy dataset also allows the same locations to be analysed by several independent descriptions of the surface.

Research on green spaces in London provides a reference for this study. Doick et al. (2014) and Vaz Monteiro et al. (2016) have shown that cooling near green spaces changes with alterations in the scale, vegetation and distribution of these spaces. Although these studies measured air temperature instead of Landsat surface temperature, they show that the surroundings of a greenspace are relevant. Each selected patch is shown next to a comparison area, and the same study boundary and observation years are used.

3.2 Spatial Extent and Units of Analysis

The Greater London administrative boundary defines the extent of the land-cover screening and the common reporting area. It aligns the analysis with the GLA datasets and planning area. Urban development and heat exchange extend beyond this administrative boundary, so area-wide temperatures should not be interpreted as defining the extent or intensity of London's urban heat island.

Neighbouring cells in this range that have the same mapped transition were grouped into patches. The selected patches are the regions of vegetation analysis. For temperature analysis, a patch and an adjacent comparison polygon were selected. The empirical cases comprise U28, U106 and U167 for urbanisation and G14, G55 and G73 for greening. Each has a corresponding comparison polygon, giving six pairs and twelve analysed areas.

The paired structure offers a local reference for the change in temperature, but the comparison polygons are observational reference areas and not experimentally designated controls. The purpose of the site selection did not involve formal matching or random allocation. The analytical unit is still a polygon and its corresponding comparison area. Raster cells within a polygon are not independent site replicates; each category contains three change sites.

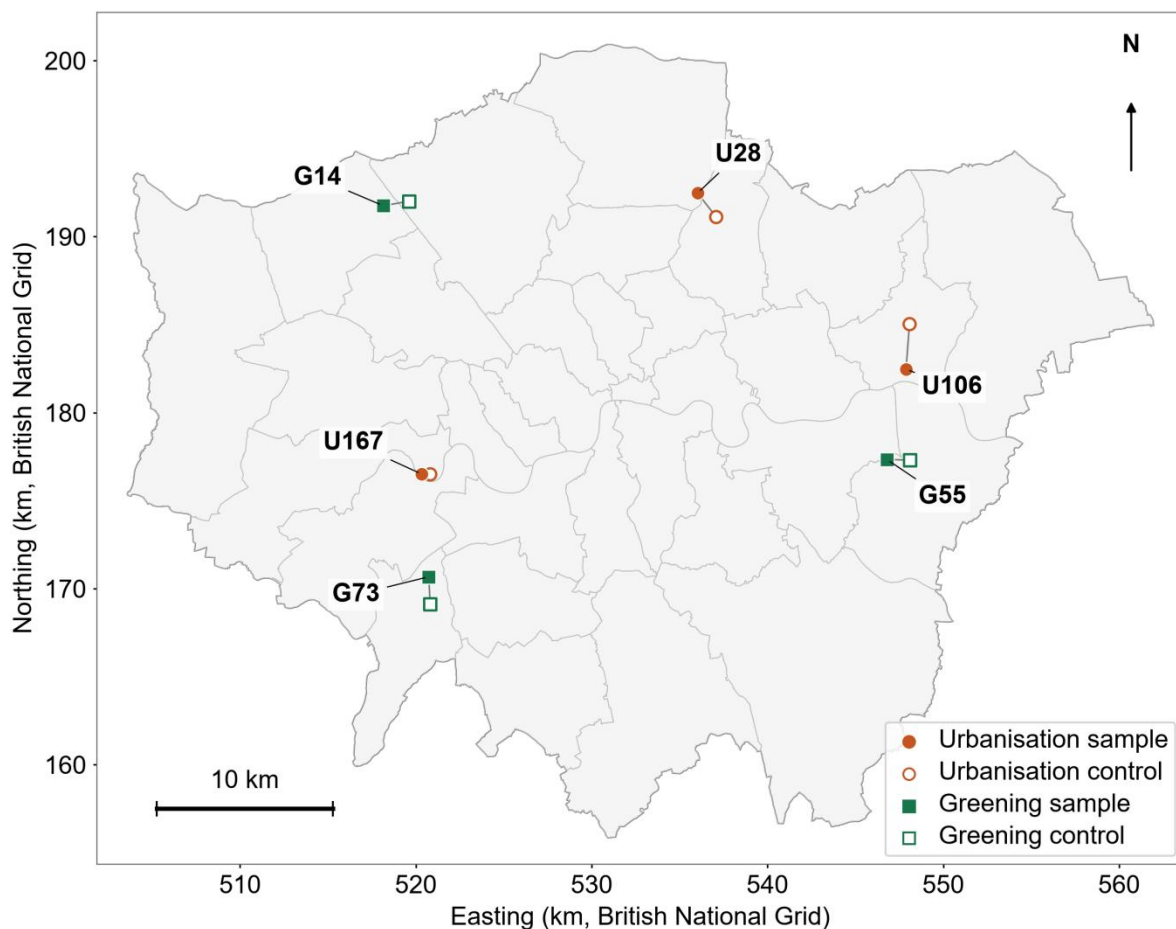


Figure 3.1 Greater London and the six sample-control pairs

The six selected sample polygons and their corresponding control polygons within Greater London. Filled symbols identify samples and open symbols controls; lines join each pair. Symbols mark polygon centroids and are not proportional to area. Borough boundaries provide geographic context. Source: Greater London boundary and borough layers in the study GIS project; study sample and control polygons.

3.3 Temporal Scope and Dataset Roles

The temporal framework uses 2018 as the initial year and 2022 and 2025 as later observations. Urbanisation comprises valid non-Built pixels in 2018 classified as Built in both later years; its initial covers include Water, Trees, Flooded Vegetation, Crops, Bare Ground and Rangeland. Greening comprises Built or Bare Ground pixels in 2018 classified as Trees or Rangeland in both later years. The categories therefore describe different transition rules, rather than equal and opposite exchanges between built and green surfaces. Repeated later classes indicate persistence across the mapped observations but do not establish the physical change date.

The Esri and Impact Observatory time series supplies annual 10 m land-cover categories for locating change. GLA mapping, based mainly on 2022 aerial data, describes finer-scale vegetation composition (Greater London Authority, 2024b). The National Trees Outside Woodland Map supplies a further record of qualifying canopy outside inventoried woodland, drawing on inputs spanning 2017-2024 (Forestry Commission, 2025). The layers distinguish total vegetation from canopy, but their different observation periods and definitions prevent direct annual comparison. In particular, the TOW publication year is not a single acquisition date.

The principal thermal measure is the spatial mean of pixel-wise June-August median Landsat temperature within each polygon. Summer-mean rasters provide a parallel sensitivity comparison. The delivered products use a 30 m grid, which should not be equated with the resolving power of the original thermal observations (U.S. Geological Survey, 2024). Seasonal aggregation reduces dependence on a single acquisition but retains the clear-sky and daytime sampling characteristics of the satellite record. Comparing the two aggregation statistics establishes whether conclusions depend on how the available summer observations are summarised.

3.4 From Mapped Change to Paired Thermal Comparison

City-wide screening and detailed site analysis have different roles. The screening describes the extent and patch characteristics of mapped change. The selected pairs allow closer examination of vegetation and temperature, but do not represent all candidate patches. Metropolitan totals are therefore reported separately from the findings for the six pairs.

Two temperature measures are considered: the difference between a site and its comparison area within each summer, and the change in this difference from 2018. A site can be relatively warm in absolute terms but cooler than the reference area, or it can be absolutely cool but still have a larger relative temperature excess.

Group averages summarise the three urbanisation pairs and the three greening pairs, while individual results show how much the cases differ. Green-cover and canopy fractions help describe this variation because broad vegetation classes can contain surfaces with different shading and evaporative properties. These fractions describe the periods represented by their source datasets, rather than all three thermal years.

3.5 Interpretive Framework

Physically, it is expected that conversion to built-up areas will increase heat storage and reduce the water available for evaporation; at the same time, vegetation will moderate daytime surface heating through shade and evapotranspiration (Oke, 1982; Wong et al., 2021). However, the responses may differ with the initial cover, canopy, patch shape, surrounding surfaces and weather conditions. The direction and size of the change are taken into account in the comparison.

The agreement among the cover products and some relative temperature changes supports interpretation of the site. A different time, place, or group may be needed for the analysis. Analysis can find these associations, but it cannot attribute the temperature change solely to land-cover change.

4 Methodology

4.1 Research Design and Literature Search

Utilise secondary Earth Observation and environmental mapping data to conduct a quantitative retrospective case-control study. First, metropolitan land-cover screening was performed to identify a change patch and its surrounding areas for the following analysis. The annual land-cover classifications in the three observation years from 2018 to 2025 were all different. Independent vegetation layers were used to describe the patches, and the general thermal index used was summer land-surface temperature (LST). The first observation unit was a site-control pair, not an individual raster cell. Three urbanisation pairs and three greening pairs were selected for measurement in each of the six summers.

The datasets served different parts of the retrospective comparison. Annual land-cover maps located candidate changes, finer-resolution vegetation products described their composition, and thermal composites measured summer surface conditions. By comparing each site over time and with neighbouring ones, most of the stable mapped cover was excluded from the temperature change analysis. The three summers were regarded as independent comparison periods, and therefore insufficient data were available for a long-term temperature trend analysis.

Literature searching used topic-based web searches, publisher platforms, university repositories and official data-provider websites. Searches combined terms concerning urban heat islands, surface urban heat islands, land-surface temperature, Landsat, land-cover change, urban greening, tree canopy, remote sensing and London. Relevant review papers provided an initial conceptual framework, and empirical studies were selected for their treatment of surface composition, spatial scale, thermal measurement or land-cover change. Product definition and processing requirements were taken from the official documents. The search was a targeted narrative review without a registered systematic review screening protocol.

The literature offered the following three methods. First, LST was kept as a surface parameter instead of being used interchangeably with air temperature, and thus aligned with the distinctions proposed by Voogt and Oke (2003) and Zhou et al. (2019). Second, repeated summer observations were aggregated instead of choosing one image for each year, reducing dependence on an individual acquisition. Third, existing land-cover classifications were used because the project lacked comparable historical training and reference observations for producing and validating a new classification. Published studies and technical documentation were assessed separately: the former informed interpretation and alternatives, whereas the latter established what each supplied product actually measured.

4.2 Data Sources and Preparation

The Esri–Impact Observatory Sentinel-2 land-use and land-cover time series provided 10 m categorical rasters for 2018, 2022 and 2025. The same class names were used for post-classification comparisons in the selected years (Esri and Impact Observatory, 2026; Karra et al., 2021). Published accuracy evidence was considered to be within its time and place. The 2017–2021 evaluation did not constitute a local validation of the supplied 2022 and 2025 London maps (Impact Observatory, 2022). Cloud and NoData labels were excluded from valid classified area.

Spatial operations were undertaken in ArcGIS Pro using British National Grid, EPSG:27700. Land-cover inputs were restricted to the Greater London study boundary, and raster coordinates, dimensions, cell sizes and origins were checked before comparison. Although all three source classifications had 10 m cells, the supplied 2018 raster origin differed from those of 2022 and 2025. Nearest-neighbour resampling to the supplied change-mask grid established a common categorical alignment without introducing interpolated class codes. An independent reconstruction using that alignment reproduced both supplied change

masks with no differing pixels. The common grid was therefore defined by the change-mask geometry rather than assumed to coincide with the unmodified 2018 raster.

The annual class areas were determined by dividing the three-year common valid extent by three. The 2018-2025 transition matrix used the valid intersection of those two years and recorded each origin-destination pair separately. Areas derived from these rasters were calculated in 10m projected cells, and each cell was 0.01 ha. These raster totals were distinguished from the geodesic areas subsequently recorded for individual candidate polygons. Thermal rasters retained their separate 30 m output grid. Resampling them to 10 m would not have increased their thermal detail.

The GLA Tree Canopy and Green Cover Mapping product supplied detailed vegetation information based mainly on aerial imagery acquired in 2022, despite its 2024 publication date (Greater London Authority, 2024b). The National Trees Outside Woodland map supplied an additional canopy layer produced by Forest Research and published by the Forestry Commission in 2025. Its underlying observations span 2017–2024, and its coverage concerns qualifying tree canopy outside woodland rather than all trees or a uniform 2025 survey (Forestry Commission, 2025). Both sources were treated as supplementary descriptions of vegetation, not as annual change records.

The thermal input comprised nine GeoTIFF files: a summer-mean LST raster, summer-median LST raster and valid-observation-count raster for each study year. The composites were derived from 39 Landsat Collection 2 Level-2 Tier 1 scenes acquired during June–August: nine Landsat 8 scenes in 2018, six Landsat 8 and eight Landsat 9 scenes in 2022, and eight scenes from each platform in 2025. Scene identifiers and acquisition dates were retained with the source rasters. The operational product and its processing conventions were checked against EROS and USGS documentation (Earth Resources Observation and Science (EROS)

Center, 2020; U.S. Geological Survey, 2024). The seasonal rasters used British National Grid coordinates and degrees Celsius and were retained separately from derived site statistics.

Table 4.1 Data sources and analytical roles

Dataset	Time and scale	Role
Esri–Impact Observatory LULC	2018, 2022, 2025; 10 m	Persistent-change screening and categorical comparison
GLA green cover and tree canopy	2024 release; mainly 2022 aerial inputs	Independent vegetation fractions within candidate polygons
National Trees Outside Woodland Map	Version 1, 2025; inputs 2017–2024	Qualifying canopy outside mapped woodland
Landsat 8/9 C2 Level-2 LST	June–August 2018, 2022, 2025; 30 m grid, 100 m native thermal scale	Seasonal median, mean and clear-sky observation counts
Greater London boundary	Administrative vector boundary	Common clipping and metropolitan reporting extent

Sources: Esri and Impact Observatory (2026); Greater London Authority (2024b); Forestry Commission (2025); Earth Resources Observation and Science (EROS) Center (2020); U.S. Geological Survey (2024).

4.3 Change Detection and Candidate Selection

Two binary rules identified persistent mapped changes. Urbanisation comprised valid pixels assigned any non-Built class in 2018 and Built in both 2022 and 2025. With Built coded as 7, this was expressed as $L_{2018} \neq 7$, $L_{2022} = 7$ and $L_{2025} = 7$, subject to valid classification in every year. The rule included Water as a possible starting class, alongside vegetation and Bare Ground; water-to-built transitions were not excluded. Greening comprised pixels assigned Built or Bare Ground in 2018 and either Trees or Rangeland in both later years. Its class-code rule was $L_{2018} \in \{7, 8\}$, $L_{2022} \in \{2, 11\}$ and $L_{2025} \in \{2, 11\}$. Trees and Rangeland formed a shared destination group, so movement between these two classes in 2022 and 2025 still satisfied the greening definition.

Requiring agreement in the destination group across two later maps reduced reliance on an isolated annual label. The resulting masks represented differences from the 2018 baseline that persisted in the 2022 and 2025 classifications. They did not establish the precise date of conversion or require that every intervening annual map showed the same condition. Urbanisation and greening therefore denoted mapped transitions. They did not independently confirm a construction project, planting intervention or change in land use, particularly where a later Built label coincided with substantial vegetation in another product.

Contiguous pixels were grouped by eight-neighbour connectivity, and contact occurred at either an edge or a corner. Grouped rasters were converted to polygons without boundary simplification, and the geometry of the classified cells was retained. Polygon areas were calculated using geodesy in hectares, and candidates of at least one hectare were kept. The threshold reduced small and fragmented mapped changes, but it was still a feasible starting point for thermal extraction. It was not guaranteed that all of the retained polygons would have a large, even thermal footprint; narrow shapes would lose most of their area after an inward buffer operation. The resulting selection pools contained 269 urbanisation and 93 greening candidates.

Three candidates from each category were selected manually for detailed analysis. The final identifiers were U28, U106 and U167 for urbanisation, and G14, G55 and G73 for greening. Selection was purposive, with no random draw or systematic ranking. For each selected patch, an equal-shaped and equal-area copy was positioned within 3 km to form a comparison region. Urbanisation controls occupied predominantly stable non-built cover, whereas greening controls occupied stable Built cover. Full-polygon class compositions were checked across the three years; the small changing Built component in the U28 control was retained and documented rather than treated as complete class stability.

GLA green cover, GLA tree canopy and TOW canopy were intersected separately with all retained candidate polygons. Each fraction was the intersected cover area divided by the full polygon area. Category medians summarised the candidate pools, with the six selected sites examined individually. Tree canopy was not added to total green cover, since the categories overlap. The fractions were used to assess whether independent vegetation mapping supported the candidate cover labels. They did not validate the historical transitions. Equivalent intersections were unavailable for controls, so vegetation fractions could not be used to assess vegetation balance within the pairs.

4.4 Thermal Processing and Zonal Measurement

Landsat surface-temperature scenes and their quality bands were accessed through the Microsoft Planetary Computer catalogue. Before compositing, QA_PIXEL bits 0–5 excluded fill, dilated cloud, cirrus, cloud, cloud shadow and snow. Stored ST_B10 digital numbers had to be greater than zero; after conversion to Celsius, values outside -20 to 80°C were excluded as a broad plausibility screen. The remaining per-scene rasters were reprojected by nearest-neighbour resampling to a common 30 m EPSG:27700 grid and clipped to the Greater London boundary. Collection 2 provides an operational retrieval with atmospheric and emissivity information, rather than a temperature inferred solely from an uncorrected thermal-band brightness value (Malakar et al., 2018).

The product guide specifies the transformation from the stored surface-temperature value to Kelvin as $\text{ST_B10} \times 0.00341802 + 149.0$; subtraction of 273.15 gives degrees Celsius (U.S. Geological Survey, 2024). The conversion was applied during source preprocessing. The seasonal GeoTIFFs were already in Celsius and were not converted again. The 30 m cell size described the distributed output grid. Landsat 8 and 9 thermal observations have a native 100 m spatial resolution, so adjacent output cells were not treated as

independent 30 m thermal measurements. Temperature data was still at the coarse sensor level in the areas with fine-resolution cover boundaries.

Summer-Median LST was the first thermal index. At each raster location, the seasonal median of the available clear-sky observations was taken, and a mean composite was generated. These were daytime satellite overpass measurements and not continuous records of the whole day or all-weather data. Neither composite was a summer mean air temperature, a daily minimum or a daily maximum. The median was chosen to reduce the influence of isolated high or low values, although few observations were available at some locations. Mean composites were used to test whether the findings depended on this choice.

Each of the twelve site and control polygons was buffered inward by 30 m before temperature extraction. The same interior geometry was used in every year. This removed part of the boundary zone and reduced direct inclusion of neighbouring land covers, while leaving the possibility of mixing within the larger native thermal footprint. Zonal statistics then calculated the arithmetic spatial mean of all valid output cells assigned to each interior polygon. The principal site value was therefore a spatial mean of pixelwise seasonal medians, not a median across the polygon and not a mean of all original acquisitions pooled together.

The contributing cell count was retained alongside every zonal mean. The resulting COUNT field described the number of 30 m output cells contributing spatially, not the number of clear-sky acquisitions underlying each cell. Temporal coverage was measured separately using the valid-observation-count rasters, which counted contributing scene values at each cell. The twelve regions and three summers yielded 36 primary temperature values, which were re-extracted from the supplied median rasters and reproduced the original zonal means. This check confirmed consistency between the reported statistics, their polygon geometry and the supplied temperature surfaces.

4.5 Paired Analysis and Sensitivity

Thermal comparisons were made first within each site–control pair. If $S_{i,y}$ is the spatial mean of the summer-median raster for change site i in year y , and $C_{i,y}$ is the corresponding control value, the contemporaneous contrast was $D_{i,y} = S_{i,y} - C_{i,y}$. A positive contrast indicated a warmer change site in that summer, whereas a negative contrast indicated a cooler site. Absolute temperatures and contrasts were both retained so that a cool baseline site undergoing relative warming remained distinguishable from a site that was already warmer than its control.

Changes in the paired contrast were measured against 2018 as $R_{i,y} = D_{i,y} - D_{i,2018}$. Equivalently, this subtracted the control's temperature change from the change site's temperature change over the same interval. Values were calculated for 2018–2022 and 2018–2025, with the 2022–2025 interval describing subsequent movement. This baseline adjustment removed the initial level difference algebraically and supplied a local comparative measure. It was interpreted as observed relative thermal change, not as a causal difference-in-differences estimate, because controls had not been selected through rigorous covariate matching and parallel pre-change trajectories had not been established.

Group summaries were unweighted arithmetic means of the three pairs in each change category. All the selected pairs were given equal weights, and the largest polygon was not allowed to dominate the comparison. Pair-level values were presented with the group mean to determine whether there was a uniform trend or varied responses among the individuals. The individual output cells did not increase the sample size: there were three selected pairs per category, not a separate replicate for each cell or annual observation. Directions and magnitudes of differences between cases were analysed; no population-level inference was made. Calculations used unrounded values, and reported temperatures and changes were rounded to two decimal places.

A supplementary sensitivity analysis repeated the complete zonal extraction and paired calculations using the supplied summer-mean rasters. The same twelve interior polygons and the same weighting rules were retained, isolating the effect of changing the temporal compositing statistic. Pair-level and group-level results were compared to identify changes in magnitude or sign. Such differences indicated sensitivity to temporal aggregation.

Observation support was also examined within each interior polygon by summarising the acquisition-count raster for each year. These checks described temporal coverage separately from spatial cell support and identified unequal sampling between sites, controls and years. No new minimum-observation threshold was imposed, and the original geometry was preserved throughout.

4.6 Reliability, Alternatives and Ethics

Processing consistency was checked using the common raster alignment, explicit change rules and fixed polygon interiors. The agreement between reconstructed masks and supplied masks, and between independently extracted and original zonal means, provided direct checks of computational reproducibility. Independent reaggregation of the 39 retained per-scene rasters also reproduced all nine seasonal rasters without differing pixels. These checks concerned processing consistency rather than the accuracy of the underlying observations. Classification reliability still depended on the source product, while thermal reliability depended on atmospheric correction, emissivity assumptions and the available clear-sky sampling (Impact Observatory, 2022; U.S. Geological Survey, 2024).

Historical aerial-image verification was not completed. GLA and TOW layers provided some supporting data but could not determine the 2018 condition of all sites or when the conversion occurred. Disagreements between products remained unresolved and were treated as uncertainty in the mapped change. The same rule applied to controls: equal geometry and close proximity improved comparability, but baseline temperature, surrounding morphology,

moisture availability and vegetation structure were not standardised. A small purpose-driven sample was used to support detailed comparisons of the selected cases, and wider representation requires a larger-scale, more organised design.

Spatial support was a further constraint on measurement. After inward buffering, the retained regions contained between one and sixteen 30 m output cells; G55 and its control each contained only one. Such small interiors remained sensitive to grid position and surrounding surfaces within the native thermal footprint. Repeat the investigation for larger compact patches, try a different buffer distance, and set an explicit observation-count threshold. Dated historical reference images, more pre-change summers and controls matched on baseline cover and urban form, would enhance the interpretation of relative changes.

A new Sentinel-2 classification could tailor classes to London but would require defensible historical training and validation data. Field measurements and mobile temperature surveys could characterise contemporary microclimates, but could not reconstruct the earlier summers. Weather stations directly measure air temperature, but their locations and spatial coverage may not be the same as those of the selected patches. Coarser thermal products would increase the temporal coverage but reduce the resolution of small urban changes. The combination used here prioritised retrospective availability and site-scale spatial information, but still maintained the distinction between surface temperature and atmospheric exposure (Weng, 2009; Zhou et al., 2019).

The study used the available environmental data and did not conduct recruitment, interviews or collect personal information. Ethical responsibilities concerned accurate source attribution, compliance with data licences, preservation of source material and faithful reporting of the procedures actually completed. Separately analyse published product accuracy and local validation, and map uncertain changes as candidate regions. Satellite LST is a surface-temperature index that does not show how hot it is for people or harm to health.

5 Results

5.1 Extent and Configuration of Mapped Change

The comparison identified 1,675.71 ha of mapped urbanisation and 900.53 ha of mapped greening before the minimum-patch criterion was applied. These totals represent 167,571 and 90,053 aligned 10 m cells respectively. Urbanisation therefore occupied approximately 1.86 times the area of greening under the specified rules. These totals are not a net balance of development and vegetation change. The urbanisation rule includes all valid non-Built origins, whereas the greening rule requires Built or Bare Ground origins and persistent Trees or Rangeland destinations. The yearly classifications and candidate distributions are shown in Figures 5.1 and 5.2, respectively.

Rangeland had the largest proportion of the urbanisation mask at 972.69 hectares and accounted for 58.05% of the total area. Trees contributed 334.37 ha and Crops 261.29 ha. Water accounted for a further 100.50 ha, with smaller contributions from Bare Ground and Flooded Vegetation. Urbanisation therefore included mapped water-to-built conversion as well as conversion of terrestrial surfaces. Within the greening mask, 892.35 ha originated as Built and 8.18 ha as Bare Ground. The predominant greening pathway was therefore from the Built class rather than the recovery of exposed ground.

Connected-patch screening retained 269 urbanisation candidates and 93 greening candidates. Their recorded geodesic areas totalled 591.90 ha and 164.38 ha respectively (Table 5.1). Approximately 35.3% of the urbanisation mask area and 18.3% of the greening mask area remained in these candidate sets, with minor differences between raster and polygon area conventions. This large reduction shows that much of the mapped transition occurred in components below the one-hectare selection threshold. Urbanisation candidates were more numerous, and their total retained area was about 3.60 times the greening total.

The typical candidate was nevertheless small in both categories. Median planar patch areas were approximately 1.47 ha for urbanisation and 1.38 ha for greening, while the largest candidates were approximately 40.99 ha and 11.77 ha. The contrast in total area therefore reflects the larger number of urbanisation patches as well as a longer upper tail of patch sizes. The selected sites formed a small set of case comparisons within this wider distribution. Their thermal results are reported separately from the metropolitan mapping totals.

Table 5.1 Mapped changes and retained candidate patches

Measure	Urbanisation	Greening
Mapped change before patch selection (ha)	1,675.71	900.53
Retained candidate patches	269	93
Total retained geodesic area (ha)	591.90	164.38
Median planar patch area (ha)	1.47	1.38
Largest planar patch area (ha)	40.99	11.77
Selected thermal sites	3	3

Source: classified-raster and candidate-polygon analysis. Raster totals use 10 m projected cell area; retained totals use recorded geodesic polygon areas. Minimum retained area is approximately 1 ha.

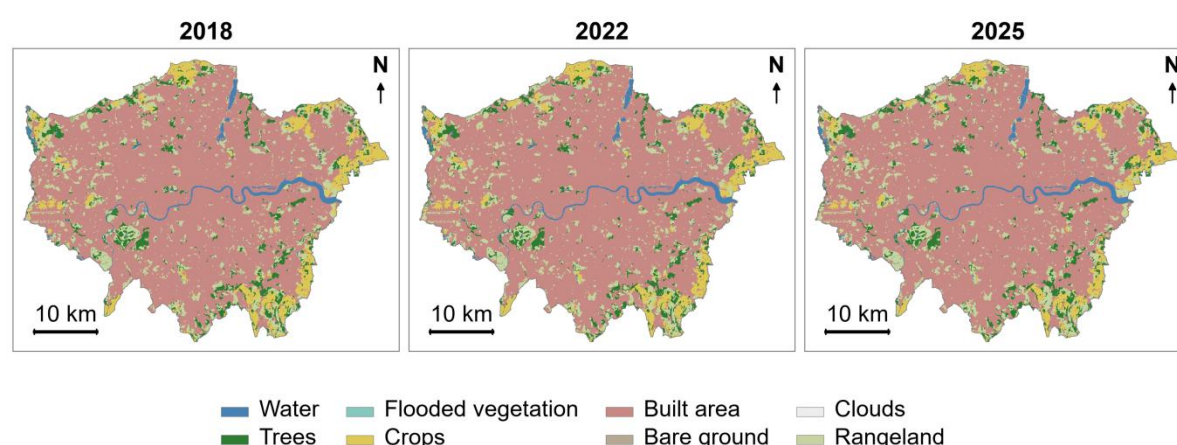


Figure 5.1 Annual land-cover classifications

Esri Sentinel-2 land-cover classifications for 2018, 2022 and 2025, clipped to Greater London. Classes use the same legend in every panel. Built area is a categorical map label rather than a direct measurement of impervious-surface percentage. Source: Esri and Impact Observatory (2026); land-cover rasters and study polygons processed in ArcGIS Pro.

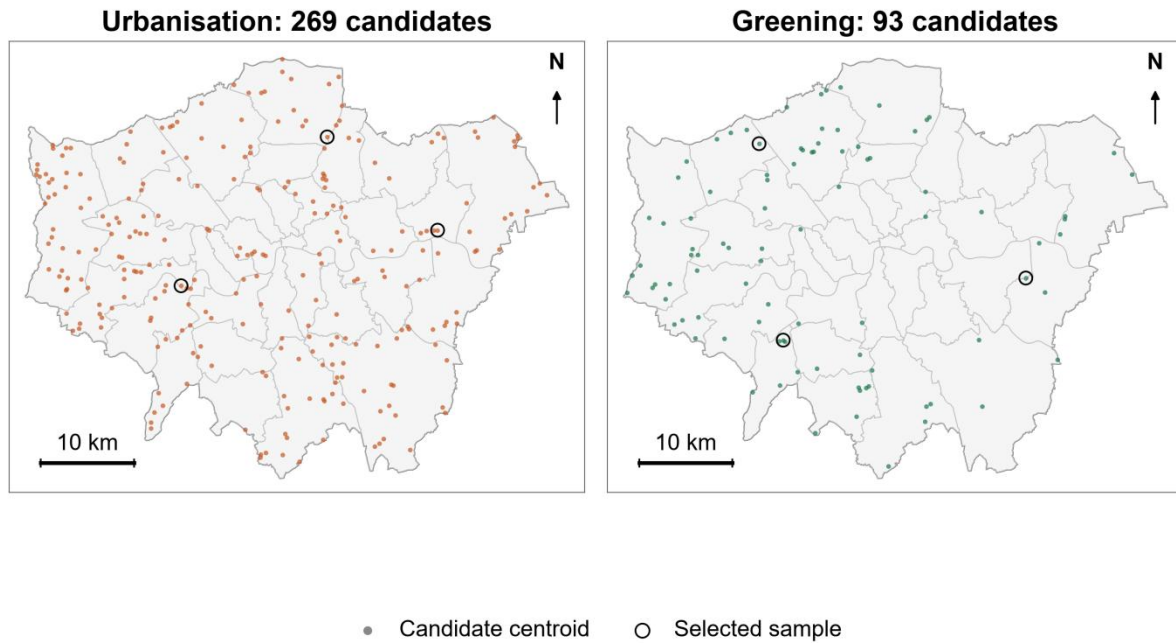


Figure 5.2 Spatial distribution of retained candidate patches

Locations of 269 urbanisation and 93 greening candidate patches retained by the approximately one-hectare minimum-area rule. Small symbols mark patch centroids; black rings identify the three selected samples in each group. Symbol sizes do not represent patch area. Source: Esri and Impact Observatory (2026); land-cover rasters and study polygons processed in ArcGIS Pro.

5.2 Selected Sites and Vegetation Composition

The three urbanisation sites for thermal analysis were U28, U106 and U167, and the three greening sites were G14, G55 and G73. The original site areas at G55 and U106 were about 1.29 ha and 3.92 ha, respectively. Each comparison polygon had the same shape and area as its corresponding site. The centroids of U167 and U106 were 486m and 2567m away from each other, and both were within the three-kilometre search radius. Identical shapes and areas controlled polygon geometry, but not initial cover or temperature.

The local land-cover sequences distinguish the six cases (Figures 5.3 and 5.4). U28 and U167 were dominated by Rangeland in 2018, with smaller Water components, while U106 was predominantly Crops. All three were classified entirely as Built within their original polygons in 2022 and 2025. The greening sites were entirely Built in 2018. G14 became Rangeland throughout its polygon in both later maps. G55 and G73 also became

predominantly Rangeland, with smaller Trees components. At G55 the Trees fraction decreased from 18.60% in 2022 to 13.95% in 2025; at G73 it decreased from 1.83% to 0.37%. The selected greening therefore largely reflected a transition towards low-vegetation classes, not a widespread transition to the Trees class.

The comparison polygons remained broadly stable in the annual classifications. All three greening comparisons were entirely Built in each study year. U106 and U167 had entirely Rangeland comparison polygons, while the U28 comparison retained approximately 97–99% Rangeland with a small Built component. The stable mapped categories provide a useful local reference for the changes observed at the selected sites. They also show that the two change categories were referenced to different surface types: mainly open vegetation for urbanisation and Built surfaces for greening.

Independent vegetation mapping showed that the candidate categories were less sharply separated by vegetation composition than their change labels might suggest. Across all retained candidates, median GLA green cover was 86.63% for urbanisation and 96.28% for greening. Median GLA tree canopy was 29.42% and 27.07%, while median TOW canopy was 10.13% and 9.02%. Thus, the urbanisation candidate set was not generally a set of vegetation-free surfaces. Greening candidates had higher median total green cover but slightly lower median canopy fractions in both canopy products.

Vegetation composition varied among the six selected sites (Table 5.2 and Figure 5.5). GLA green cover was 28.76% at U28, 59.99% at U106 and 86.45% at U167, compared with 96.80–98.76% at the three greening sites. G14 and G73 had relatively extensive GLA tree canopy, at 41.03% and 39.10%; G55 had 11.96%. TOW fractions were 28.42% at G14, 12.36% at G55 and 11.90% at G73. U106 had no intersecting canopy in either canopy product. These measurements support the predominantly vegetated character of the greening sites but also reveal substantial vegetation within two mapped urbanisation sites. The

temperature results therefore concern these particular mixed-cover locations rather than idealised end-members of entirely built and entirely vegetated land.

Table 5.2 Selected site areas and independent vegetation cover

Site	Area (ha)	Green cover (%)	GLA canopy (%)	TOW canopy (%)
U28	2.97	28.76	6.98	3.82
U106	3.92	59.99	0.00	0.00
U167	2.59	86.45	12.88	6.16
G14	3.08	97.87	41.03	28.42
G55	1.29	96.80	11.96	12.36
G73	2.73	98.76	39.10	11.90

Sources: study polygons; GLA (2024b) and Forestry Commission (2025) cover intersections. Fractions use full polygons before inward buffering. The three vegetation measures overlap and are not additive.

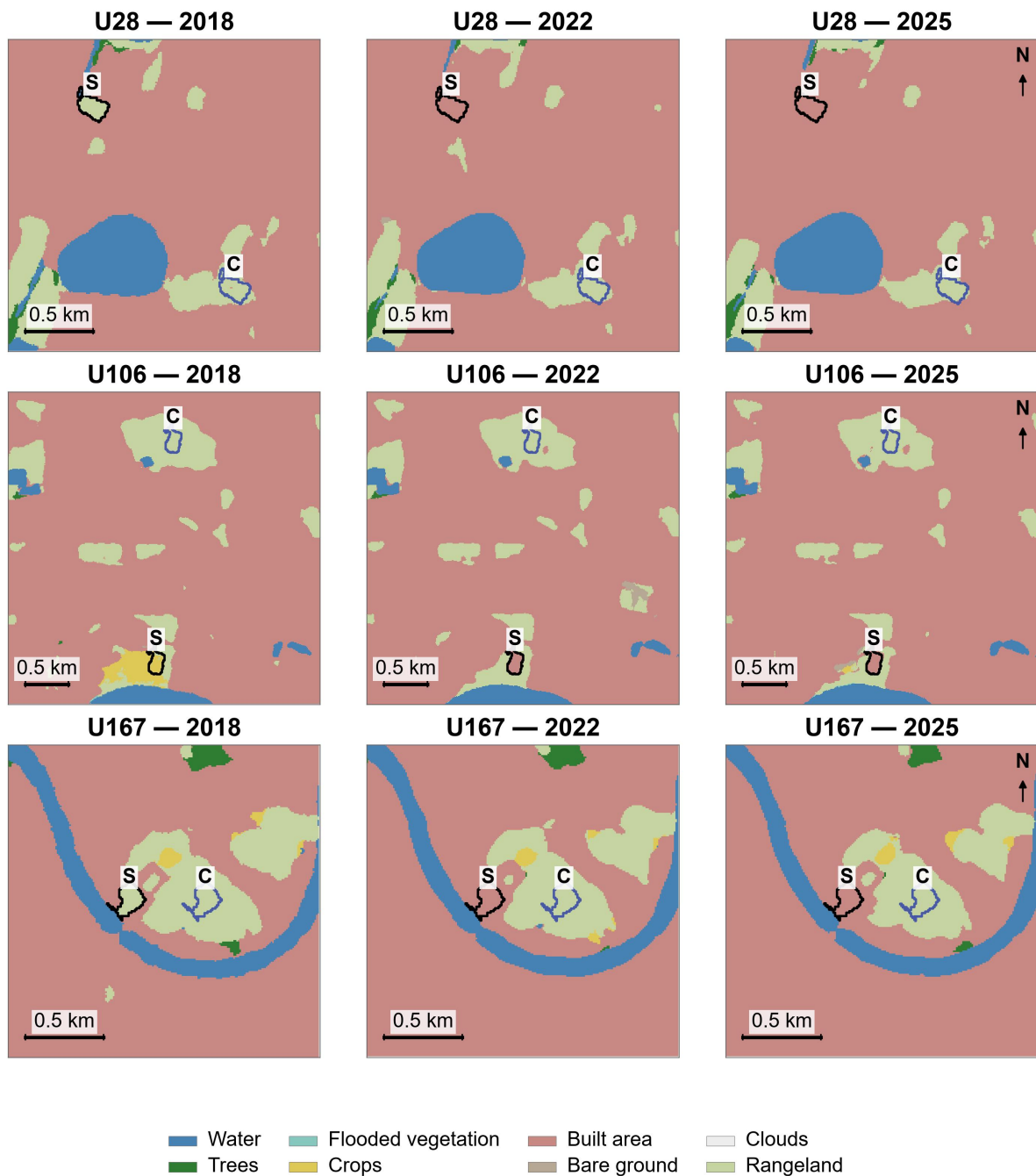


Figure 5.3 Urbanisation sample and control land-cover sequences

Local land-cover classifications around the three urbanisation sample–control pairs in 2018, 2022 and 2025. Black boundaries and S mark full sample polygons; blue boundaries and C mark the paired controls. The same map extent is retained across years within each row. Temperature extraction uses the interiors after a 30 m inward buffer. Source: Esri and Impact Observatory (2026); land-cover rasters and study polygons processed in ArcGIS Pro.

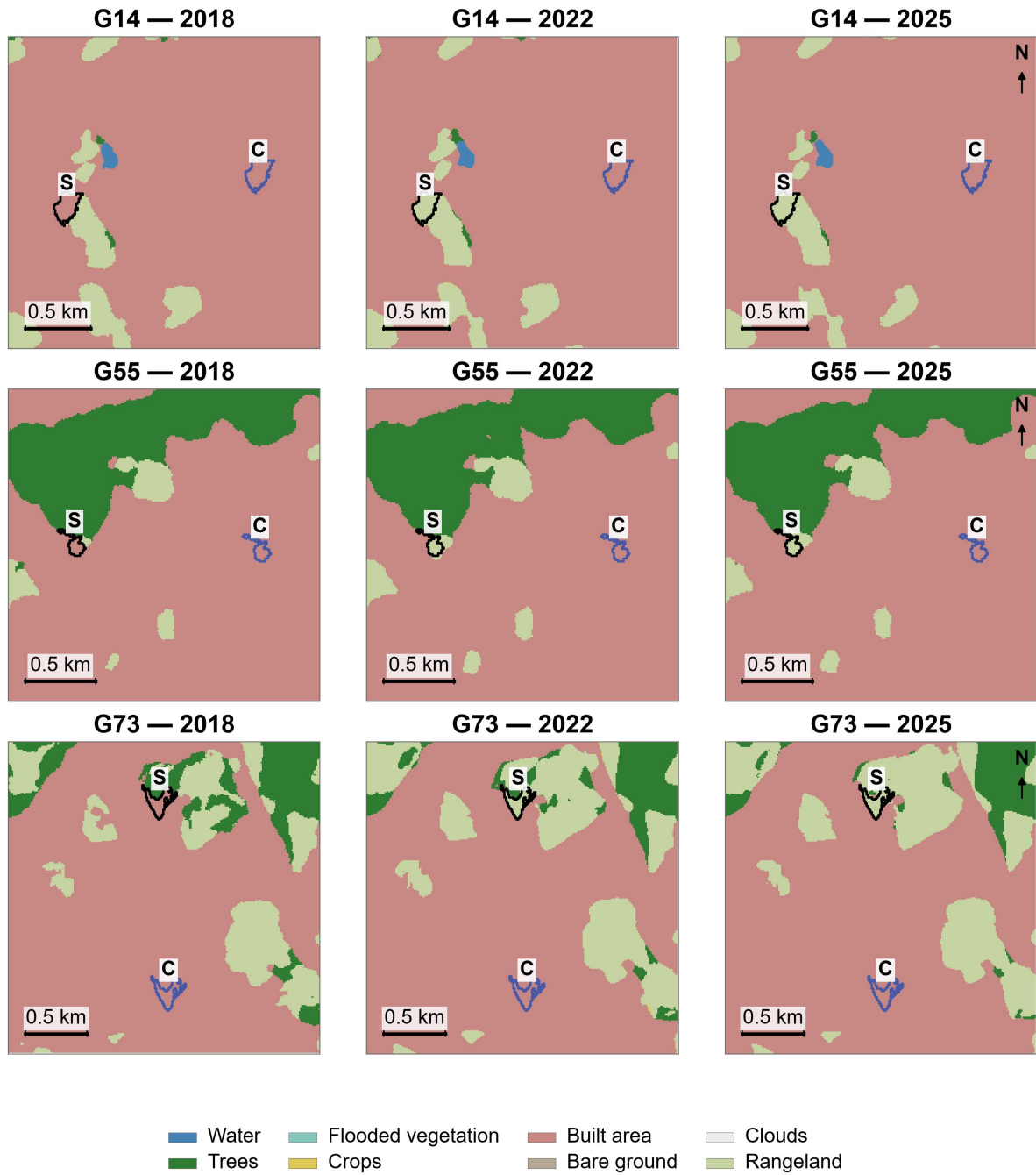


Figure 5.4 Greening sample and control land-cover sequences

Local land-cover classifications around the three greening sample–control pairs in 2018, 2022 and 2025. Black boundaries and S mark full sample polygons; blue boundaries and C mark the paired controls. The same map extent is retained across years within each row.

Temperature extraction uses the interiors after a 30 m inward buffer. Source: Esri and Impact Observatory (2026); land-cover rasters and study polygons processed in ArcGIS Pro.

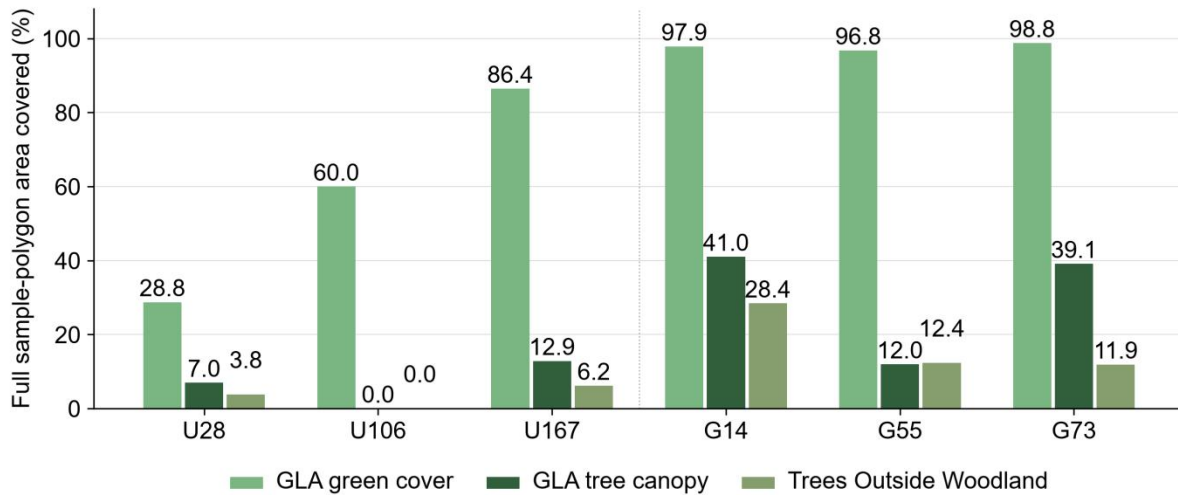


Figure 5.5 Green-cover and tree-canopy proportions

Area fractions from the supplied GLA green-cover, GLA tree-canopy and Trees Outside Woodland intersections for the six full sample polygons. The three layers measure overlapping features and must not be summed. U106 has no tree-canopy or TOW intersection in the supplied outputs. These layers describe vegetation during their respective source observation periods; they do not establish the timing of conversion. Source: Greater London Authority (2024b) and Forestry Commission (2025); spatial intersections with the study polygons.

5.3 Metropolitan Temperature and Observation Support

The spatial mean of the Greater London summer-median LST raster in 2018, 2022 and 2025 was 36.54°C, 38.32°C and 35.47°C, respectively. Therefore, the intermediate summer was 1.78°C warmer than the baseline, and the final summer was 1.06°C cooler. Figure 5.6 shows the distribution of the city in each year using the same temperature scale. The city-wide sequence provides a reference for the local comparisons; a higher value in 2022 or a lower value in 2025 was not limited to the selected land-cover-change sites. Valid thermal coverage was similar in total extent across the three rasters, at approximately 1.77 million 30 m grid cells per year, but the number of contributing clear-sky observations varied spatially (Figure 5.7). Across the metropolitan valid-observation rasters, the median count was five in 2018, six in 2022 and five in 2025. The corresponding mean counts were 4.57, 5.94 and 5.35. Individual valid cells ranged from one observation to maxima of eight, ten and eleven

respectively. Seasonal aggregation therefore combined different amounts of temporal information across the mapped extent.

In the selected site and comparison interiors, the contributing seasonal observations ranged from three to eight per grid cell. The urbanisation pairs generally had larger spatial supports and were divided into six-to-sixteen cells per polygon. Greening support was more uneven: G14 and its comparison contained eleven and ten cells, G55 and its comparison contained one each, and G73 and its comparison contained three and two. The number of extracted cells stayed the same across the three median-composite years for each individual polygon. The site means consequently represented different amounts of spatial averaging.

The inward buffer explains much of this difference. It reduced G55 from approximately 1.29 ha to 0.083 ha and G73 from 2.73 ha to 0.232 ha. G14 retained approximately 1.033 ha from an original 3.08 ha. Figure 5.8 shows the remaining interiors and thermal support. The extraction from G55 represents a single delivered-grid value, while the other site statistics average several values. These counts describe the support of the reported means; the original thermal observations have a coarser resolving scale than the 30 m output grid. The full regional temperatures and counts are provided in Appendix B.

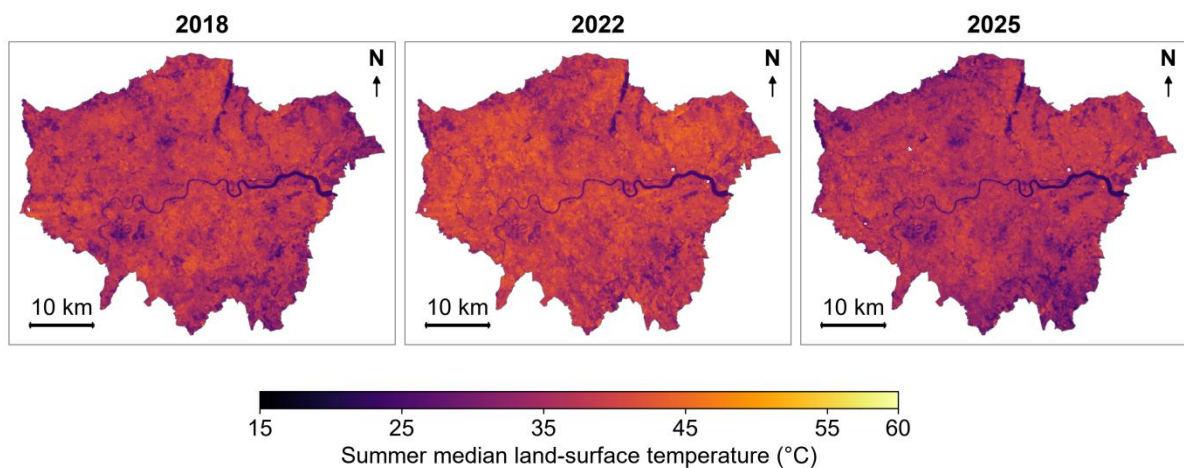


Figure 5.6 Summer median land-surface temperature

Pixelwise median land-surface temperature for June–August in 2018, 2022 and 2025. All panels use the same 15–60°C colour scale. White gaps are NoData. These are clear-sky satellite surface temperatures on a 30 m output grid, not air temperatures or continuous all-weather seasonal temperatures. Source: Calculated from Landsat Collection 2 Level-2 composites and study polygons (Earth Resources Observation and Science (EROS) Center, 2020).

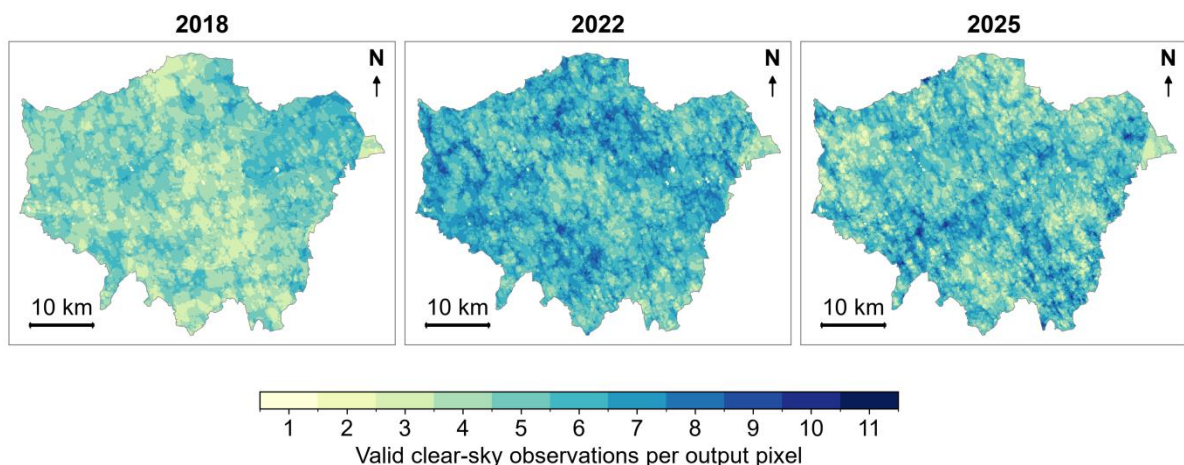


Figure 5.7 Clear-sky observation support

Number of valid June–August observations contributing to each output pixel in 2018, 2022 and 2025. The count scale is shared between panels. Spatial and annual differences in observation support affect the composition of the seasonal temperature summaries. Source: Calculated from Landsat Collection 2 Level-2 composites and study polygons (Earth Resources Observation and Science (EROS) Center, 2020).

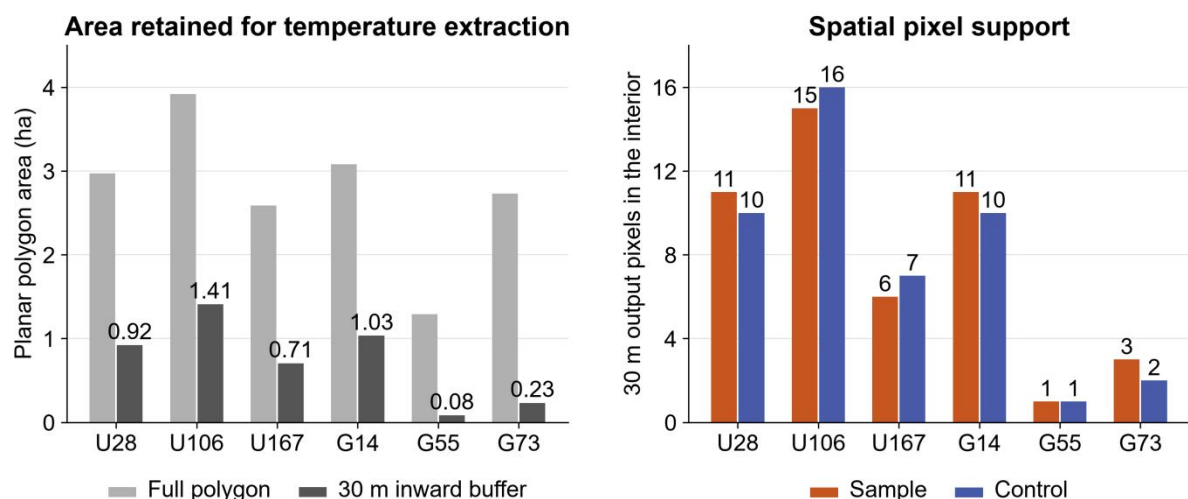


Figure 5.8 Polygon area and temperature-pixel support

Left: BNG planar areas of full samples and their interiors after a 30 m inward buffer; paired full controls have equal geometric area. Right: numbers of valid 30 m output pixels used in sample and control zonal statistics, unchanged across the three comparison years. G55 retains only one output pixel in each polygon. Counts are spatial support and must not be interpreted as independent observations at native 30 m thermal resolution. Source: study site and control polygons for area measurements; Landsat Collection 2 Level-2 composites for valid-cell counts (Earth Resources Observation and Science (EROS) Center, 2020).

5.4 Paired Temperature Changes at Urbanisation Sites

The three urbanisation sites all increased in summer-median LST between 2018 and 2022 and remained warmer than their own baseline in 2025. Their unweighted mean rose from 34.70°C to 40.52°C and then declined to 36.74°C. Comparison-area means were 38.54°C, 40.41°C and 38.61°C. Consequently, the urbanisation sites warmed more than their comparisons over both intervals measured from 2018. The mean paired relative changes were +3.94°C in 2022 and +1.96°C in 2025 (Table 5.3). Individual Trajectories and Baseline-Adjusted Differences are shown in Figures 5.9 and 5.11.

U28 had the largest proportional increase. The temperatures in 2018 and 2022 were 30.80°C and 37.48°C, respectively; then, in 2025, they dropped to 35.56°C, and the comparison values were 34.83°C, 34.41°C, and 36.49°C. The site therefore gained 6.68°C by 2022 while the comparison cooled by 0.42°C, producing a +7.11°C relative change. By 2025

the relative increase was $+3.09^{\circ}\text{C}$. U28 remained slightly cooler than its comparison in the final year, but its initial temperature advantage had narrowed substantially.

U106 and U167 showed smaller positive relative changes. U106 warmed by 0.34°C between 2018 and 2025, while its comparison cooled by 1.26°C , giving $+1.60^{\circ}\text{C}$ after differencing. U167 warmed by 1.01°C while its comparison cooled by 0.19°C , giving $+1.20^{\circ}\text{C}$. Their 2018–2022 relative changes were $+3.73^{\circ}\text{C}$ and $+0.98^{\circ}\text{C}$ respectively. Therefore, all three pairs had a positive direction for the main median-composite index, but their magnitudes and initial site-comparison contrasts were different.

U106 shows relative warming but remains cooler than its comparison. Its site was 7.64°C cooler than its comparison in 2018 and remained 6.03°C cooler in 2025. A positive relative change thus did not imply that the changed site had become the hotter member of the pair. At category level, the initial mean site–comparison difference of -3.83°C narrowed to -1.87°C by 2025. The principal urbanisation result is this relative warming across the selected pairs, not a general statement that every mapped urbanisation site was warmer than neighbouring open land.

Table 5.3 Paired relative temperature changes from 2018

Pair	Relative change to 2022	Site change to 2025	Control change to 2025	Relative change to 2025
U28	+7.11	+4.76	+1.67	+3.09
U106	+3.73	+0.34	-1.26	+1.60
U167	+0.98	+1.01	-0.19	+1.20
G14	-0.68	-0.56	-1.76	+1.20
G55	+3.17	+0.18	-0.60	+0.78
G73	-3.38	-3.84	-0.26	-3.58
Urbanisation mean	+3.94	+2.04	+0.07	+1.96
Greening mean	-0.30	-1.41	-0.88	-0.53

Source: seasonal-median raster zonal statistics. All values are °C relative to 2018. Relative change is site change minus control change. Category means weight the three pairs equally. Differences are calculated before rounding.

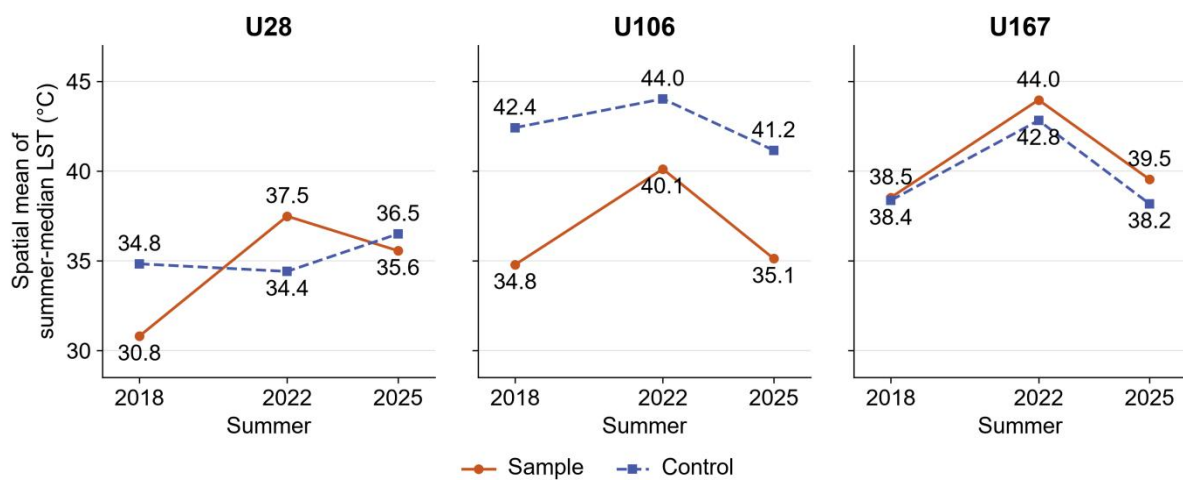


Figure 5.9 Urbanisation sample and control temperatures

Temperature comparison for the three urbanisation pairs. Each value is the spatial arithmetic mean of the supplied summer-median LST raster in the inward-buffered polygon. Lines connect the three observed summers for comparison and do not indicate a continuous temperature trend. Source: Calculated from Landsat Collection 2 Level-2 composites and study polygons (Earth Resources Observation and Science (EROS) Center, 2020).

5.5 Paired Temperature Changes at Greening Sites

The greening sites had lower absolute LST than their Built comparison polygons in all three summers. Their mean temperatures were 35.59°C in 2018, 36.93°C in 2022 and

34.18°C in 2025, compared with 38.98°C, 40.62°C and 38.11°C at the comparisons. The mean temperature advantage was therefore 3.40°C at baseline, 3.69°C in 2022 and 3.93°C in 2025. This persistent contrast is consistent with the substantial green-cover fractions observed at the selected sites, but part of the contrast was already present before the mapped change interval. The individual site trajectories are as follows: Figure 5.10.

Relative Changes were uneven. G14 cooled by 0.56°C between 2018 and 2025, and its comparison cooled by 1.76°C. Therefore, the paired relative change was +1.20°C; although it had dropped in absolute terms, the temperature difference was decreasing. G55 increased by 0.18°C; the reference decreased by 0.60°C, so the difference was +0.78°C. G73 followed a different pattern; the temperature at the site dropped by 3.84°C, which was significantly higher than the 0.26°C decrease at the reference site, and its corresponding relative change was -3.58°C. The three responses cannot be represented by the group mean alone. The greening-group mean relative change was -0.30°C for 2018–2022 and -0.53°C for 2018–2025. However, the median across the three 2018–2025 pair-level relative changes was +0.78°C. The negative mean was driven by G73, whose relative cooling outweighed the positive values at G14 and G55. G73 also showed relative cooling in 2022, whereas G55 showed relative warming in both later years and G14 changed direction. The strongest recurring cooling signal within this category was therefore specific to G73 rather than common to all three sites.

Under the primary composite, the urbanisation-group relative change exceeded the greening-group mean by approximately 2.50°C over 2018–2025. This difference combined relative warming across all urbanisation pairs with opposing responses among greening pairs. The categories also used different reference covers: predominantly non-built controls for urbanisation and Built controls for greening. The group contrast therefore describes these paired settings, rather than a like-for-like comparison of two interventions.

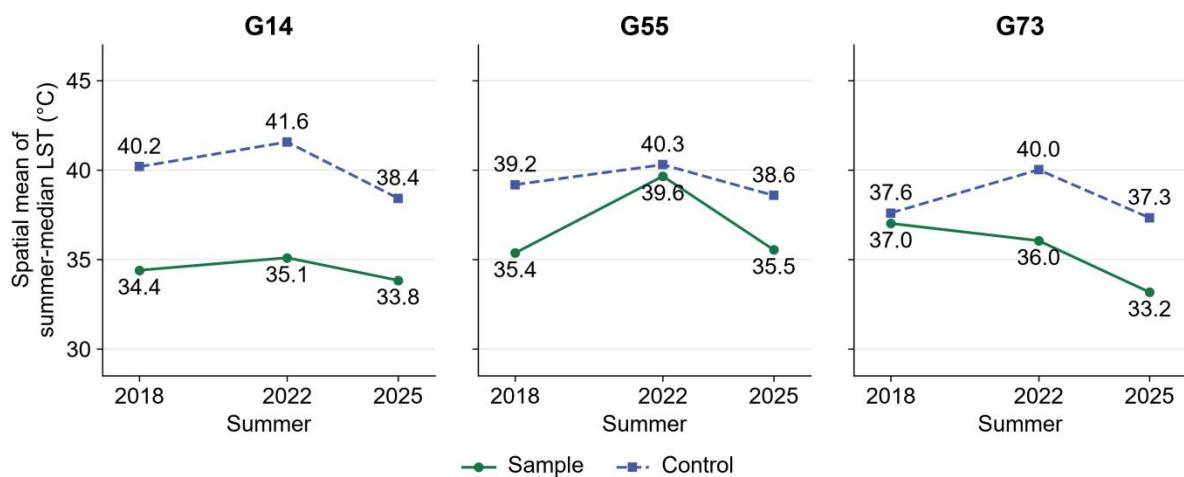


Figure 5.10 Greening sample and control temperatures

Temperature comparison for the three greening pairs. Each value is the spatial arithmetic mean of the supplied summer-median LST raster within the inward-buffered polygon. Lines connect the three observed summers for comparison and do not imply a continuous temperature trend. Source: Calculated from Landsat Collection 2 Level-2 composites and study polygons (Earth Resources Observation and Science (EROS) Center, 2020).

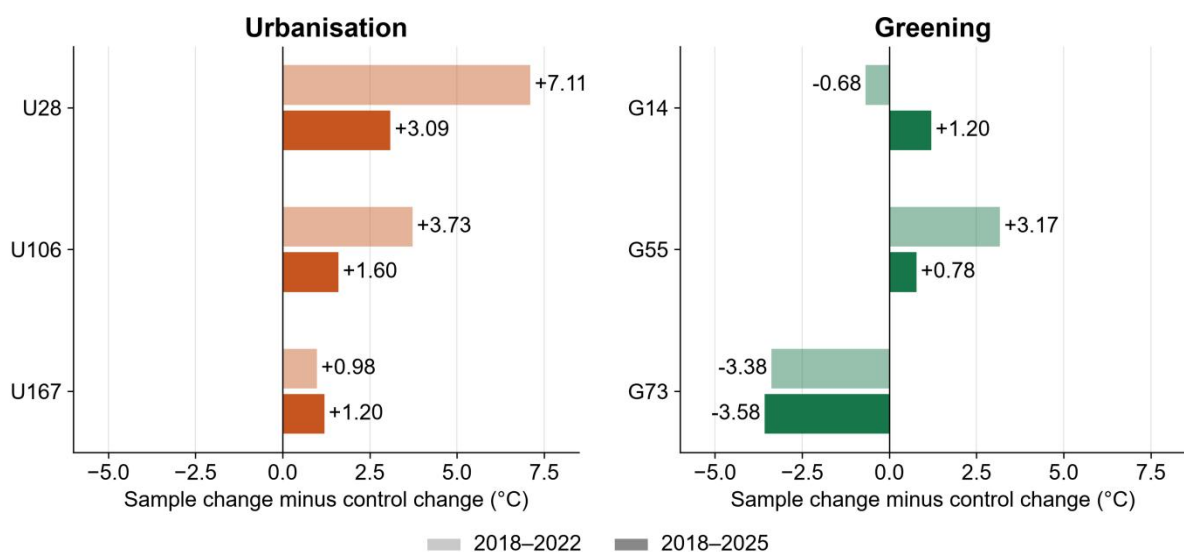


Figure 5.11 Temperature change relative to each control

For each pair, relative change equals the sample temperature change minus the control temperature change over the same interval. Positive values indicate greater warming, or less cooling, at the sample. These are descriptive paired contrasts; the six sites were not randomly selected. Source: Calculated from Landsat Collection 2 Level-2 composites and study polygons (Earth Resources Observation and Science (EROS) Center, 2020).

5.6 Sensitivity to Seasonal Aggregation

Repeating the same polygon analysis with the summer-mean LST rasters changed the estimated magnitudes and, in some cases, their direction (Table 5.4 and Figure 5.12). The

urbanisation-group mean paired relative change for 2018-2025 was still positive at +1.00°C, compared with +1.96°C for the median composite. U28 and U106 were still positive at +1.61°C and +1.52°C, respectively. U167 changed from +1.20°C to -0.13°C. Therefore, the category-level warming direction was kept, but agreement for every individual urbanisation pair relied on the aggregation measure.

The greening-group mean changed from -0.53°C in the median composite to +1.10°C in the mean composite. G14 recorded +3.38°C, G55 +0.20°C and G73 -0.29°C in the mean-based comparison. G73 was the only greening site with relative cooling over 2018-2025, but its size was significantly smaller than that of the median-based result. Under mean aggregation, the greening group no longer showed average relative cooling, and its mean paired change was close to that of the urbanisation group.

The temperature ordering was more consistent: each greening site was cooler than its Built comparison in every year under both seasonal summaries. This persistent contrast was clearer than the estimated change in that contrast, which depended on the aggregation statistic.

Table 5.4 Sensitivity of 2018–2025 relative change to seasonal aggregation

Pair	Median composite (°C)	Mean composite (°C)
U28	+3.09	+1.61
U106	+1.60	+1.52
U167	+1.20	-0.13
G14	+1.20	+3.38
G55	+0.78	+0.20
G73	-3.58	-0.29
Urbanisation mean	+1.96	+1.00
Greening mean	-0.53	+1.10

Source: paired zonal analysis of the same twelve interiors. Positive values indicate relative warming; negative values indicate relative cooling. The composite is calculated through time before the spatial zonal mean.

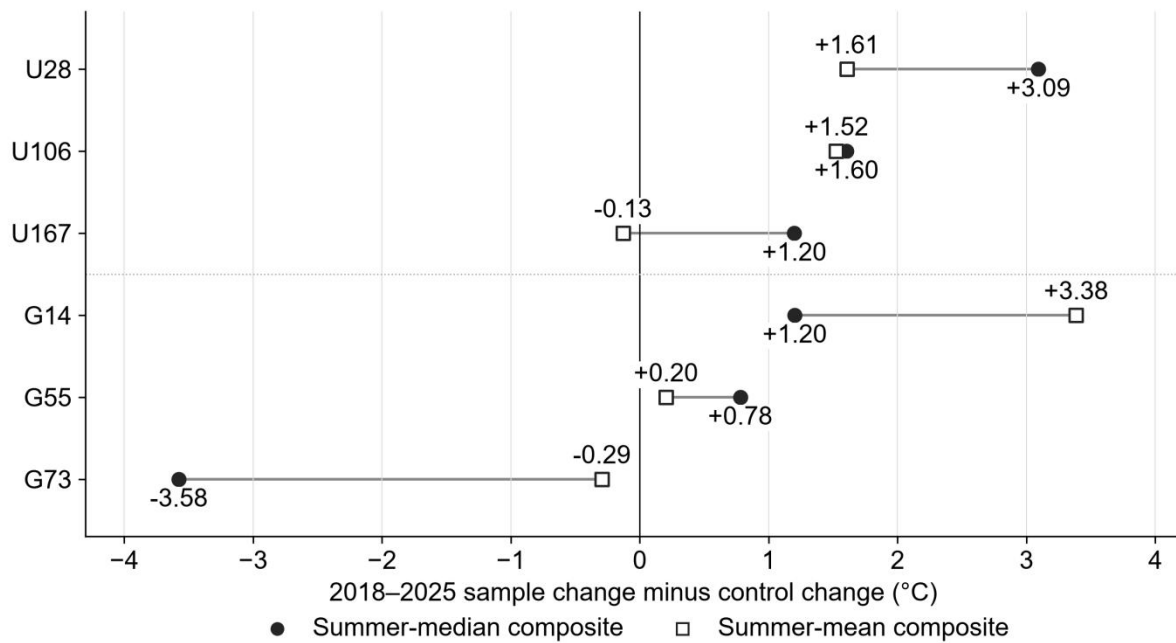


Figure 5.12 Sensitivity to seasonal temperature aggregation

2018-2025 paired relative temperature changes were calculated using summer-median and summer-mean composites for the same interior polygons. Squares show the supplementary summer-mean analysis, which is calculated from the existing temperature rasters using the same twelve sites and control interiors. A change in the size and sign indicates that temporal aggregation modifies the individual-pair conclusion for greening. Source: Calculated from Landsat Collection 2 Level-2 composites and study polygons (Earth Resources Observation and Science (EROS) Center, 2020).

6 Discussion

6.1 Urbanisation and Relative Surface Warming

All three urbanisation sites warmed relative to their comparison areas between 2018 and 2025 in the summer-median analysis. The paired changes ranged from $+1.20^{\circ}\text{C}$ at U167 to $+3.09^{\circ}\text{C}$ at U28, with U106 recording $+1.60^{\circ}\text{C}$. Their unweighted mean was $+1.96^{\circ}\text{C}$. The positive group mean was therefore not driven by a single site. The mean relative change was larger in 2022 ($+3.94^{\circ}\text{C}$) than in 2025.

Relative warming did not mean that every urbanisation site became hotter than its comparison area. U106 remained 6.03°C cooler than its reference in 2025, compared with 7.64°C cooler in 2018. Its paired change therefore represents a narrowing of an existing difference. U28 similarly remained 0.94°C cooler in 2025 after beginning 4.03°C cooler. U167 had a different starting position: its 2018 excess of 0.16°C increased to 1.36°C in 2025. The common result was relative warming, even where a site remained cooler than its comparison.

This pattern is consistent with the surface-energy mechanisms described by Oke (1982) and Arnfield (2003). Conversion to built surfaces can reduce evaporative cooling and change the absorption and storage of radiation. The annual classifications place all three urbanisation sites in Built area in 2022 and 2025, following mainly Rangeland at U28 and U167 and Crops at U106 in 2018. The thermal observations are therefore consistent with a loss of some of the cooler surface conditions associated with their initial covers. Building form, shade, surface moisture and surrounding development remain possible contributors to the magnitude of each response because the broad Built category does not describe these properties separately.

The 2018-2025 urbanisation mean exceeded the greening mean by 2.50°C in the principal analysis. The summer-mean sensitivity analysis substantially changes that contrast: urbanisation averages $+1.00^{\circ}\text{C}$ and greening $+1.10^{\circ}\text{C}$, leaving little group separation. The

urbanisation group remained positive under both methods, but it did not consistently warm more than the greening group. U106 and U28 retain positive relative changes with summer means, at $+1.52^{\circ}\text{C}$ and $+1.61^{\circ}\text{C}$, while U167 changes to -0.13°C . The between-group contrast also depends on the comparison areas: urbanisation sites were compared mainly with non-built cover, whereas greening sites were compared with Built cover. The two group means therefore do not form a symmetric test of urbanisation against greening.

Relative warming was weaker in 2025 than in 2022. A persistent Built classification was not accompanied by a steadily increasing temperature difference: U28 and U106 both moved closer to their initial contrasts after 2022, while U167's relative excess increased slightly. The data therefore support persistence of the direction of change from 2018, rather than monotonic warming throughout the interval. A surface can remain in the same broad cover class while its thermal response varies between summers.

6.2 Heterogeneity of Greening Responses

The greening mean concealed opposing site responses. The mean 2018-2025 paired change was -0.53°C , but G14 and G55 changed by $+1.20^{\circ}\text{C}$ and $+0.78^{\circ}\text{C}$, respectively. Only G73 showed relative cooling of -3.58°C . Therefore, the median of the paired changes was $+0.78^{\circ}\text{C}$. The small mean relative cooling was due to G73 and had a large case-level variation.

G73 showed the strongest relative cooling pattern in the greening group. The absolute temperature in 2025 was 3.84°C lower than in 2018, and the comparison area dropped by 0.26°C . It also showed a -3.38°C relative change in 2022. Therefore, most of the final contrast was already present in the intermediate year and remained in 2025. The above directions are in line with the expected reduction in daytime surface heating after vegetation growth. However, the small thermal area of the site limits the spatial representativeness of this time-consistent response.

G14 was cooler than its comparison in all three years, including a 4.59°C difference in 2025. However, the initial difference was larger, at 5.79°C. Its absolute temperature declined by 0.56°C while the comparison declined by 1.76°C, producing relative warming over the full interval. G55 also retained a cooler absolute temperature than its comparison throughout, but its temperature changed little between 2018 and 2025 and the reference cooled. For both sites, remaining cooler than the comparison in 2025 did not mean that this temperature advantage had increased since 2018.

Variation among the sites is in line with the literature on vegetation cooling. Wong and Gunawardena have shown that the extent of cooling depends on vegetation structure, water supply and urban form (2021, 2017). These factors may differ in the sites of the same general change category. Doick et al. (2014) and Vaz Monteiro et al. (2016) have also linked greenspace cooling to size and location in the London air-temperature studies. Their numerical cooling estimates should not be directly equated with the present paired changes: their measurements concern nocturnal air temperature, whereas this study summarises daytime radiometric surface temperature.

6.3 Vegetation Composition and the Meaning of Land-Cover Classes

GLA green cover was high at all three greening sites, ranging from 96.80% to 98.76%. This supports their interpretation as predominantly vegetated during the GLA observation period. Their canopy fractions were less uniform. GLA tree cover was 41.03% at G14, 39.10% at G73 and 11.96% at G55. Thus, near-complete green cover did not imply equivalent vegetation structure. The two are different in terms of heat because a grass-covered area and a tree-covered area are exposed to sunlight and shade the ground differently.

Schwaab et al. (2021) found that urban trees were associated with stronger surface cooling than treeless green spaces in European cities. The present results support retaining that distinction in site description, but the six cases do not establish a canopy-temperature

response function. G14 and G73 both had substantial GLA canopy fractions, yet their relative temperature changes differed in sign. The TOW fractions also differed from the GLA estimates: G14 had 28.42% TOW canopy and G73 11.90%. Product definition, observation timing and the distinction between woodland and trees outside woodland affect these values. Averaging the two estimates would not resolve these differences in coverage and definition.

The urbanisation cases reveal an even sharper tension between products. Despite being classified entirely as Built area in the later annual maps, U167 had 86.45% GLA green cover and U106 59.99%; U28 had 28.76%. U167 also contained 12.88% GLA tree cover. These differences may reflect the dates represented by the products, the spatial mixture admitted within a categorical pixel, differences in class definitions or classification error. The available layers do not identify which explanation dominates at each site. Therefore, there is uncertainty in interpreting the mapped transition and positive relative temperature change at U167 due to this discrepancy.

Vegetation fractions refer to the entire site polygons, and temperatures only cover their inward-buffered areas. Vegetation near the border can help to reduce the former but is not distributed uniformly in the latter. Another reason not to assume that the whole canopy coverage of a polygon directly corresponds to the interior temperature. The independent layers strengthen the description of vegetation during their observation periods, but historical aerial imagery would be needed to confirm the initial cover and establish whether an apparent Built-to-vegetation or vegetation-to-Built conversion represents the physical sequence implied by the classification.

6.4 Seasonal Variability and the Interpretation of Comparison Areas

Both site groups were warmest in 2022. Mean temperature at the urbanisation sites increased from 34.70°C in 2018 to 40.52°C in 2022 before falling to 36.74°C in 2025. The greening mean rose from 35.59°C to 36.93°C and then fell to 34.18°C. Similar movement

occurred across most comparison areas. Such variation shows why a later temperature difference cannot be assigned entirely to land-cover conversion. Bassett et al. (2021), using a much longer reconstruction of London's nocturnal heat island, demonstrated the importance of climate-driven variability in urban temperature records. Their variable and time span differ from this study, but both studies show why interannual variation must be considered.

U28 shows why the paired changes cannot be explained by a uniformly hotter 2022 summer. Its site warmed by 6.68°C between 2018 and 2022 while the comparison cooled by 0.42°C, producing a relative increase of 7.11°C. Between 2022 and 2025, the site cooled by 1.92°C and the comparison warmed by 2.09°C; thus, the difference decreased. The difference may be due to local surface variations or differences in the observations that entered the seasonal composites; these were not separated.

A stable broad land-cover label does not create a corresponding thermal baseline or an altered environment. U106 and its comparison differed by 7.64°C in 2018, U28 by 4.03°C and G14 by 5.79°C. These initial contrasts are large relative to several of the later changes under discussion. U106 also began mainly as Crops, whereas its comparison was Rangeland throughout. The annual maps can identify categorical persistence without resolving differences in vegetation condition, irrigation, soil moisture, shading or adjacent materials. The selected comparison areas therefore supply useful local references, but they do not reproduce the changed sites' unobserved temperature histories.

Subtracting the baseline difference removes a fixed initial offset mathematically; it does not establish that the two areas would have followed parallel temperature trajectories without conversion. Only one initial year is available, and the timing of physical change has not been independently verified. A parallel pre-change trajectory cannot be tested. The paired statistic therefore describes observed relative change rather than a verified effect of conversion. U167 began with a smaller thermal mismatch, but its land-cover discrepancy remained unresolved.

Agreement in the direction of the median-based urbanisation changes supports a common pattern within these cases, not a controlled comparison.

6.5 Spatial and Temporal Support of the Thermal Evidence

The summer-mean sensitivity check changes the greening interpretation materially. Its 2018-2025 mean paired change becomes $+1.10^{\circ}\text{C}$, compared with -0.53°C under summer medians. G14 changes from $+1.20^{\circ}\text{C}$ to $+3.38^{\circ}\text{C}$, G55 from $+0.78^{\circ}\text{C}$ to $+0.20^{\circ}\text{C}$, and G73 from -3.58°C to -0.29°C . Thus, the signs of the three individual full-interval changes persist, but their magnitudes alter enough to reverse the group mean. G73 remains the sole relative-cooling case, with a much smaller mean-composite estimate. This does not establish which statistic is closer to a continuously observed summer temperature; it shows that the estimated group cooling is sensitive to the distribution of the available observations.

Every greening site was cooler than its Built comparison in each year under both summer-median and summer-mean aggregation. However, their changes from 2018 varied between sites and depended on the seasonal summary. The negative primary group mean should therefore not be interpreted as a uniform cooling effect of greening.

The most consequential spatial limitation is the difference between the delivered 30 m grid and the original thermal observation scale. Landsat 8 and 9 thermal bands are acquired at 100 m and resampled to 30 m for delivery (U.S. Geological Survey, n.d.). A count of 30 m cells therefore overstates the number of independently resolved thermal areas if interpreted literally as a count of separate measurements. Adjacent output cells can contain information derived from the same broader thermal neighbourhood. This matters when the change polygons are small and their interiors occupy only a fraction of a nominal thermal footprint.

G55 is the clearest example. Its inward-buffered site interior contributed one 30 m output cell in each year, as did its comparison interior. The spatial mean is consequently the value of a single delivered grid cell. G73 contributed three cells at the site and two at the

comparison. Because G73 drove the negative greening mean, its limited spatial support directly affects the group interpretation. The inward buffer reduces the direct inclusion of boundary cells, but a 30m setback cannot ensure that all surrounding-surface influence from observations taken at 100m has been removed. G73 is still an informative candidate for cooling, and its magnitude requires further verification.

Temporal support also differs across locations and years. G73's site interior had three valid observations in 2018, five in 2022 and four in 2025. G55 had six in each year, while the U28 comparison changed from five observations in 2018 to eight in 2022 and three or four in 2025. A median calculated from these observations summarises the available sample and is less sensitive than a mean to an isolated extreme value. It does not become the median of continuously observed summer conditions. Differences in acquisition dates can remain even where two areas have the same number of valid values, so observation counts alone do not demonstrate identical meteorological sampling.

The operational Landsat temperature product provides a consistent retrieval framework, but retrieval uncertainty remains distinct from sampling uncertainty. Atmospheric correction and surface emissivity affect the conversion from measured thermal radiance to temperature (Malakar et al., 2018). The use of the same product family makes the processing basis comparable; it does not independently verify the temperature of every London polygon. No site-level temperature measurements were available for such validation.

These constraints affect the findings differently. The urbanisation group mean remains positive with both temperature statistics, although individual cases are less consistent in the sensitivity check. The greening mean changes sign, while two pairs have very small thermal interiors. Equal weighting also gives the single-cell G55 result the same contribution as larger interiors. The six purposive pairs cannot provide a London-wide cooling or warming coefficient.

6.6 Implications for Urban Greening and Development Assessment

Both temperature summaries recorded a positive average relative change at the urbanisation sites. The city-wide urbanisation mask also includes non-vegetated initial classes, so its total area should not be described entirely as vegetation loss. An assessment concerned only with the final site's absolute temperature could miss a reduction in a pre-existing cool condition, as illustrated by U106 and U28. Compare the sites at different times and in different environments to gain a fuller understanding. Record the amount of new construction and the loss of vegetation, permeable surfaces and shade.

High GLA green-cover percentages coincided with cooler absolute temperatures than the selected comparisons, but were not associated with uniform cooling from 2018. Greening assessment should therefore distinguish existing cool surfaces from newly created cooling, and tree canopy from low vegetation. London Plan Policy G5 and the Urban Greening Factor provide a framework for incorporating vegetation into development (Greater London Authority, 2021, 2023). The present evidence suggests that thermal assessment can complement this framework by documenting the location, composition and persistence of greening rather than assuming that a single green-area percentage predicts the temperature outcome.

The spatial setting also matters for translating these findings into practice. A small vegetated patch may provide shade or improve conditions for people even when Landsat cannot isolate its temperature from surrounding surfaces. Conversely, a cooler satellite surface does not establish lower night-time air temperature, reduced indoor exposure or a health benefit of a specified magnitude. The London field studies demonstrate how monitoring at ground level can address cooling distance and nocturnal conditions that the present imagery cannot resolve (Doick et al., 2014; Vaz Monteiro et al., 2016). Combining

those observations with repeated surface mapping would allow future site assessments to connect the mapped intervention with the conditions relevant to its users.

Dated aerial imagery is needed to resolve the high GLA vegetation fractions at U167 and U106 and confirm the chronology of the greening sites. Additional pre-change summers and comparison areas selected for similar initial cover, temperature and surroundings would make the relative-change interpretation stronger. Larger thermal interiors or finer-scale measurements would be more suitable for G55 and G73. The above optimisations will determine whether the positive urbanisation group contrast and different greening responses are stable under improved spatial and temporal control.

7 Conclusion

7.1 Land-Cover Change and the Selected Cases

This dissertation examined mapped land-cover change and summer land-surface temperature in Greater London through annual classifications, independent vegetation layers and six site-comparison pairs. The analysis distinguished urbanisation, defined as valid non-Built cover in 2018 followed by Built cover in 2022 and 2025, from greening, defined as Built or Bare Ground followed by Trees or Rangeland. The masks covered 1,675.71 ha and 900.53 ha, respectively. Patch screening retained 269 urbanisation candidates and 93 greening candidates, with recorded geodesic areas of 591.90 ha and 164.38 ha. Urbanisation was therefore more extensive under the applied definitions, although its initial classes included water and bare surfaces as well as vegetation.

Vegetation layers showed high contemporary green cover at the three selected greening sites, ranging from 96.80% to 98.76%, and had different canopy compositions. They also showed a significant difference from the annual Built classification at U167 and U106. Based on the annual maps, the candidates meet the explicit requirements, but the vegetation layers provide a more detailed and sometimes conflicting description of the selected areas. The records support targeted site investigation, and different product dates and definitions have been kept in their interpretation.

7.2 Thermal Findings

The principal summer-median analysis identified positive 2018-2025 relative temperature changes in all three urbanisation pairs. Their mean paired change was +1.96°C, comprising +1.60°C at U106, +1.20°C at U167 and +3.09°C at U28. U106 and U28 remained cooler than their comparisons in 2025, so relative warming represented a reduction in an initial temperature advantage. This development-associated change is not apparent from the final year's absolute temperatures alone.

The greening sites showed heterogeneous thermal changes. The mean paired change was -0.53°C , but G14 and G55 recorded relative increases of $+1.20^{\circ}\text{C}$ and $+0.78^{\circ}\text{C}$; only G73 cooled relative to its comparison, by 3.58°C . All greening sites nevertheless remained cooler than their Built comparison areas in every study year. Cool surfaces were observed consistently, but additional cooling over the study interval was not.

The summer-mean analysis gave a different greening group result. The urbanisation mean remained positive at $+1.00^{\circ}\text{C}$, although U167 had a small negative paired change. The greening mean reversed to $+1.10^{\circ}\text{C}$ as G73's cooling estimate weakened. The positive urbanisation group direction and the cooler absolute temperatures of greening sites persisted across both aggregation methods. The sign of the greening mean depended on the aggregation statistic. The negative median-based estimate cannot therefore be treated as a general greening response.

7.3 Strength and Scope of the Evidence

The paired analysis describes six selected cases rather than a general causal effect. Comparison areas were chosen manually, initial thermal contrasts were sometimes large, and one initial year cannot establish parallel pre-change behaviour. The mapped changes were not independently dated through historical aerial imagery. The data cannot show what each site's temperature would have been without conversion.

Spatial support is particularly important for the greening findings. G55's buffered site and comparison each contain one 30 m output cell, while G73 contains three and two. The original thermal observations have a coarser 100 m scale, so these cells cannot be treated as independent fine-scale measurements. The results are for the daytime surface temperatures under clear skies during three summers. They offer evidence of local urban thermal contrasts, not a long-term climate trend, near-surface air temperature or metropolitan urban-rural heat-island intensity.

Fixed polygons and a common summer window were used as the extraction basis, but the acquisition dates were not uniform. Repeating the extraction from the mean rasters kept the analysed areas constant while testing a different summary of summer temperature. This comparison identified which findings depended on the choice of seasonal statistic.

7.4 Implications and Further Work

Development assessments should compare temperature changes with nearby reference areas, as well as record final temperatures. A development can remain relatively cool while losing part of its initial advantage. For greening, the consistent absolute contrasts support preserving cool vegetated areas, while differences among sites favour attention to canopy, low vegetation and surrounding surfaces. A high green-cover percentage alone does not establish how much additional cooling has occurred.

Further work should confirm transition dates with historical imagery, extend the pre-change temperature record and select comparisons with similar initial cover and thermal conditions. A relatively large interior or finer-scale thermal observations would directly reduce the uncertainty at G55 and G73. Compare the summer means and medians to determine if they have been affected by seasonal aggregation. On average, the urbanisation sites warmed relative to their references in both summaries, and while the greening sites were cooler than the references, there was no uniform additional cooling. Verify the transition dates and use more comparable controls to determine how much of the difference resulted from land-cover change.

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Appendix A Literature Review Matrix

Table A.1 Literature review matrix

Author(s)	Title	Theme	Method	Key findings
Oke (1982)	The energetic basis of the urban heat island	Urban energy balance	Physical synthesis of radiative, turbulent and storage processes explaining temperature differences between urban and surrounding environments.	Urban warming arises from interacting changes in radiation, evaporation, heat storage, urban geometry and anthropogenic heat. The explanation provides a process basis for land-cover comparisons while showing why a single mapped surface characteristic cannot determine the complete thermal response.
Voogt and Oke (2003)	Thermal remote sensing of urban climates	Surface temperature and measurement	Critical review of thermal remote-sensing observations, retrieval issues and their interpretation within heterogeneous urban environments.	Radiometric surface temperature differs from canopy-layer air temperature. Surface geometry, viewing direction, emissivity and measurement scale affect observed thermal patterns. Satellite imagery can describe spatial contrasts, but interpretation requires an explicit distinction between the observed surface and the atmosphere experienced by residents.

Author(s)	Title	Theme	Method	Key findings
Weng (2009)	Thermal infrared remote sensing for urban climate and environmental studies: methods, applications, and trends	Thermal retrieval and urban applications	Review of land-surface-temperature retrieval, relationships with land cover, spatial scale and applications to urban environmental analysis.	Urban temperature interpretation depends on retrieval assumptions and heterogeneous surface composition. The review identifies value in sub-pixel surface descriptors and integration with complementary observations, rather than relying entirely on broad land-use classes to explain thermal contrasts.
Schwaab et al. (2021)	The role of urban trees in reducing land surface temperatures in European cities	Canopy and surface cooling	Comparison of Landsat surface temperature and high-resolution land-cover information across 293 European cities.	Urban trees generally had lower surface temperatures than continuous urban fabric, while treeless green spaces produced smaller cooling contrasts. Relationships varied across Europe and through the season. The study compares established cover types rather than measuring a universal cooling effect following new planting.
Doick et al. (2014)	The role of one large greenspace in mitigating London's nocturnal urban heat island	London greenspace and air temperature	Five-month monitoring of a large central London greenspace and an adjacent urban street, examining cooling magnitude and distance.	Summer nocturnal cooling varied through time and extended beyond the greenspace boundary. Reported cooling distances ranged approximately 20-440 m, with an average summer reduction of 1.1°C over those distances. These are air-temperature findings rather than satellite surface-temperature effects.

Author(s)	Title	Theme	Method	Key findings
Vaz Monteiro et al. (2016)	The impact of greenspace size on the extent of local nocturnal air temperature cooling in London	Patch size and nocturnal cooling	Air-temperature monitoring around eight London greenspaces ranging from 0.2 to 12.1 ha.	Cooling distance increased with greenspace, canopy and grass area under the observed conditions. Very small sites produced little substantial cooling in their surroundings. The findings support attention to patch geometry and vegetation, but do not define a universal satellite detection threshold.
Bassett et al. (2021)	Climate driven trends in London's urban heat island intensity reconstructed over 70 years using a generalized additive model	London temporal variability	Generalised additive modelling combined recent observations and climate information to reconstruct nocturnal heat-island variability over 1950-2019.	The reconstructed series showed substantial seasonal and annual variation and no significant central-London trend under the model's treatment of urban form. The result concerns nocturnal UHI intensity and demonstrates the difficulty of interpreting sparse dates as a long-term trend.
Semudara et al. (2024)	Impact of urban expansion on urban heat: a case study of Greater London	London land-cover and thermal change	Landsat comparisons for 2000, 2013 and 2022, combining supervised land-cover classification, NDVI and surface-temperature analysis.	The chapter reports expansion of developed land and warmer conditions in its latest image. Its London application demonstrates an optical-thermal workflow, while discrete acquisitions and different sensors limit attribution of the temperature differences to urban expansion alone.

Author(s)	Title	Theme	Method	Key findings
Karra et al. (2021)	Global land use / land cover with Sentinel 2 and deep learning	Existing annual land-cover products	Deep-learning classification of Sentinel-2 observations and evaluation of a global 10 m land-cover product.	Demonstrated the feasibility of consistent global land-cover mapping using optical observations. Reported performance concerns the evaluated product and reference sample. Broad classes support large-area screening but do not independently establish the accuracy of later local land-cover transitions.
Malakar et al. (2018)	An operational land surface temperature product for Landsat thermal data: methodology and validation	Operational Landsat temperature retrieval	Development and validation of an operational algorithm that derives surface temperature from Landsat thermal observations using atmospheric and emissivity information.	Provides a documented basis for consistent Landsat temperature processing and evaluates retrieval performance against reference observations. Validation supports the operational approach; atmospheric correction, emissivity and spatial representativeness remain relevant to the interpretation of individual urban pixels.
Ermida et al. (2020)	Google Earth Engine open-source code for land surface temperature estimation from the Landsat series	Reproducible thermal processing	Open-source statistical mono-window retrieval workflow for Landsat, evaluated against observations from 12 validation stations.	Reported overall root mean square errors around 2 K for the evaluated retrieval and sample. The workflow demonstrates reproducible archive processing, but its validation error should not be assigned to every Landsat product or treated as site-specific accuracy for London.

Author(s)	Title	Theme	Method	Key findings
Brousse et al. (2022)	Evidence of horizontal urban heat advection in London using 6 years of data from a citizen weather station network	Heat transport and spatial context	Analysis of hourly observations from 1,560 suitable citizen weather stations across south-east England and Greater London during 2015-2020.	Identified horizontal redistribution of urban heat, including effects on downwind suburban and green areas. Temperature reflects surrounding and upwind conditions as well as local cover, so nearby reference areas may share thermal influences beyond their mapped boundaries.
Brousse et al. (2024)	Cool roofs could be most effective at reducing outdoor urban temperatures in London (United Kingdom) compared with other roof top and vegetation interventions: a mesoscale urban climate modeling study	Intervention scenarios and temperature timing	Mesoscale modelling compared roof and vegetation interventions during two hot July 2018 days in London.	Cool roofs produced the greatest modelled metropolitan air-temperature reduction among the tested interventions. Green-roof daytime cooling did not translate into an equivalent two-day mean reduction because night-time responses differed.
Stewart and Oke (2012)	Local Climate Zones for urban temperature studies	Urban morphology and site comparability	Development of a 17-class framework describing urban and natural landscapes through surface structure, cover and human activity.	Provides a physically interpretable alternative to vague urban-rural labels. Building form and surface composition distinguish thermal environments within the city. These characteristics help identify relevant dimensions for comparing sites, although assigning a class alone does not guarantee equivalent temperature histories.

Author(s)	Title	Theme	Method	Key findings
Zhou et al. (2019)	Satellite remote sensing of surface urban heat islands: progress, challenges, and perspectives	SUHI definitions and uncertainty	Review of satellite-based SUHI evidence, including sensors, temporal sampling, reference surfaces, spatial scales and analytical approaches.	Reported SUHI patterns depend on acquisition time, season, urban boundaries and reference definitions. Consistent sampling and explicit uncertainty are essential for comparison. A daytime surface-temperature difference should not automatically be interpreted as air-temperature exposure, causal land-cover change or a long-term climate trend.

Sources: the publications cited in the author column; full bibliographic details appear in the reference list.

Appendix B Regional Temperature Data

Table B.1 Regional summer temperatures and spatial support

Region	2018 (°C)	2022 (°C)	2025 (°C)	Cells	Interior (ha)
U28 S	30.80	37.48	35.56	11	0.922
U28 C	34.83	34.41	36.49	10	0.922
U106 S	34.78	40.11	35.12	15	1.409
U106 C	42.42	44.02	41.15	16	1.409
U167 S	38.52	43.96	39.54	6	0.705
U167 C	38.36	42.82	38.18	7	0.705
G14 S	34.39	35.09	33.83	11	1.033
G14 C	40.18	41.56	38.42	10	1.033
G55 S	35.36	39.65	35.54	1	0.083
G55 C	39.18	40.29	38.58	1	0.083
G73 S	37.01	36.05	33.17	3	0.232
G73 C	37.59	40.01	37.33	2	0.232

Source: primary zonal results reproduced from the summer-median Landsat rasters. S denotes the change site and C its comparison. Cells are valid 30 m output-grid cells, with the same count in each of the three years; areas are BNG planar interiors after a 30 m inward buffer.

Table B.2 Valid seasonal observation counts within the analysed interiors

Region	2018 range (mean)	2022 range (mean)	2025 range (mean)
U28 S	6–7 (6.27)	6–7 (6.82)	6–7 (6.91)
U28 C	5–5 (5.00)	8–8 (8.00)	3–4 (3.40)
U106 S	6–6 (6.00)	5–5 (5.00)	5–6 (5.93)
U106 C	5–5 (5.00)	6–6 (6.00)	7–7 (7.00)
U167 S	4–4 (4.00)	6–6 (6.00)	7–7 (7.00)
U167 C	4–5 (4.71)	6–7 (6.57)	7–7 (7.00)
G14 S	6–6 (6.00)	7–7 (7.00)	5–5 (5.00)
G14 C	4–4 (4.00)	6–6 (6.00)	3–4 (3.90)
G55 S	6–6 (6.00)	6–6 (6.00)	6–6 (6.00)
G55 C	6–6 (6.00)	7–7 (7.00)	4–4 (4.00)
G73 S	3–3 (3.00)	5–5 (5.00)	4–4 (4.00)
G73 C	4–5 (4.50)	6–6 (6.00)	5–6 (5.50)

Source: valid-observation-count rasters. Each entry is the minimum–maximum number of seasonal clear-sky observations across the polygon’s output cells, followed by their spatial mean. These counts are not independent study sites.

Appendix C Land Cover and Processing Definitions

Table C.1 Class codes and change definitions

Code or rule	Definition
1	Water
2	Trees
4	Flooded Vegetation
5	Crops
7	Built
8	Bare Ground
9	Snow/Ice
10	Cloud, excluded from valid comparisons
11	Rangeland
Urbanisation	Any valid non-Built class in 2018; Built in both 2022 and 2025.
Greening	Built or Bare Ground in 2018; Trees or Rangeland in both 2022 and 2025.
Patch definition	Eight-neighbour grouping; unsimplified polygons; minimum area approximately 1 ha.
Thermal region	Original polygon buffered inward by 30 m; fixed geometry in all years.

Source: Esri and Impact Observatory (2026) class definitions and the implemented GIS processing rules.

Table C.2 Annual land-cover areas on the three-year common valid extent

Class	2018 (ha)	2022 (ha)	2025 (ha)
Water	3,440.19	3,490.60	3,525.85
Trees	9,479.82	9,033.68	9,337.52
Flooded Vegetation	46.83	36.19	51.90
Crops	10,962.63	10,946.14	9,065.58
Built	116,304.68	116,755.03	117,322.73
Bare Ground	21.16	35.58	27.79
Rangeland	19,169.71	19,127.80	20,093.65
Total	159,425.02	159,425.02	159,425.02

Source: aligned annual classifications on the three-year common valid extent. Cloud and NoData are excluded; area is calculated from projected 10 m cells.

Table C.3 Land-cover transition areas between 2018 and 2025

2018 class	1	2	4	5	7	8	11
1	3,243.73	22.30	6.55	8.37	128.98	0.00	30.27
2	38.35	8,117.54	5.61	113.98	564.96	0.91	638.55
4	12.90	1.79	23.86	0.26	3.77	0.00	4.25
5	40.96	374.66	4.80	8,139.10	431.69	8.50	1,962.93
7	139.33	283.07	3.99	134.17	114,684.03	6.30	1,053.79
8	0.07	0.06	0.00	0.00	6.73	6.16	8.14
11	50.51	538.16	7.09	670.04	1,502.61	5.92	16,395.73

Source: aligned 2018 and 2025 classifications on their common valid extent. Rows are 2018 class codes and columns are 2025 class codes; values are hectares. Codes are defined in Table C.1. This two-date matrix differs from the three-date persistent-change masks.