

Article

A Reproducible Multi-Scale Workflow for Assessing Heat-Aware Walkability in Andean Intermediate Cities: Application to Loja, Ecuador

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Abstract

Urban heat and walkability are often assessed separately, although pedestrians experience street connectivity, topography, vegetation, and thermal exposure simultaneously. This study develops a reproducible open-data workflow to examine the spatial relationship between walkability potential and surface thermal pressure in Loja, Ecuador, an intermediate Andean city shaped by valley morphology, steep slopes, uneven urban expansion, and heterogeneous green-space distribution. The analysis combines Landsat-derived land surface temperature, OpenStreetMap urban-form indicators, DEM-derived slope, composite spatial indicators, and spatial autocorrelation across 100 m, 250 m, and 500 m grids. The results show that walkability potential, observed LST-based heat intensity, and walkability–heat balance is spatially structured rather than randomly distributed. At the 250 m scale, heat-intensity clusters were spatially selective, indicating that surface thermal pressure is concentrated in specific parts of the retained analytical grid rather than uniformly distributed across the city. The 250 m grid provided the most interpretable balance between local detail and spatial stability for this case study, while the 100 m and 500 m grids revealed the sensitivity of the results to spatial aggregation. The study does not measure physiological thermal comfort or pedestrian heat stress. Instead, it offers an exploratory diagnostic framework for identifying where pedestrian-supportive urban form and surface thermal pressure overlap or diverge. This approach can help data-constrained intermediate cities prioritize areas for field verification, shade assessment, green-infrastructure planning, and more detailed pedestrian-level thermal studies.

Keywords: land surface temperature; heat-aware walkability; walkability–heat balance; spatial autocorrelation; Andean intermediate cities



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1. Introduction

Urban heat has become a persistent environmental concern because it connects land-cover transformation with outdoor comfort, energy demand, public health, and the everyday experience of urban space. The replacement of vegetated or permeable surfaces by impervious materials alters surface properties such as albedo, emissivity, heat storage, and moisture availability, producing higher land surface temperatures and reinforcing surface urban heat island conditions [1,2]. Satellite-derived land surface temperature has therefore become a central variable for observing intra-urban thermal contrasts, particularly where field-based microclimatic monitoring is limited or spatially discontinuous [3]. This

perspective is not only technical. It allows the thermal consequences of urbanization to be examined in relation to the material and morphological structure of the city.

The effects of urban heat are not confined to thermal maps. Higher urban temperatures influence outdoor comfort, increase cooling-energy demand, intensify health risks, and reshape how people use streets, parks, plazas, and other public spaces [4,5]. Urban overheating has been associated with increased cooling loads and altered building energy performance [6,7], while heatwaves can aggravate exposure in urban areas by reinforcing thermal stress and limiting nocturnal recovery [8,9]. The social dimension of this problem is equally relevant: thermal vulnerability depends not only on climatic exposure, but also on access to cooling resources, adaptive capacity, urban morphology, and socio-spatial inequality [10–12].

For pedestrian-oriented planning, heat becomes especially relevant when it intersects with the spatial conditions that support or restrict walking [13,14]. A street network may be dense, central, and well connected, yet still uncomfortable if it is exposed to high surface temperatures and lacks shade or nearby vegetation [15]. Conversely, cooler areas may offer limited everyday value if they are steep, disconnected, or distant from services. Built-environment research has long associated walkability with combinations of density, street connectivity, landuse configuration, and access to destinations [16]. In a warming city, however, these attributes cannot be interpreted in isolation from thermal exposure. A highly walkable urban fabric may simultaneously concentrate impervious surfaces and surface heat, while a thermally favorable area may remain functionally inaccessible for daily pedestrian movement.

Green infrastructure complicates this relationship in productive ways [17]. Vegetated spaces, tree canopy, parks, vertical greenery, and other nature-based interventions can reduce heat through shade, evapotranspiration, altered surface properties, and changes in local radiative exchange [18,19]. Empirical studies have shown that urban parks, green spaces, and green–grey contrasts may produce measurable thermal differences, although the magnitude of cooling depends on vegetation structure, spatial configuration, surrounding morphology, and local climatic conditions [20,21]. For this reason, mapped green coverage should not be treated automatically as cooling capacity. A polygon classified as park, garden, grass, or forest may differ substantially in canopy density, irrigation, accessibility, surface material, and effective shading at pedestrian level.

Despite the growing literature on urban heat, many analyses remain concentrated in large metropolitan areas, while intermediate cities are less visible in methodological and empirical debates. This imbalance matters for Latin American and Andean contexts, where urban expansion, topographic constraint, data limitations, and environmental exposure often converge. The literature on urban heat vulnerability increasingly recognizes the need to examine exposure and adaptive capacity beyond major metropolitan regions [11,12]. Intermediate cities may not display the scale of thermal risk observed in megacities, but their planning systems frequently operate with fewer spatial datasets, less monitoring infrastructure, and limited capacity for detailed field-based thermal assessment.

Loja, Ecuador, provides a useful empirical application for a methodological workflow of this type. As an intermediate Andean city, its urban form is shaped by slope, valley morphology, uneven expansion, and a street network conditioned by terrain. The analytical challenge is therefore different from that of flatter metropolitan regions where heat and walkability are often modelled mainly through density, land cover, and network indicators. In Loja, slope modifies pedestrian effort; proximity to green space does not necessarily imply comfortable or accessible walking conditions; and compact urban areas may combine high accessibility with stronger surface thermal pressure. A spatial diagnostic for this

context needs to integrate thermal evidence, street-network structure, green coverage, building intensity, accessibility, and topographic constraint within a single framework.

The thermal component of the workflow is based on Landsat 9 Collection 2 Level-2 Surface Temperature. These products are distributed as scaled integers, and surface temperature is recovered by applying the official multiplicative factor of 0.00341802 and additive offset of 149.0 before conversion from Kelvin to Celsius [22]. The dataset provides atmospherically compensated surface temperature and includes quality-assessment information that allows unreliable pixels to be filtered before analysis [23]. A conservative QA-based filtering strategy is used here: cells without valid strict QA-masked LST (Land Surface Temperature) are excluded rather than interpolated. This decision avoids assigning synthetic thermal values to areas affected by unreliable or unavailable observations, even if it produces spatial gaps in the final heat-intensity and comfort maps.

The urban-form component relies on OpenStreetMap because it offers reproducible spatial data in contexts where official municipal datasets may be fragmented, unavailable, or difficult to access. OSM data extracted after September 2012 are distributed under the Open Database License, ODbL 1.0, which allows reuse with attribution and share-alike conditions [24]. In this study, OSM is used to derive road-network density, intersection density, building coverage, green coverage, distance to green areas, and hydrographic reference layers. These variables are not treated as exhaustive measurements of the city, but as transparent open-data approximations of built and environmental structure.

Spatial autocorrelation analysis is used to move beyond visual interpretation of maps. Global Moran's *I* evaluate whether the constructed indices show non-random spatial structure, while Local Indicators of Spatial Association identify statistically significant local concentrations of high or low values. LISA statistics allow global spatial association to be decomposed into location-specific contributions, making it possible to distinguish broad spatial structure from localized clusters and spatial outliers [25]. For heat-aware walkability analysis, this distinction is useful because a city may show overall spatial clustering while only a limited proportion of its area forms statistically significant heat-intensity clusters.

The choice of spatial unit also affects interpretation. Gridded analysis offers a practical way to compare surface heat, walkability-related indicators, and comfort across a heterogeneous city, but the size of the analytical cell can influence variance, correlation, and spatial clustering. The modifiable areal unit problem remains a central concern when spatial data are aggregated into alternative areal units [26]. A fine grid may capture local heterogeneity while increasing fragmentation and no-data gaps; a coarser grid may stabilize patterns but smooth meaningful intra-urban contrasts. To avoid presenting one resolution as self-evidently correct, the workflow is implemented at 100, 250, and 500 m. The multi-scale design does not remove scale effects, but it allows their influence to be examined explicitly.

The article is therefore positioned as a methodological contribution with an empirical application. The workflow combines Landsat-derived LST, OpenStreetMap indicators, DEM-derived slope, composite spatial indices, and autocorrelation analysis to evaluate heat-aware walkability under data-constrained conditions. In this study, heat-aware walkability is defined as the spatial relationship between pedestrian-supportive urban form and observed surface thermal pressure, evaluated through composite indicators derived from open geospatial data. The concept does not refer to physiological thermal comfort or to behavioral responses of pedestrians to heat. Instead, it captures the degree of spatial balance or mismatch between built-environment conditions that are typically associated with walkability (e.g., connectivity, accessibility, slope, and green proximity) and land surface temperature as a proxy for surface thermal exposure. The term "sensitive" is used here in a comparative spatial sense, referring to how the balance between walkability-related conditions and surface heat varies across the urban structure, rather than to the

vulnerability or adaptive response of pedestrians. Accordingly, the proposed workflow should be interpreted as a spatial diagnostic of co-occurring conditions rather than as a direct measure of heat-related walking experience.

Despite the parallel growth of urban heat and walkability research, the two bodies of literature have largely developed independently. Studies on LST and surface urban heat islands focus on thermal remote sensing, land-cover analysis, and heat mitigation at the city or neighborhood scale [1–3,27], while walkability research has concentrated on street-network connectivity, density, landuse mix, and pedestrian behavior [16,28–30]. The spatial intersection of these dimensions—where thermally exposed areas coincide with pedestrian-supportive urban form, or where cooler zones remain functionally inaccessible—has received limited methodological treatment, particularly for intermediate cities in Latin America and the Andes. The few studies that address both dimensions tend to focus on large metropolitan areas with dense monitoring infrastructure, leaving smaller cities without a transferable open-data procedure for joint thermal and walkability assessment. This study addresses that gap by proposing a reproducible spatial workflow that treats heat exposure and walkability as coupled rather than independent urban conditions.

In this context, the study is guided by four research questions:

1. How are land surface temperature, urban-form indicators, green coverage, slope, and accessibility distributed across the analytical urban area of Loja?
2. To what extent do walkability potential, observed LST-based heat intensity, and walkability–heat balance exhibit spatial autocorrelation across 100 m, 250 m, and 500 m grids?
3. Where do statistically significant local clusters of heat intensity emerge after correction for multiple local tests?
4. Which analytical scale provides the most interpretable balance between intra-urban detail and spatial stability for heat-aware walkability assessment?

The article is positioned as an exploratory methodological contribution with an empirical application. Loja is used as a testing ground for a reproducible open-data workflow that identifies spatial relationships between walkability potential, observed surface thermal pressure, green access, and topographic constraint. The study does not claim to provide a validated model of pedestrian heat exposure or physiological thermal comfort. Instead, it offers a transparent diagnostic framework for identifying locations where additional field-based climatic, behavioral, and design assessment should be prioritized.

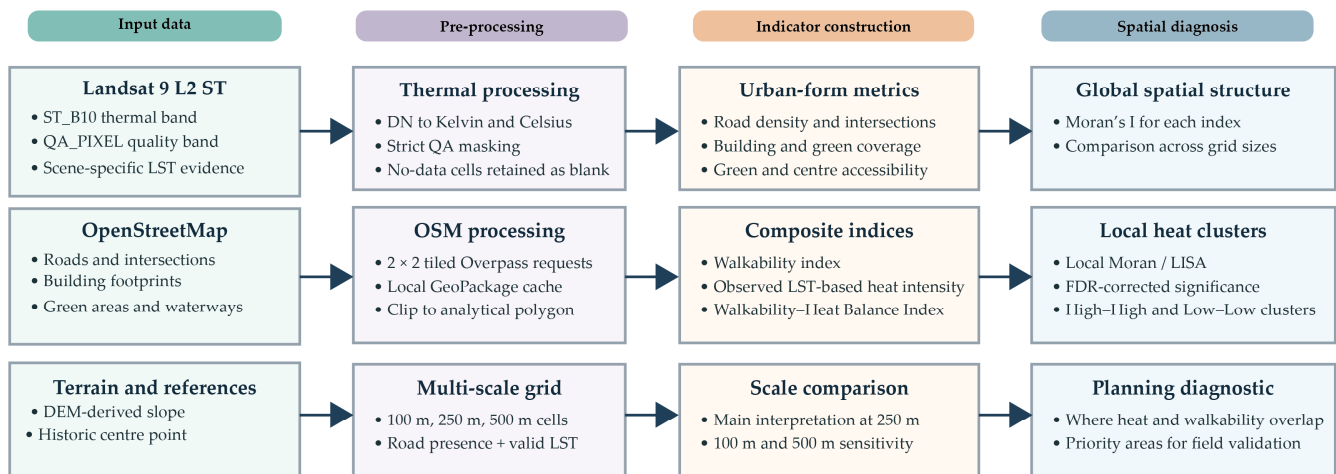
2. Materials and Methods

2.1. Methodological Framework and Empirical Application

The workflow integrates five analytical components: satellite-derived land surface temperature, OpenStreetMap-based indicators of urban form, DEM-derived slope, composite spatial indices, and spatial autocorrelation analysis. These components were processed across three regular grid resolutions—100, 250, and 500 m—to evaluate the sensitivity of the results to spatial aggregation. This multi-scale structure is central to the methodological design because spatial statistics and composite indicators can change when the same variables are summarized within different areal units. The dataset and R script have been publicly archived in Zenodo and are available through the Data Availability Statement.

Loja was used as an empirical application because its Andean topographic setting offers a demanding test for the workflow. In this urban context, pedestrian accessibility is not defined only by network density or centrality. Slope, green-space proximity, surface heat, road configuration, and built-up intensity interact over short distances. The city therefore provides a setting for testing whether an open-data workflow can connect thermal

exposure and walkability-related conditions in a spatially explicit and reproducible way. The overall workflow is summarized in Figure 1.



Note. LST = land surface temperature; OSM = OpenStreetMap; LISA = Local Indicators of Spatial Association; FDR = false discovery rate.

Figure 1. General workflow for assessing heat-aware walkability using open geospatial data, Landsat-derived LST, composite indices, and spatial autocorrelation.

All composite indicators in this study are treated as heuristic spatial indicators. They are intended to support exploratory comparison across urban cells and grid resolutions, not to function as validated measurement scales. This distinction is important because the workflow relies on open geospatial proxies rather than field observations of pedestrian behavior, detailed urban-design audits, or microclimatic comfort measurements.

2.2. Empirical Study Area and Analytical Boundary

The workflow was applied to Loja, Ecuador, an intermediate Andean city characterized by a valley setting, slope variation, and uneven spatial expansion. Rather than using a rectangular bounding box, the analysis used a manually digitized polygon that follows selected points around the main urbanized area. This decision was adopted to better approximate the spatial envelope of the city while keeping the boundary reproducible within the code.

The analytical polygon was defined in WGS84 coordinates and later transformed to UTM Zone 17S, EPSG:32717, for metric operations. Lengths, areas, distances, slopes, and grid-based spatial metrics were calculated in the projected coordinate system. The final WGS84 boundary coordinates were:

- −79.210440, −3.963070,
- −79.197737, −3.966324,
- −79.187952, −3.973859,
- −79.182631, −3.987730,
- −79.181601, −4.012731,
- −79.184519, −4.033109,
- −79.192930, −4.046123,
- −79.199454, −4.051260,
- −79.213702, −4.047150,
- −79.225031, −4.032938,
- −79.233958, −4.013930,
- −79.235331, −4.004683,
- −79.231383, −3.975914,
- −79.226233, −3.968208,

- $-79.210440, -3.963070$

The polygon should be interpreted as an analytical boundary rather than as an official municipal limit. This distinction matters because all grid counts, density values, LST summaries, and spatial autocorrelation results are conditional on the adopted study extent.

A map of the analytical polygon should be inserted after this subsection. If a clean boundary map is not generated separately, the road-density map at 250 m can be used because it displays the final spatial frame and retained analytical cells. The study area and its geographic location within Loja City are presented in Figure 2.

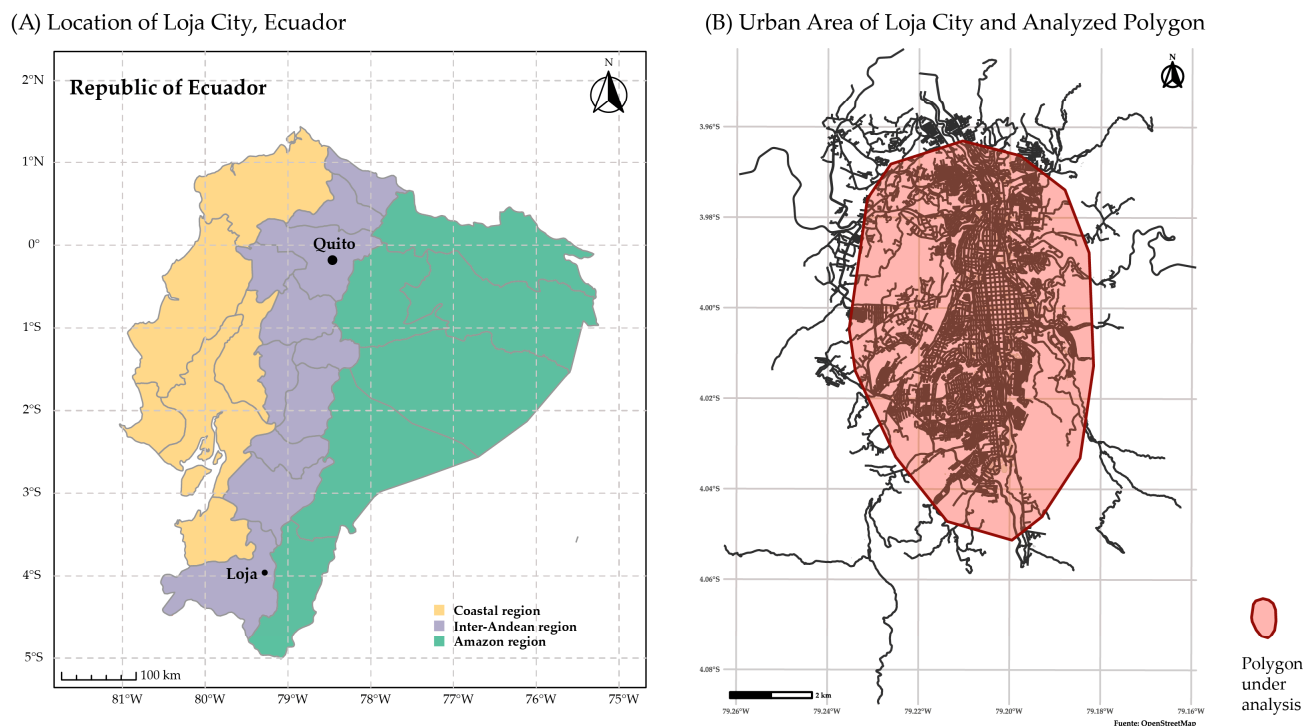


Figure 2. Location and Urban Context of the Analyzed Area in Loja City, Ecuador. (A) Location of Loja City, Ecuador. (B) Urban area of Loja City showing the analyzed polygon (highlighted in red).

The manually delineated boundary was used to approximate the continuous urbanized area of Loja while excluding extensive rural or non-urban surroundings that could dilute urban-form and thermal indicators. This analytical choice was necessary because the study focuses on intra-urban relationships between road structure, surface thermal pressure, green coverage, slope, and accessibility rather than on the full municipal territory. However, the boundary should not be interpreted as an official administrative limit.

2.3. Data Sources and Analytical Variables

The workflow combines raster data, vector data, and derived spatial indicators. Landsat 9 Collection 2 Level-2 Surface Temperature was used to represent observed surface thermal conditions [31]. OpenStreetMap data provided road networks, building footprints, green areas, and waterways. A digital elevation model was used to derive slope, and a manually defined historic-center point was used to calculate a simple central-accessibility metric. Table 1 summarizes the datasets, derived variables, and analytical role of each component.

Table 1. Data sources, derived variables, and analytical role.

Component	Source	Derived Variable	Analytical Role
Land surface temperature	Landsat 9 Collection 2 Level-2 ST_B10	Land surface temperature (°C)	Observed surface thermal condition
Quality mask	Landsat 9 QA_PIXEL	Strict QA mask	Exclusion of unreliable thermal pixels
Road network	OpenStreetMap highway features	Road length and road density	Proxy for street-network availability
Street intersections	OpenStreetMap road vertices	Intersection density	Proxy for network connectivity
Buildings	OpenStreetMap building polygons	Building coverage (%)	Proxy for built-up intensity
Green areas	OpenStreetMap leisure and land-use polygons	Green coverage (%) and distance to green areas	Proxy for vegetation presence and green accessibility
Terrain	Digital elevation model (DEM)	Mean slope in degrees	Topographic constraint in the walkability index

2.4. Software Environment

All analyses were implemented in R (version 4.3.3; R Foundation for Statistical Computing, Vienna, Austria) [32] using RStudio (version 2023.09.1; Posit Software, PBC, Boston, MA, USA) [33] as the integrated development environment. Spatial vector processing relied on sf linked to GEOS 3.13.0, GDAL 3.10.1, and PROJ 9.5.1, with spherical geometry disabled through sf_use_s2(FALSE). Raster processing was performed with terra 1.8.60. Data wrangling used tidyverse 2.0.0, including dplyr 1.2.1, tidyr 1.3.1, readr 2.2.0, tibble 3.3.1, stringr 1.6.0, purrr 1.2.2, forcats 1.0.0, and lubridate 1.9.4.

Elevation data were obtained with elevatr 0.99.0. Plots were produced using ggplot2 3.5.2, patchwork 1.3.2, viridis 0.6.5, svglite 2.1.3, and ggspatial 1.1.10. Spatial autocorrelation analyses were performed with spdep 1.4.2. Raster extraction used exactextractr 0.10.0. OpenStreetMap acquisition used osmdata 0.2.5. Correlation visualization support was provided by corrplot 0.95, and Excel-compatible output support was available through writexl 1.5.4. Execution timing and progress messages used tictoc 1.2.1.

2.5. OpenStreetMap Acquisition, Tiling, and Local Caching

OpenStreetMap data were extracted in May 2026, ensuring temporal proximity to the Landsat acquisition date (14 April 2026) and minimizing inconsistencies between the urban-form and thermal datasets. OpenStreetMap data were acquired through Overpass API. Because the final analytical polygon was larger than the previous test area, the OSM cache was regenerated. To reduce the probability of timeout errors, the study area was divided into a 2×2 tile grid, and each OSM layer was requested separately by tile. This tile-based strategy reduced the size of individual API calls and allowed the workflow to complete even when one request initially returned a temporary gateway timeout.

The following OSM layers were requested: road features from the highway key, buildings from the building key, green areas from leisure and landuse keys, and rivers or streams from the waterway key. After tile-level downloads, the features were merged, geometry columns were standardized, duplicate features were removed where identifiable, incompatible geometries were corrected where possible, and the resulting layers were saved as local GeoPackage files. Subsequent executions loaded these cached layers directly, avoiding repeated Overpass requests.

2.6. Landsat 9 Land Surface Temperature Processing

Land surface temperature was derived from the Landsat 9 Collection 2 Level-2 scene: LC09_L2SP_010063_20260414_20260415_02_T1. The workflow used the ST_B10 raster and the corresponding QA_PIXEL raster. The surface temperature band was converted from scaled digital numbers to Kelvin using the official scale factor and offset and then converted to Celsius:

$$LST_K = DN \times 0.00341802 + 149.0 \quad (1)$$

$$LST_{\circ C} = LST_K - 273.15 \quad (2)$$

where DN is the original digital number in the Landsat ST_B10 raster. Three LST layers were prepared: strict QA-masked LST , relaxed QA-masked LST , and unmasked LST . The strict mask excluded pixels flagged as fill, dilated cloud, cirrus, cloud, cloud shadow, or snow. This strict QA-masked LST layer was selected because it provided sufficient valid observations while preserving a conservative quality criterion.

Throughout the study, Landsat-derived LST is interpreted as observed surface thermal pressure for the acquisition date, not as air temperature, urban climate, pedestrian heat exposure, or physiological thermal comfort. This distinction is maintained in the construction and interpretation of all thermal and balance indicators.

2.7. DEM-Derived Slope and Accessibility Variables

Topographic slope was included because terrain strongly conditions pedestrian movement in Loja. Elevation data were retrieved with elevatr 0.99.0, reprojected to EPSG:32717, and converted to slope in degrees using raster terrain functions. Mean slope was then extracted for each analytical cell.

Two accessibility variables were calculated from cell representative points. The first was Euclidean distance to the nearest OSM green polygon. The second was Euclidean distance to a manually defined historic-center point located at longitude = -79.2042 ; latitude = -3.9931 .

These distances were used as simple spatial proxies. They do not represent network travel distance, sidewalk quality, entrance availability, perceived safety, or route-specific pedestrian effort. Their role is to capture first-order spatial proximity within a reproducible open-data framework.

2.8. Multi-Scale Grid Construction and Analytical Cell Selection

Three regular square grids were generated over the analytical polygon: 100, 250, and 500 m. The grids were intersected with the polygon, and the effective area of each resulting cell was calculated. Boundary cells were retained with their actual intersected area, rather than being forced into complete square units.

The analytical grid was then filtered to retain cells with both road presence and valid LST . This decision aligned the analysis with the study objective: evaluating heat-aware walkability where urban street structure and reliable thermal observations overlap.

2.9. Urban-Form Indicators

Road density was calculated as the total length of OSM road segments intersecting each grid cell, normalized by cell area:

$$D_{road} = \frac{L_{road}}{A_{cell}} \times 10,000 \quad (3)$$

where D_{road} is road density in meters per hectare, L_{road} is the road length within the cell, and A_{cell} is the effective cell area in square meters.

Building and green coverage were calculated through exact geometric intersections between OSM polygons and grid cells:

$$C_{building} = \frac{A_{building}}{A_{cell}} \times 100 \quad (4)$$

$$C_{green} = \frac{A_{green}}{A_{cell}} \times 100 \quad (5)$$

where $C_{building}$ and C_{green} represent the percentage of the cell covered by buildings and green areas, respectively.

Intersection density was derived from the road network. Road geometries were converted to vertices, coordinates were rounded to reduce duplicate-node noise, and points with a node frequency of at least three were treated as intersections. These points were spatially joined to the grid and normalized by cell area:

$$D_{intersection} = \frac{N_{intersection}}{A_{cell}} \times 10,000 \quad (6)$$

This approach provides an operational proxy for street-network connectivity using only open road geometry. It does not distinguish formal road intersections from all pedestrian-relevant crossings, nor does it account for signalization, crossing safety, sidewalk presence, or traffic stress.

2.10. Composite Walkability Index

All variables used in the composite indices were standardized using z-scores. The walkability index combined road density, intersection density, green coverage, distance to green areas, distance to the historic center, and slope. Shorter distances to green areas and the historic center were transformed into higher accessibility scores by reversing the sign of the standardized distance variables:

$$WI = 0.25Z_{road} + 0.25Z_{intersection} + 0.20Z_{green} + 0.15Z_{access_green} + 0.10Z_{access_center} - 0.25Z_{slope} \quad (7)$$

where WI is the walkability index. The positive terms represent spatial conditions interpreted as supportive of walking, while slope is treated as a constraint. The WI is a heuristic composite indicator of spatial walkability potential. It is designed for screening and spatial comparison, not for predicting observed walking behavior. The weighting structure is transparent and theoretically informed, but it is not empirically calibrated for Loja. Therefore, the index should be interpreted as a diagnostic approximation of favorable pedestrian-supportive spatial conditions.

The weights assigned to each component follow a structure consistent with established composite walkability indices in the built-environment literature. Road density and intersection density together receive the highest combined weight (0.50) because street-network availability and connectivity are the most consistently reported determinants of pedestrian activity across urban contexts [16,28,34]. Green coverage and green accessibility receive intermediate weights (0.20 and 0.15) reflecting their dual role as environmental amenity and thermal buffer, while proximity to the historic center (0.10) captures a first-order centrality proxy. Slope receives a penalty weight (−0.25) commensurate with its role as a primary physical constraint on pedestrian movement in Andean settings. These weights are not empirically calibrated using observed walking behavior in Loja and should therefore be interpreted as theoretically informed starting values. Sensitivity to alternative weighting schemes is an acknowledged limitation discussed in Section 4.8.

The weights assigned to the walkability index were defined as theoretically informed starting values rather than as empirically calibrated coefficients. Road density and inter-

section density each receive a weight of 0.25 because the index prioritizes the availability and connectivity of the street network, which are among the most widely used spatial components in composite walkability measures. Green coverage receives a weight of 0.20 because vegetated areas may contribute both to environmental quality and to the perceived attractiveness of pedestrian environments. Access to green areas receives a weight of 0.15, reflecting the importance of proximity to open and vegetated spaces, while access to the historic center receives a smaller weight of 0.10 as a first-order proxy for centrality. Slope receives a negative weight of -0.25 because terrain is a major physical constraint on pedestrian movement in Loja's Andean setting.

The *WI* should be interpreted as an indicator of spatial walkability potential rather than as a complete measure of walkability. It captures open-data proxies related to street-network availability, connectivity, green presence, green proximity, central accessibility, and slope constraint. It does not measure sidewalk continuity, sidewalk width, pavement quality, universal accessibility, crossing safety, traffic exposure, landuse mix, active frontage, perceived safety, shade continuity, pedestrian counts, or route choice. Therefore, the index identifies areas where spatial conditions may be more supportive of walking, but it does not measure walking behavior or pedestrian experience directly.

2.11. Observed *LST*-Based Heat Intensity Index

The observed *LST*-based Heat Intensity Index combined land surface temperature, building coverage, and green coverage. *LST* received the highest weight because the index was intended to remain primarily thermal. Building coverage was included as a proxy for built-up intensity, while green coverage was included as a mitigating component.

$$UHII = 0.60Z_{LST} + 0.25Z_{building} - 0.15Z_{green} \quad (8)$$

where *UHII* is the observed *LST*-based urban heat intensity index. The *UHII* is likewise a heuristic composite indicator. It represents the co-occurrence of observed surface temperature, built-up intensity, and mapped green coverage, but it should not be interpreted as a validated model of heat generation, pedestrian exposure, or urban climate. Because *LST* was obtained from a single Landsat scene, the heat index represents a date-specific surface thermal condition rather than seasonal or annual thermal exposure.

The heat intensity index was also constructed as a theoretically informed composite indicator. *LST* receives the dominant weight of 0.60 because the purpose of the index is to represent observed surface thermal pressure. Building coverage receives a secondary positive weight of 0.25 because it serves as an open-data proxy for built-up intensity and impervious surface concentration. Green coverage receives a negative weight of -0.15 because vegetation may mitigate surface thermal conditions, although this effect is not assumed to be uniform because OSM green polygons do not distinguish tree canopy, grass, irrigated surfaces, or paved green spaces.

The selected weights are therefore heuristic and diagnostic, not empirically calibrated. The index should be interpreted as an observed *LST*-based heat-intensity indicator rather than as a causal model of heat production. Alternative specifications are evaluated in the sensitivity analysis to test whether the main spatial patterns depend strongly on the baseline weighting structure.

2.12. Walkability–Heat Balance Index (*WHBI*)

Urban comfort was formulated as the difference between walkability and heat intensity:

$$WHBI = WI - UHII \quad (9)$$

where *WHBI* is the walkability–heat balance index. The *WHBI* combines the two heuristic indicators to show where walkability potential and surface thermal pressure appear more or less spatially compatible. It is therefore a screening indicator for exploratory planning diagnosis rather than a validated measurement of urban comfort. Higher values indicate locations where walkability-related spatial conditions are stronger relative to surface thermal pressure, while lower values indicate areas where heat intensity outweighs pedestrian-supportive characteristics.

This index should be interpreted as a spatial balance indicator between urban form and surface heat conditions. It does not represent physiological thermal comfort, as it does not incorporate air temperature, humidity, wind speed, mean radiant temperature, exposure duration, or subjective perception. Its purpose is to support spatial comparison and prioritization within an open-data planning framework.

2.13. Spatial Autocorrelation and LISA Analysis

Spatial autocorrelation was assessed with global Moran's *I* and Local Indicators of Spatial Association. Global Moran's *I* was calculated for the walkability index, the observed *LST*-based heat intensity index, and the walkability–heat balance index at each grid resolution. Local Moran statistics were then used to identify local clusters of heat intensity.

Spatial weights were constructed using queen contiguity, where cells sharing an edge or vertex were considered neighbors. Because the analytical grid retained only cells with road presence and valid *LST*, the resulting neighbor graph contained several subgraphs. The retained analytical grids produced 17 subgraphs at 100 m, 4 at 250 m, and 2 at 500 m. Zero-policy handling was used so that observations without standard neighbor continuity could remain in the analysis.

Permutation-based Local Moran statistics were calculated with 999 simulations. *p*-values were adjusted using the Benjamini–Hochberg false discovery rate procedure. The LISA classification distinguished three categories: High–High, Low–Low, and Not significant.

2.14. Multi-Scale Sensitivity Assessment

The same workflow was repeated at 100, 250, and 500 m. This allowed the analysis to evaluate whether the spatial structure of walkability, heat intensity, and comfort was stable across aggregation levels. The 100 m grid captured fine-grained intra-urban variation but increased fragmentation and the number of spatial subgraphs. The 500 m grid reduced local heterogeneity and provided a smoother representation. The 250 m grid was used as the main interpretive scale because it retained sufficient analytical cells while reducing excessive fragmentation.

2.15. Weight-Sensitivity Assessment

To evaluate the robustness of the composite indicators, a weight-sensitivity assessment was added to the workflow. The baseline walkability index and observed *LST*-based heat-intensity index were compared with alternative weighting schemes designed to test whether the main spatial patterns depended strongly on the selected theoretical weights.

For the walkability index, the sensitivity scenarios included: (i) an equal-weight specification for all positive walkability components, with slope retained as a negative constraint; (ii) a network-emphasis scenario assigning greater importance to road density and intersection density; and (iii) an accessibility-emphasis scenario assigning greater importance to access to green areas and access to the historic center. For the heat-intensity index, the scenarios included: (i) an *LST*-dominant specification; (ii) a balanced specification distributing weights more evenly across *LST*, building coverage, and green coverage; and (iii) a reduced-*LST* specification designed to test whether the spatial pattern remained stable when surface temperature was less dominant.

The baseline and alternative indices were compared using Spearman rank correlation, changes in global Moran's I, and visual comparison of the spatial distribution of the *WHBI*. The purpose of this assessment was not to identify a single optimal weighting structure, but to evaluate whether the main conclusions were robust to reasonable alternative specifications.

3. Results

3.1. Workflow Execution and Reproducible Output Generation

The workflow was successfully implemented across the three planned grid resolutions: 100 m, 250 m, and 500 m. It produced the expected spatial layers, tabular outputs, composite indicators, autocorrelation statistics, and exported maps for each analytical scale.

The OpenStreetMap download was completed using a 2×2 tiled strategy. This was important because direct requests over the full polygon initially produced timeout errors. By dividing the area into four smaller queries, the script obtained all required OSM layers and then merged, cached, transformed, and clipped them to the analytical polygon. As shown in Table 2, the final clipped layers included 4136 road segments, 828 buildings, 139 green polygons, and 25 river or stream segments.

Table 2. OpenStreetMap features downloaded and retained after clipping to the final analytical polygon.

Layer	Features Downloaded/Cached	Features Retained After Clipping
Roads	4339	4136
Buildings	853	828
Green areas	140	139
Rivers/streams	56	25

3.2. Landsat Quality Diagnostics and Valid Thermal Coverage

The Landsat 9 Collection 2 Level-2 scene provided sufficient valid thermal observations within the final analytical polygon. The strict QA mask retained 21,545 valid LST pixels, whereas the relaxed QA mask retained 25,318 pixels, and the unmasked raster contained 50,419 pixels. Because the strict QA layer preserved adequate spatial coverage at both the raster and analytical-grid levels, it was selected for all subsequent analyses. A summary of the Landsat quality diagnostics and pixel retention is presented in Table 3.

Table 3. Landsat 9 *LST* quality diagnostics for the final analytical polygon.

<i>LST</i> Layer	Valid Pixels	Use in Final Analysis
Strict QA mask	21,545	Selected
Relaxed QA mask	25,318	Diagnostic only
No QA mask	50,419	Diagnostic only

Under the strict QA mask, *LST* values ranged from 19.14 °C to 38.10 °C, with a mean of 30.25 °C and a median of 30.75 °C. These results indicate that the selected Landsat scene captured a substantial intra-urban surface-temperature gradient across the study area. The spatial distribution of strict QA-masked *LST* aggregated to the 250 m analytical grid is shown in Figure 3.

The strict QA strategy improves the reliability of retained *LST* observations but reduces spatial completeness, especially at the finest grid scale. Therefore, blank cells in the *LST* and heat-intensity and heat-balance maps should be interpreted as excluded analytical units rather than as cooler or less problematic areas. This distinction is central to the

interpretation of the results: the analysis describes the spatial structure of cells where reliable LST and road-network presence overlap, not the full continuous urban surface.

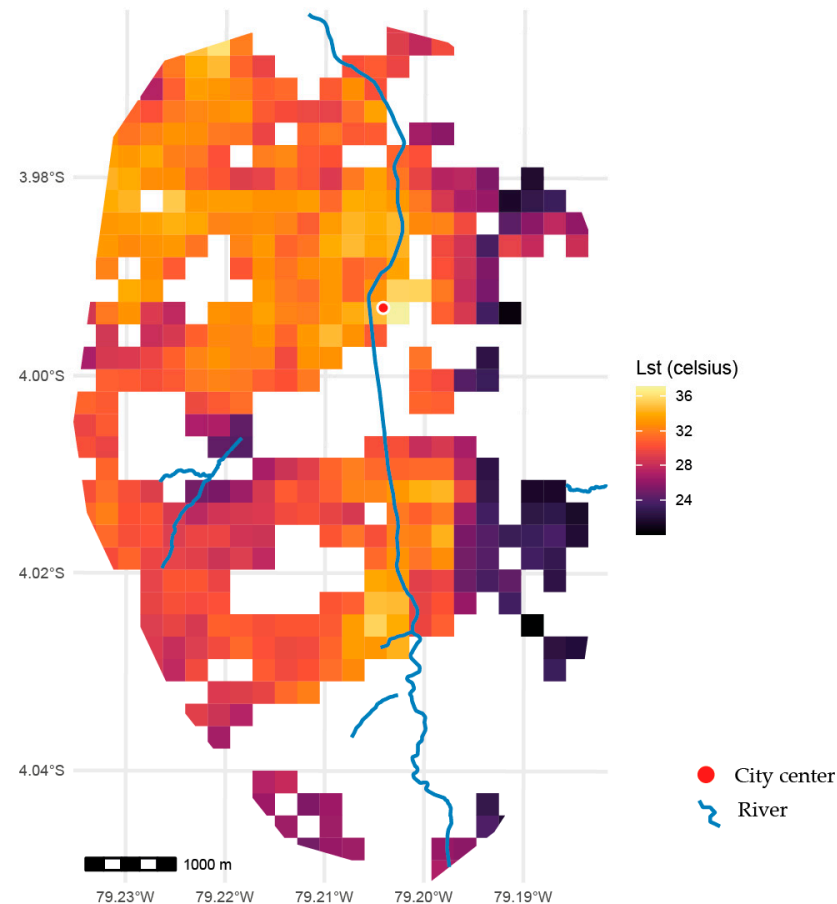


Figure 3. Strict QA-masked Landsat 9 land surface temperature aggregated to the 250 m analytical grid. Blank cells in this map should be interpreted as analytical no-data units, not as low-temperature areas. They occur where the cell lacked valid strict QA-masked LST or did not meet the road-presence criterion used to define the retained analytical grid.

3.3. Analytical Grid Coverage Across Spatial Scales

The final analytical polygon generated 4654 cells at the 100 m resolution, 779 cells at 250 m, and 208 cells at 500 m prior to analytical filtering. After retaining only cells containing both road presence and valid strict QA-masked LST observations, the final analytical dataset consisted of 1650 cells at 100 m, 427 cells at 250 m, and 150 cells at 500 m.

This filtering procedure is important because all subsequent analyses, maps, and statistical summaries were conducted using the retained road-and-LST analytical grid rather than the entire polygon extent. Table 4 summarizes grid coverage before and after filtering for each spatial resolution. The strict QA-masked LST layer was retained consistently across all three grid scales.

Table 4. Grid-level analytical coverage after road-presence and strict QA-masked LST filtering.

Grid Size	Cells Before Filtering	Cells with Road + Strict LST	Selected LST Layer
100 m	4654	1650	Strict QA mask
250 m	779	427	Strict QA mask
500 m	208	150	Strict QA mask

The 250 m grid was selected as the primary interpretive scale because it preserved meaningful intra-urban spatial variation while reducing the excessive fragmentation observed at the 100 m resolution. The 500 m grid was retained as a coarser-scale sensitivity assessment. Figure 4 presents the retained analytical grid and the spatial distribution of road density at the 250 m resolution.

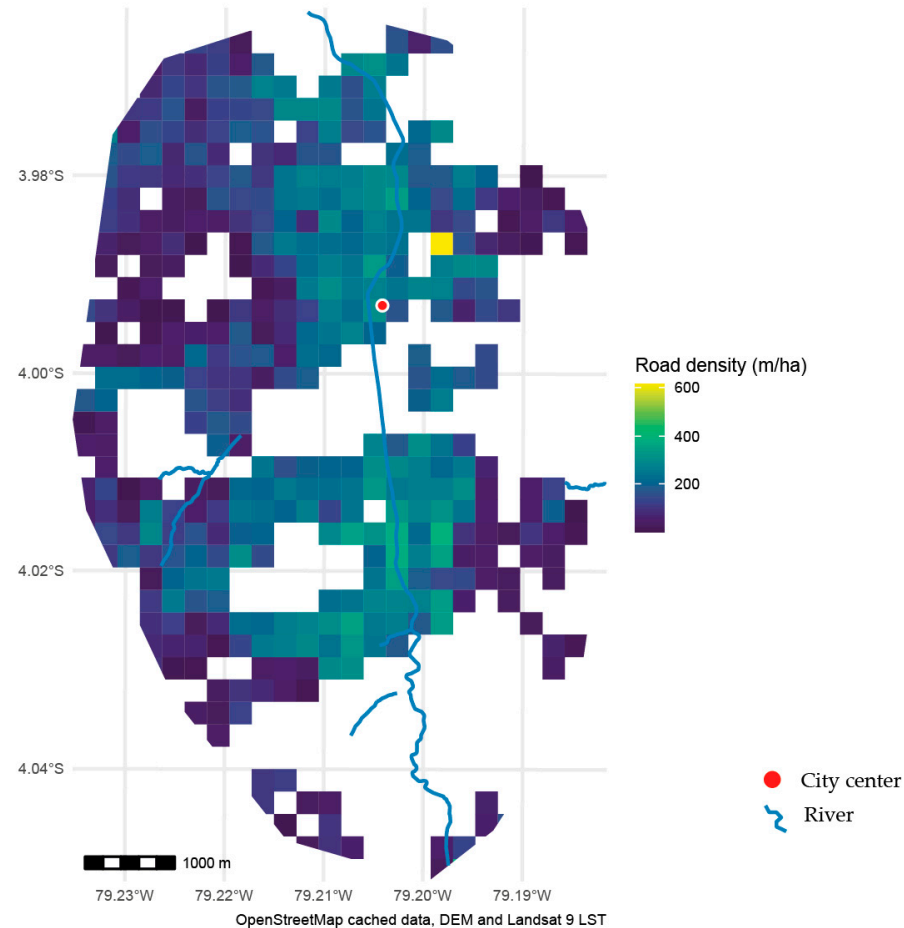


Figure 4. Road density and retained analytical grid at the 250 m scale.

3.4. Descriptive Patterns at the Primary 250 m Scale

At the 250 m scale, 427 analytical cells were retained. Mean LST was 30.0 °C, with values ranging from 20.1 °C to 37.1 °C. The distribution confirms that the polygon captures substantial surface-temperature heterogeneity across the urban area.

Urban-form indicators also showed strong spatial variability. Mean road density was 153 m/ha, although values ranged from 1.34 to 616 m/ha. This indicates that the retained grid includes both sparsely connected peripheral or edge cells and highly connected urban sectors. Intersection density averaged 0.270 intersections per hectare, with a maximum of 4.64 intersections per hectare. Building coverage was generally low, with a mean of 1.23%, but reached a maximum of 61.2% in some cells. Green coverage was also unevenly distributed: the median was 0%, while the maximum reached 74.6%.

Topography remained a relevant condition across the retained cells. Mean slope at 250 m was 9.50°, with values ranging from 1.82° to 24.6°. The mean distance to the nearest green area was 504 m, and the mean distance to the historic center was 2660 m. Table 5 summarizes the descriptive statistics for the main variables at the 250 m scale.

The relatively low mean building coverage should be interpreted cautiously. It reflects the proportion of each retained grid cell covered by OSM building-footprint polygons, not

the total impervious surface or built-up land cover. Several factors may contribute to the low average value: incomplete building-footprint mapping in OpenStreetMap, the inclusion of large grid cells containing roads, open spaces, slopes, river corridors, or partially developed areas, and the fact that many retained cells contain road presence and valid *LST* but limited mapped building polygons. The high maximum value indicates that some cells do capture dense built-up conditions, but the mean is reduced by the large number of cells with sparse or absent mapped building footprints. Therefore, building coverage should be interpreted as an open-data proxy for mapped building-footprint intensity rather than as a complete measure of urban imperviousness or built-up density.

Table 5. Descriptive statistics of the main variables at the 250 m scale.

Variable	<i>n</i>	Mean	SD	Min	Q25	Median	Q75	Max
Building coverage (%)	427	1.23	4.58	0	0	0	0	61.2
Distance to center (m)	427	2660	1238	103	1797	2623	3401	6343
Distance to green area (m)	427	504	438	0	167	371	730	1947
Green coverage (%)	427	1.85	7.69	0	0	0	0	74.6
Intersection density (per ha)	427	0.27	0.435	0	0	0.16	0.48	4.64
<i>LST</i> (°C)	427	30	3.25	20.1	28.6	30.5	32.3	37.1
Mean slope (degrees)	427	9.5	4.02	1.82	6.67	9	11.6	24.6
Road density (m/ha)	427	153	97.9	1.34	62.2	144	236	616
Walkability–heat balance index	427	~0	0.819	−1.88	−0.559	−0.0545	0.475	4.35
Urban heat intensity index	427	~0	0.674	−2.07	−0.335	0.0667	0.456	2.19
Walkability index	427	~0	0.792	−1.79	−0.57	−0.124	0.483	4.12

Note: The mean *LST* value reported corresponds to the rounded average of the retained 250 m analytical grid cells.

3.5. Associations Between Urban Form, *LST*, Walkability, and Comfort

The Spearman correlation matrix at the 250 m scale shows coherent relationships among urban form, accessibility, thermal conditions, and the composite indices. Road density was strongly correlated with intersection density ($\rho = 0.768$), confirming that denser road fabrics also tend to contain more network nodes. Road density was also positively associated with building coverage ($\rho = 0.432$), green coverage ($\rho = 0.474$), and *LST* ($\rho = 0.312$).

The relationship between *LST* and urban form was moderate rather than extreme. *LST* was positively correlated with road density ($\rho = 0.312$), intersection density ($\rho = 0.252$), and building coverage ($\rho = 0.267$). Its association with green coverage was weaker ($\rho = 0.114$). This weak positive relationship with green coverage should be interpreted cautiously and is reported in Table 6 because it is counterintuitive and requires explicit interpretation. It does not imply that vegetation increases surface temperature. More plausibly, it reflects co-location patterns in which some green areas are embedded within consolidated urban sectors that also contain denser infrastructure or higher surface temperatures.

Slope showed a consistent negative relationship with several urban-form and thermal variables. It was negatively associated with *LST* ($\rho = -0.414$), walkability ($\rho = -0.575$), road density ($\rho = -0.381$), and intersection density ($\rho = -0.310$). This pattern supports the decision to include slope as a constraint in the walkability index.

The walkability index was strongly associated with road density ($\rho = 0.885$), intersection density ($\rho = 0.839$), green coverage ($\rho = 0.618$), and negatively associated with distance to green areas ($\rho = -0.760$) and slope ($\rho = -0.575$). These associations indicate that the index behaves consistently with its conceptual structure.

The urban heat intensity index was strongly correlated with *LST* ($\rho = 0.937$), which confirms that the index remains primarily driven by observed surface temperature. Walkability–heat balance was positively associated with walkability potential ($\rho = 0.565$) and negatively

associated with heat intensity ($\rho = -0.460$). This confirms that comfort functions as a comparative balance between pedestrian-supportive spatial conditions and surface thermal pressure.

Table 6. Selected Spearman correlations among urban-form, thermal, walkability, and comfort indicators at the 250 m scale.

Relationship	Spearman's ρ	Interpretation
Road density–intersection density	0.768	Strong association between road density and network-node density
Road density–walkability index	0.885	Road density is a major contributor to walkability
Intersection density–walkability index	0.839	Connectivity strongly supports walkability
Green coverage–walkability index	0.618	Green presence contributes positively to the index
Distance to green area–walkability index	−0.760	Cells closer to green areas tend to be more walkable
Mean slope–walkability index	−0.575	Steeper terrain reduces walkability
<i>LST</i> –heat intensity index	0.937	Heat index is primarily driven by observed <i>LST</i>
<i>LST</i> –green coverage	0.114	Weak positive association; likely reflects co-location of green polygons within consolidated urban sectors rather than a causal thermal effect of vegetation
Walkability index–walkability–heat balance index	0.565	Comfort increases where walkability conditions are better
Heat intensity index–walkability–heat balance index	−0.460	Comfort decreases where heat intensity is stronger
<i>LST</i> –walkability–heat balance index	−0.422	Higher surface temperature reduces comfort scores

A summary of the most relevant Spearman correlations among urban-form, thermal, walkability, and comfort indicators at the 250 m scale is presented in Table 6.

3.6. Spatial Distribution of Walkability, Heat Intensity, and Urban Comfort

The 250 m maps reveal that walkability, heat intensity, and urban comfort are spatially structured but not perfectly aligned. The walkability index highlights areas where road density, intersection density, green coverage, accessibility, and lower slope combine to produce relatively favorable pedestrian conditions. Lower walkability values tend to occur in cells with weaker street-network structure, greater distance to green areas, or stronger topographic constraints.

The heat intensity index is more closely linked to the spatial distribution of observed *LST*. Since the index gives the highest weight to *LST*, its map should be interpreted primarily as a surface thermal-pressure diagnostic, adjusted by built-up intensity and green coverage. The heat-intensity map may show blank cells where the strict QA-masked *LST* was unavailable or where road presence was absent. These gaps are not zero values; they are excluded analytical cells.

The Walkability–Heat Balance Index shows a more composite spatial pattern. Cells with higher comfort values correspond to places where walkability-related conditions outweigh heat intensity. Lower comfort values occur where heat intensity is stronger relative to the pedestrian-supportive components of the index. Figure 5 provides a comparative visualization of the spatial distribution of walkability, observed *LST*-based heat intensity, and urban comfort at the 250 m analytical scale, allowing direct visual assessment of their spatial correspondence and divergence across the study area.

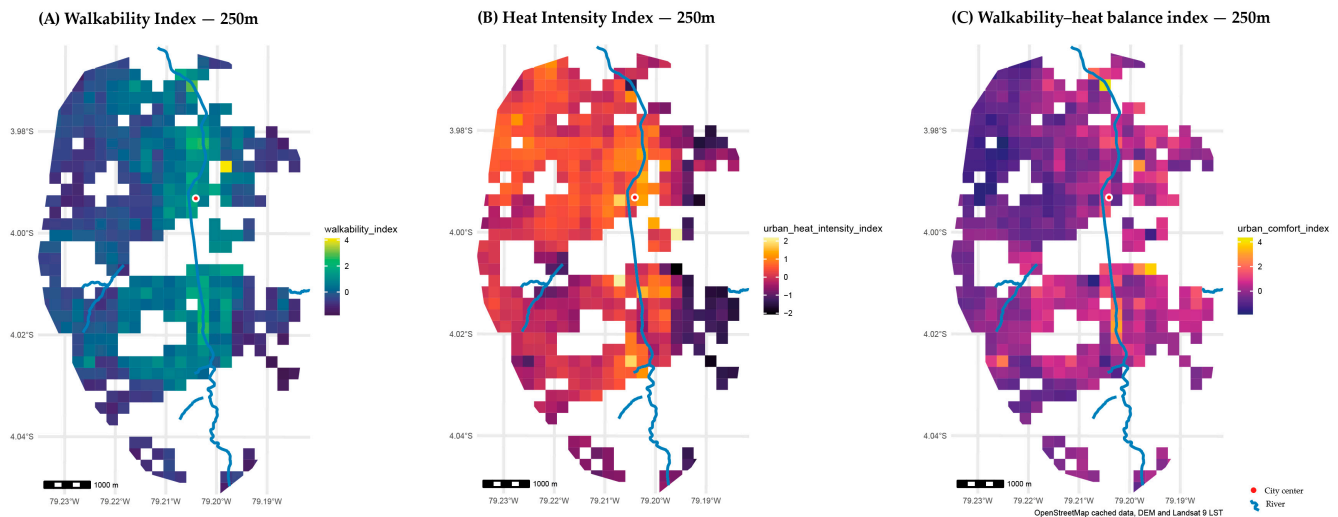


Figure 5. Spatial comparison of walkability, observed *LST*-based heat intensity, and urban comfort at the 250 m scale. (A) Spatial distribution of walkability conditions. (B) Spatial distribution of heat intensity derived from *LST* observations. (C) Spatial distribution of the walkability–heat balance (urban comfort) index.

3.7. Global Spatial Autocorrelation Across Grid Scales

Global Moran’s *I* confirmed that all three indices were spatially autocorrelated at all grid resolutions. This means that walkability, heat intensity, and urban comfort are not randomly distributed across the retained analytical grid.

At the 250 m scale, Moran’s *I* was 0.628 for walkability, 0.668 for observed *LST*-based heat intensity, and 0.493 for urban comfort. All values were statistically significant. Heat intensity showed the strongest spatial autocorrelation at 250 m, followed by walkability and comfort.

Across scales, heat intensity was consistently clustered, with Moran’s *I* values of 0.773 at 100 m, 0.668 at 250 m, and 0.600 at 500 m. Walkability also remained strongly autocorrelated, increasing from 0.615 at 100 m to 0.692 at 500 m. Urban comfort showed positive spatial autocorrelation at all scales, ranging from 0.493 at 250 m to 0.580 at 100 m.

Table 7 summarizes the Global Moran’s *I* results for walkability, observed *LST*-based heat intensity, and urban comfort across the three analytical grid scales, providing the statistical basis for the subsequent cross-scale spatial comparison.

Table 7. Global Moran’s *I* for walkability, observed *LST*-based heat intensity, and urban comfort across grid scales.

Grid Size	Index	Moran’s <i>I</i>	<i>p</i> -Value	Interpretation
100 m	Walkability	0.615	<0.001	Strong positive spatial autocorrelation
100 m	Observed <i>LST</i> -based heat intensity	0.773	<0.001	Very strong positive spatial autocorrelation
100 m	Urban comfort	0.580	<0.001	Strong positive spatial autocorrelation
250 m	Walkability	0.628	<0.001	Strong positive spatial autocorrelation
250 m	Observed <i>LST</i> -based heat intensity	0.668	<0.001	Strong positive spatial autocorrelation
250 m	Urban comfort	0.493	<0.001	Moderate-to-strong positive spatial autocorrelation
500 m	Walkability	0.692	<0.001	Strong positive spatial autocorrelation
500 m	Observed <i>LST</i> -based heat intensity	0.600	<0.001	Strong positive spatial autocorrelation
500 m	Urban comfort	0.552	<0.001	Strong positive spatial autocorrelation

Figure 6 illustrates the variation in Global Moran's I values across the three analytical grid scales, allowing direct comparison of the spatial sensitivity of walkability, observed *LST*-based heat intensity, and urban comfort.

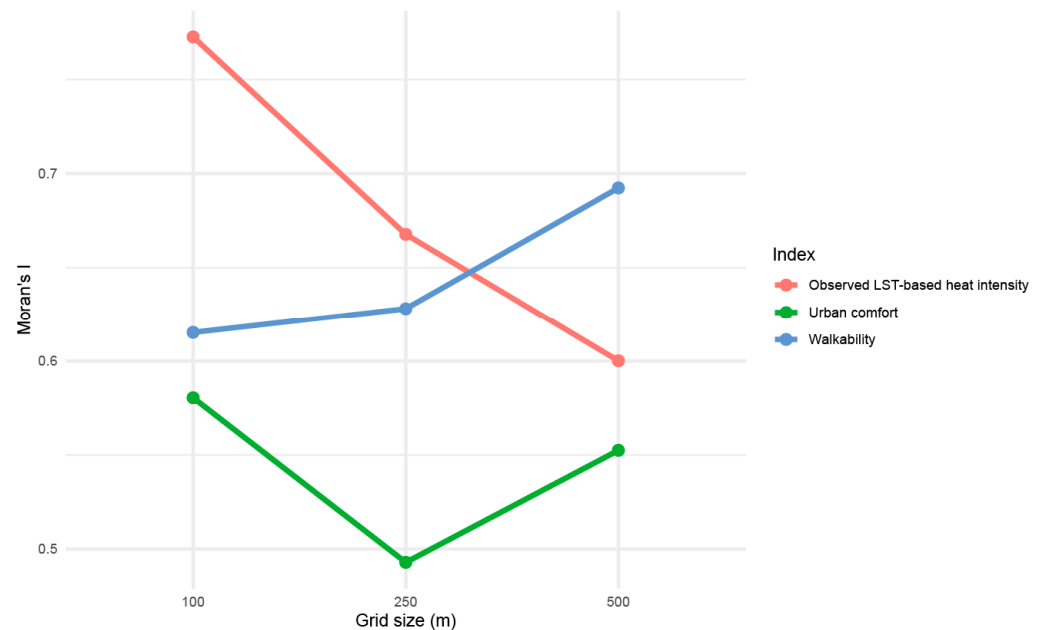


Figure 6. Multi-scale sensitivity of global Moran's I for walkability, observed *LST*-based heat intensity, and urban comfort.

3.8. Local Heat-Intensity Clusters

The LISA analysis identified statistically significant local clusters of observed *LST*-based heat intensity at all three grid resolutions after FDR correction. At 250 m, the main reporting scale, 26 cells were classified as High–High clusters, representing 6.09% of the retained analytical grid. These cells correspond to locations where high heat-intensity values are surrounded by neighboring cells with similarly high values. Low–Low clusters included 37 cells, representing 8.67% of the retained grid. The remaining 364 cells, or 85.25%, were not statistically significant.

At 100 m, the finer grid detected 171 High–High cells and 154 Low–Low cells. At 500 m, the coarser grid retained only 8 High–High cells and 11 Low–Low cells. This decrease in local cluster counts at coarser scales is expected because spatial aggregation smooths local heterogeneity.

Table 8 summarizes the distribution of FDR-corrected LISA cluster categories for the observed *LST*-based heat-intensity index across the three analytical grid scales. Figure 7 presents the spatial distribution of FDR-corrected LISA clusters for the observed *LST*-based heat-intensity index at the 250 m scale, highlighting localized concentrations of significantly high and low heat-intensity values within the retained analytical grid.

The multi-scale results indicate that the main spatial structure is not an artefact of a single grid size. Walkability, heat intensity, and urban comfort remained positively autocorrelated across all three resolutions. Still, the magnitude and local expression of clustering changed with scale.

The 100 m grid captured more detailed intra-urban variation and detected the largest number of local LISA clusters. This detail is useful for exploratory diagnosis, but it also increases fragmentation and may be more sensitive to small gaps in *LST* availability or OSM coverage. The 500 m grid produced smoother patterns and fewer local clusters, making it useful for broad structural interpretation but less suitable for identifying local intervention

areas. The 250 m grid provided the most balanced representation, retaining 427 analytical cells while preserving enough spatial detail for local interpretation.

Table 8. FDR-corrected LISA cluster summary for observed *LST*-based heat intensity.

Grid Size	Cluster Type	Number of Cells	Percentage
100 m	High–High	171	10.36%
100 m	Low–Low	154	9.33%
100 m	Not significant	1325	80.30%
250 m	High–High	26	6.09%
250 m	Low–Low	37	8.67%
250 m	Not significant	364	85.25%
500 m	High–High	8	5.33%
500 m	Low–Low	11	7.33%
500 m	Not significant	131	87.33%

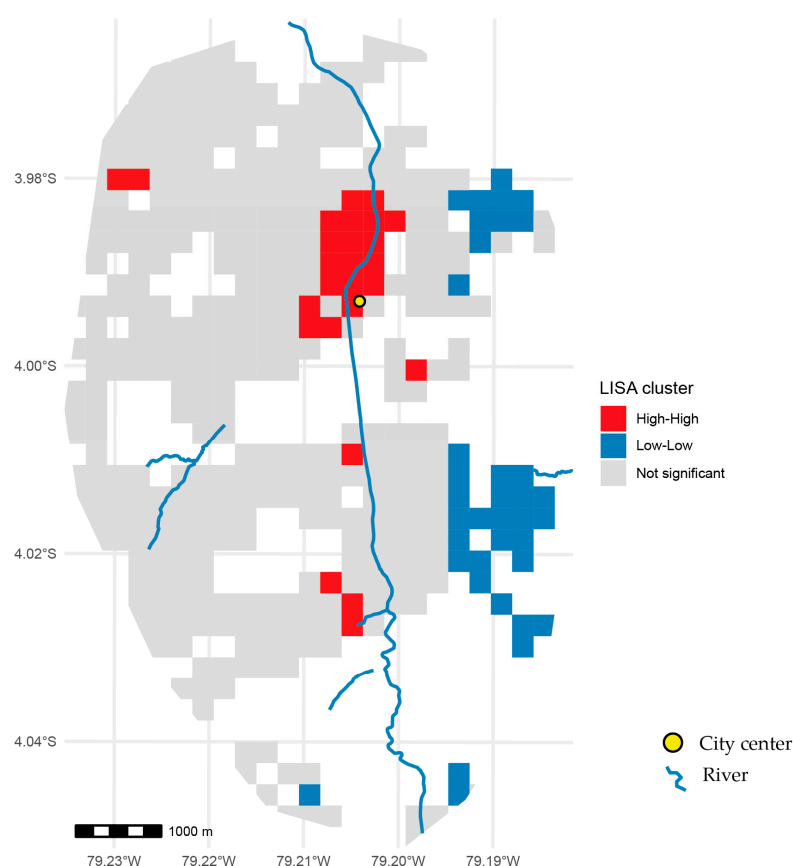


Figure 7. FDR-corrected LISA clusters of the observed *LST*-based heat intensity index at the 250 m scale.

The cross-scale comparison supports the decision to use the 250 m scale as the main reporting level, while presenting 100 m and 500 m as sensitivity analyses. This structure strengthens the methodological claim of the article because it shows that the workflow can detect stable spatial tendencies while making the effects of spatial aggregation explicit.

The selective distribution of heat-intensity clusters suggests that surface heat in Loja is not organized as a continuous urban field but as a set of localized concentrations. These concentrations are likely associated with the interaction between valley-floor urbanization, higher road-network density, built-up intensity, limited vegetation, and relatively flatter areas where urban consolidation is more feasible. In contrast, low-intensity clusters ap-

pear more consistent with less consolidated or more topographically constrained sectors, where lower built intensity, greater exposure to vegetated surfaces, or elevation-related conditions may reduce observed surface thermal pressure. This interpretation should be treated as spatially diagnostic rather than causal because the workflow does not include detailed landuse classification, street-canyon geometry, surface materials, or field-based microclimatic observations.

3.9. Sensitivity of Composite Indicators to Alternative Weighting Schemes

A sensitivity analysis was conducted to evaluate whether the spatial results depended strongly on the theoretical weights assigned to the composite indicators. The baseline Walkability Index, observed *LST*-based Heat Intensity Index, and *WHBI* were compared with alternative weighting schemes representing equal-component weights, network-emphasis, green-accessibility-emphasis, slope-constraint-emphasis, *LST*-dominant heat intensity, reduced-*LST* heat intensity, balanced thermal–urban-form specifications, and stronger green-mitigation assumptions.

At the 250 m scale, the Walkability Index showed very high stability under alternative weighting schemes. Spearman correlations between the baseline index and the alternative walkability specifications ranged from 0.984 to 0.995. Global Moran's *I* remained positive across all walkability scenarios, ranging from 0.593 to 0.700. The minimum overlap with the baseline top 20% of cells was 91.9%, while the minimum overlap with the baseline bottom 20% was 81.4%. These results indicate that the broad spatial ordering of walkability potential was not substantially altered by reasonable changes in the weighting structure.

The observed *LST*-based Heat Intensity Index also showed very high rank stability. Spearman correlations between the baseline heat-intensity index and the alternative specifications ranged from 0.989 to 0.994. Global Moran's *I* remained positive across the tested scenarios, ranging from 0.442 to 0.758. However, the local LISA classifications were more sensitive than the global ranking and autocorrelation results. The minimum High–High cluster retention was 61.5%, while the minimum Low–Low cluster retention was 47.2%. This indicates that the general heat-intensity structure was not merely an artefact of the baseline *LST* weight, but that the exact local delimitation of statistically significant clusters can change when the relative contribution of *LST*, building coverage, and green coverage is modified.

The Walkability–Heat Balance Index was more sensitive than either component alone, as expected, because it combines variation from both the walkability and heat-intensity specifications. Across the combined weighting scenarios, Spearman correlations with the baseline *WHBI* ranged from 0.935 to 0.995. Global Moran's *I* for *WHBI* ranged from 0.370 to 0.627. The minimum overlap with the baseline top 20% of *WHBI* cells was 79.1%, and the minimum overlap with the baseline bottom 20% was also 79.1%. The minimum quintile agreement across *WHBI* scenarios was 68.1%. These values suggest that the *WHBI* preserves a relatively stable broad spatial structure, although local cell rankings are more sensitive than those of the component indices.

Overall, the sensitivity analysis indicates that the broad spatial structure of the composite indicators is reasonably robust to alternative theoretical weights, particularly in terms of rank correlation and global spatial autocorrelation. At the same time, the results show that local rankings and LISA cluster membership remain partly sensitive to modelling assumptions. For this reason, the indices should be interpreted as heuristic spatial diagnostics rather than as empirically calibrated or validated measurement models. The sensitivity results support the use of the workflow for exploratory spatial prioritization while reinforcing the need for future validation using field-based microclimatic measurements, pedestrian observations, and perception-based data.

4. Discussion

4.1. A Methodological Workflow Rather than a City-Only Diagnosis

Framing this study as an exploratory diagnostic workflow is central to its contribution. Heat-aware walkability is not directly observable in a single dataset, and the available open-data layers cannot fully capture pedestrian behavior, street-level shade, sidewalk quality, route choice, or physiological thermal comfort. The workflow therefore provides a reproducible way to combine heterogeneous spatial proxies and examine whether their relationships form interpretable spatial patterns across multiple grid resolutions.

For intermediate cities, where detailed official datasets are frequently incomplete or difficult to access, this type of transparent first diagnostic layer has practical value before field surveys, pedestrian audits, or high-resolution microclimatic campaigns are feasible. Its purpose is not to produce a definitive comfort map, but to make visible where surface thermal pressure, walkability-related urban form, green access, and topographic constraint converge or diverge.

The results also show why single-variable approaches are insufficient. *LST* identifies where surfaces are relatively hot on the acquisition date, but it does not indicate whether those areas are walkable, central, steep, green-deficient, or structurally connected. Road density reveals where the network is present, but cannot distinguish thermally exposed corridors from shaded ones. Green coverage provides an environmental proxy, but its cooling effect depends on vegetation structure, canopy density, irrigation, spatial configuration, and surrounding morphology [18,20,21]. Each variable is informative in isolation; together, they produce a spatial diagnostic that cannot be obtained from any single layer alone.

4.2. Urban Heat as a Spatial Condition Embedded in Urban Form

The Landsat-derived *LST* results confirm that the analytical polygon of Loja contains a marked surface-temperature gradient on the acquisition date. These values represent land surface temperature, not near-surface air temperature, pedestrian heat exposure, or physiological thermal comfort. They should therefore be interpreted as evidence of spatial variation in observed surface thermal pressure rather than as a complete description of Loja's urban climate.

This pattern is consistent with the broader literature linking land-cover transformation, impervious surfaces, vegetation loss, and urban thermal intensification [1–3,29]. In Loja, however, the thermal pattern does not follow a simple urban–rural gradient. The city's Andean setting produces short-distance variation in slope, elevation, urban density, green-space distribution, and road-network structure. The moderate correlations between *LST* and road density, intersection density, and building coverage at the 250 m scale suggest that surface heat is related to urban consolidation without being mechanically determined by it.

The weak positive association between green coverage and *LST* at 250 m deserves careful interpretation. It does not mean that vegetation increases surface temperature. A more plausible explanation is that some OSM green polygons are embedded within consolidated urban sectors that also contain dense roads, built structures, and warmer surfaces. OSM green polygons also vary considerably in what they represent: some may correspond to tree-covered parks, while others may be grassed, exposed, fragmented, or partially paved spaces. For this reason, green coverage remains a useful but incomplete proxy. Future refinements should distinguish tree canopy, grass, shrub cover, irrigated vegetation, and shaded pedestrian corridors, since different forms of urban greening produce meaningfully different cooling effects [18,19].

The relatively low mean building coverage should also be interpreted cautiously. In this study, building coverage represents the proportion of each retained grid cell covered by

OSM building-footprint polygons, not total impervious surface or complete built-up land cover. Several factors may explain the low average value: incomplete building-footprint mapping in OpenStreetMap, the inclusion of grid cells containing roads, open spaces, river corridors, steep slopes, or partially developed areas, and the fact that many retained cells include road presence and valid *LST* but few mapped building polygons. The presence of higher maximum values indicates that dense built-up conditions are captured in some cells, while the mean is reduced by many cells with sparse mapped building footprints. Building coverage should therefore be interpreted as an open-data proxy for mapped building-footprint intensity rather than as a complete measure of urban imperviousness.

4.3. Heat-Aware Walkability as a Coupled Spatial Condition

The results reinforce the argument that walkability potential and surface heat should be evaluated together. At the 250 m scale, the walkability index responded strongly to road density, intersection density, green coverage, and proximity to green areas, while slope acted as a clear constraint. However, these variables represent spatial proxies rather than the full range of conditions that shape walking behavior. The index should therefore be interpreted as a measure of walkability potential, not as a comprehensive pedestrian-quality or behavioral walkability measure. This interpretation is conceptually coherent with established built-environment approaches to walkability, where connectivity, density, landuse configuration, and access to destinations are considered jointly [16,28,30,34].

What the Loja results add is the coexistence of pedestrian-supportive morphology and surface heat in the same locations. The positive correlation between walkability and *LST* at 250 m, although not dominant, suggests that parts of the urban fabric with stronger street-network structure may also carry warmer surface conditions. For planning, this is important: a highly connected area may be spatially walkable but exposed to higher surface thermal pressure, while a cooler area may offer limited everyday pedestrian value if it is steep, disconnected, or poorly integrated into the network.

The Walkability–Heat Balance Index (*WHBI*) was designed to capture this spatial tension rather than resolve it. It does not measure physiological comfort. Instead, it provides a comparative spatial indicator of the balance between walkability-related conditions and surface thermal pressure. At 250 m, *WHBI* values increased where pedestrian-supportive conditions were stronger relative to heat intensity and decreased where heat intensity became more dominant. Within an open-data framework, its value lies in spatial prioritization: identifying where more detailed field surveys, thermal-comfort measurements, pedestrian observations, or design interventions should be concentrated.

4.4. Spatial Autocorrelation and the Geography of Clustering

Global Moran's *I* confirmed significant positive spatial autocorrelation for walkability potential, observed *LST*-based heat intensity, and *WHBI* across all three grid sizes. At the 250 m scale, heat intensity showed the strongest spatial structure, followed by walkability potential and *WHBI*. This is consistent with the idea that surface heat tends to form spatially coherent clusters because adjacent areas often share surface materials, land-cover configuration, and urban morphology [2,3].

The LISA results qualify this global pattern. At 250 m, High–High heat-intensity clusters represented 6.09% of retained cells, and Low–Low clusters represented 8.67%. Most of the retained grid, 85.25% of cells, was not locally significant after FDR correction. These results indicate that heat intensity in Loja is spatially selective rather than continuous across the retained analytical grid. Consequently, heat-mitigation strategies should not be distributed uniformly across the city. Some areas may require targeted cooling,

shading, or surface-material interventions, while others may function as relatively cooler spatial pockets.

The LISA categories can be interpreted as different urban-thermal situations within the retained analytical grid. High–High heat-intensity clusters indicate areas where high surface thermal pressure is spatially reinforced by neighboring cells with similarly high values. In Loja, these clusters are likely associated with more consolidated valley-floor sectors, higher road-network density, greater built-up intensity, lower vegetation continuity, and heat-retaining surface materials. These areas are especially relevant for targeted field verification because they combine local heat intensity with spatial continuity.

Low–Low clusters represent areas where lower heat-intensity values are surrounded by similarly low values. These areas may correspond to less consolidated sectors, more vegetated surroundings, lower built-up intensity, elevation-related cooling effects, or topographically constrained zones where urban development is less intense. However, they should not automatically be interpreted as comfortable pedestrian environments, because lower surface thermal pressure may coincide with weaker accessibility, steeper slopes, or limited street-network integration.

Cells classified as not significant should also be interpreted carefully. They do not indicate the absence of heat-related concerns, but rather the absence of statistically significant local clustering after FDR correction. These areas may include transitional urban fabrics where heat intensity, built form, vegetation, and slope vary over short distances. The use of FDR correction is relevant because local autocorrelation tests involve multiple comparisons, and uncorrected significance levels can overstate the number of meaningful clusters. Applying a false discovery rate adjustment produces a more conservative set of locally significant results, which is appropriate for a study intended to support planning prioritization rather than maximize the apparent extent of clustering.

The spatial selectivity of the heat-intensity clusters can be interpreted through the interaction between topography and urban form. Loja's valley setting concentrates much of the urbanized fabric in relatively flatter areas, where road density, intersection density, and built coverage tend to be higher. These same areas may contain more impervious surfaces and less continuous vegetation, creating conditions consistent with higher observed *LST*-based heat intensity. By contrast, steeper or more peripheral sectors may limit urban consolidation and produce lower levels of built-up intensity, reducing the likelihood of statistically significant High–High heat-intensity clusters.

This mechanism shows that heat exposure is not simply a function of urban density. In an Andean intermediate city, topography shapes where urban growth occurs, where pedestrian movement is feasible, and where surface thermal pressure may accumulate. The observed clusters therefore reflect a spatial interaction between terrain, street-network structure, vegetation distribution, and built-up intensity. Future refinements should incorporate street-level cross-sections, surface-material surveys, tree-canopy data, and functional landuse information to distinguish, for example, dense historic areas, commercial corridors, new development zones, industrial or logistical sectors, and lower-density peripheral areas.

4.5. Scale Sensitivity and the Choice of 250 m as Main Reporting Scale

The multi-scale analysis produced an important asymmetry. Heat intensity showed decreasing spatial autocorrelation as the grid coarsened, with Moran's *I* dropping from 0.773 at 100 m to 0.600 at 500 m. Walkability moved in the opposite direction, increasing from 0.615 at 100 m to 0.692 at 500 m. This divergence is not surprising once the compositional differences between the two indices are considered. Walkability integrates multiple network and accessibility variables that tend to produce smoother spatial gradients at coarser scales, because road density and connectivity are themselves spatially autocorrelated over larger

distances. Heat intensity, by contrast, is dominated by *LST*, which retains finer-grained spatial heterogeneity that becomes progressively diluted with aggregation. *WHBI* remained positively autocorrelated at all scales but showed less stability than the two component indices, reflecting its dependence on both walkability potential and heat intensity.

In this context, the modifiable areal unit problem is not merely a technical consideration; it directly affects the interpretation of heat-aware walkability [26]. A cluster visible at 100 m may disappear at 500 m, while a broad corridor visible at 500 m may conceal local discontinuities that matter for street-level intervention. The 250 m grid offered the most workable balance for this case study: it retained sufficient analytical cells, preserved meaningful intra-urban differentiation, and produced interpretable Moran and LISA results without the excessive fragmentation observed at 100 m. This does not mean that 250 m is generally optimal for heat-aware walkability analysis. Rather, it was the most informative scale for this specific combination of Landsat-derived *LST*, OSM urban-form indicators, DEM-derived slope, QA-filtered data availability, and the analytical extent of Loja. Other cities, sensors, data sources, and planning questions may require different grid sizes or multi-scale reporting strategies.

4.6. Planning Implications for Loja and Comparable Intermediate Cities

For Loja, the results identify heat-aware walkability as a spatial planning priority. The most relevant intervention areas are not those characterized solely by high land-surface temperature or high walkability potential, but those where elevated surface thermal pressure coincides with pedestrian-supportive urban form. These overlap zones should be prioritized for field verification and detailed design assessment.

Loja's Andean topography requires a more selective planning approach than would be appropriate in flatter cities. Steep slopes constrain pedestrian movement, reduce route continuity, and limit the feasibility of uniform green-corridor strategies. Consequently, interventions should focus on slope-feasible pedestrian corridors, highly connected valley-floor routes, and locations where heat-intensity clusters intersect with everyday mobility patterns. In these areas, thermal mitigation measures may include tree-canopy reinforcement, lightweight shade structures, shaded public-transport stops, and cooler or permeable surface materials.

More specific interventions can be differentiated by urban context. In High-High heat-intensity areas with relatively strong street connectivity, priority should be given to shade-oriented pedestrian corridors, continuous tree planting where sidewalk width permits, lightweight shading structures in narrow streets, shaded bus stops, and cooler or permeable pavement in plazas and pedestrian waiting areas. In areas where heat intensity overlaps with limited green access, interventions should focus on improving shaded routes to existing parks, adding small pocket green spaces, and increasing tree canopy along connecting streets rather than only expanding mapped green polygons.

In steep sectors, interventions should be adapted to slope constraints. Instead of assuming continuous green corridors, planning should prioritize slope-feasible walking routes, resting points, shaded stairways or ramps, and vegetation strategies that do not obstruct visibility or pedestrian movement. In consolidated central areas, where road density and accessibility are higher, thermal mitigation should be integrated into street redesign, traffic calming, pedestrian crossings, and public-space upgrades. These examples illustrate how the diagnostic workflow can guide targeted field assessment and context-sensitive interventions rather than uniform citywide prescriptions.

The findings also highlight the importance of evaluating functional access to green spaces rather than relying solely on mapped green coverage. Proximity to a green area does not necessarily imply pedestrian accessibility where steep terrain, disconnected street

networks, or limited entry points restrict movement. Planning efforts should therefore prioritize shaded and accessible routes to parks, strengthen connections between isolated green areas and pedestrian corridors, and improve the usability of existing green infrastructure.

The proposed workflow can support municipal planning by identifying locations where more detailed assessments of shade availability, sidewalk quality, pedestrian activity, surface materials, and thermal exposure are most needed. Its role is diagnostic rather than prescriptive, providing a first screening layer that helps direct field investigations and prioritize investments. Although the approach is transferable to other intermediate Andean and Latin American cities, implementation strategies should be adapted to local topography, landuse patterns, mobility conditions, and planning regulations.

4.7. Limitations and Future Refinement

Several limitations bear directly on the interpretation of the results and on the conditions under which the workflow can be transferred to other contexts.

The thermal component relies on a single Landsat 9 scene (LC09_L2SP_010063_20260414_20260415_02_T1, acquired on 14 April 2026). A second scene from 16 May 2026 was evaluated but discarded due to extensive cloud cover, which reduced valid strict QA-masked pixels to a level insufficient for meaningful grid-based analysis across the study polygon. Given the limited number of available scenes and the QA-filtering requirements of the workflow, the April acquisition was the only viable option for the analysis. The *LST* pattern therefore captures the surface thermal condition of a specific date rather than a seasonal or annual average. Surface temperature varies with season, soil moisture, vegetation phenology, atmospheric state, and antecedent rainfall, and a single scene cannot represent that variability. Future applications should incorporate multi-date composites when cloud-free acquisitions are available, or combine Landsat scenes with other thermal sensors to increase temporal coverage.

A second limitation concerns the nature of *LST* itself. Satellite-derived surface temperature captures the radiometric temperature of land surfaces, which differs from near-surface air temperature and from the physiological indicators used in human thermal comfort models. Variables such as mean radiant temperature, wind speed, humidity, shade continuity, and pedestrian-level exposure are not represented in the workflow. Future work integrating field-based microclimatic measurements with the spatial framework developed here would allow a more direct assessment of outdoor thermal stress.

The composite indices introduce another limitation. The weights assigned in the walkability index and the heat intensity index are theoretically motivated rather than empirically calibrated. The added sensitivity analysis reduces this uncertainty by showing that broad spatial patterns are relatively robust under alternative weighting schemes, but it does not eliminate the need for future validation. Neither index has been validated against observed walking behavior, pedestrian counts, thermal-comfort surveys, or health outcomes in Loja. Future applications should treat the current weights as a starting point and continue testing alternative specifications, particularly in cities with different morphological or climatic profiles.

OpenStreetMap data represent an important source of uncertainty. Road networks in OSM are generally well represented in Loja, but building footprints and green-area polygons vary in completeness and thematic accuracy. Building coverage represents mapped building-footprint intensity, not total impervious surface or complete built-up density. It does not capture paved surfaces, roofs missing from OSM, parking areas, plazas, compacted surfaces, or other impervious materials that may contribute to surface heating. Future applications could improve this component by incorporating official cadastral layers,

high-resolution built-up area products, impervious-surface datasets, or building-footprint extraction from remote sensing.

Green polygons also do not distinguish tree canopy from grass, shrubs, paved plazas with scattered vegetation, or irrigated surfaces. This matters because different forms of urban greening produce different cooling effects depending on canopy density, vegetation type, spatial configuration, and surrounding morphology [18,19]. The green-space indicators used here do not capture vegetation density, tree-canopy cover, canopy height, shade provision, irrigation status, or vegetation health. Future refinements should incorporate vegetation-quality indicators such as NDVI, enhanced vegetation index, high-resolution tree-canopy layers, LiDAR-derived canopy height, or local urban-forest inventories where available. These datasets would allow the workflow to distinguish between simple green-space presence and actual cooling or shading potential.

The strict QA mask introduces potential sampling bias because retained cells are more likely to correspond to valid clear-sky observations, while areas affected by clouds, shadows, or other QA exclusions are omitted. In a topographically complex city such as Loja, this may influence the spatial distribution of valid *LST* retrievals. Therefore, blank cells should not be interpreted as thermally neutral or irrelevant, but rather as locations where reliable *LST* estimates were unavailable. The *WHBI* should thus be interpreted as conditional on data availability and QA filtering. While this conservative approach improves scientific rigor by avoiding uncertain thermal estimates, it reduces spatial completeness. Future studies should evaluate multi-date composites, alternative QA thresholds, or controlled gap-filling methods to assess potential differences between retained and excluded areas.

The manually defined analytical boundary may influence the calculated indicators because grid counts, density values, distance measures, and spatial autocorrelation statistics are conditional on the selected study extent. Including larger peripheral or rural areas could reduce average road density, building coverage, and heat-intensity values, while a more restrictive boundary could emphasize consolidated urban sectors. Therefore, the results should be interpreted as conditional on the adopted analytical polygon. Future studies could test alternative boundary definitions, such as official urban limits, built-up area classifications, or sensitivity buffers around the urban footprint, to evaluate how boundary selection affects the spatial indicators.

The accessibility variables are based on Euclidean distance rather than pedestrian network distance. These are operational proxies that do not capture network travel distance, sidewalk quality, crossing availability, route-level slope, perceived safety, or actual pedestrian behavior. This simplification may overestimate accessibility in areas where the street network is discontinuous, where steep slopes constrain movement, or where green spaces are physically close but not easily reachable through walkable routes. In Loja, this issue is particularly relevant because topography can make straight-line proximity misleading. Future applications should replace Euclidean distances with network-based accessibility measures derived from pedestrian-relevant street networks. Such measures could incorporate walking distance, route slope, intersection structure, access points to green spaces, and potentially sidewalk or crossing-quality information where available.

The spatial weights used for Moran's *I* and LISA were calculated on the retained analytical grid rather than on the full analytical polygon. Because cells without road presence or valid *LST* were excluded, the neighbor graph contained multiple subgraphs: 17 at 100 m, 4 at 250 m, and 2 at 500 m. Spatial autocorrelation results therefore describe the structure of the retained road-and-*LST* grid, not the continuous urban surface. Future versions of the workflow could compare retained-grid weights with full-polygon alternatives or test distance-based neighbor definitions to assess how the neighbor structure affects clustering results.

4.8. Overall Contribution

The main contribution of this study is the development and empirical testing of a reproducible open-data workflow for diagnosing the spatial relationship between walkability potential and surface thermal pressure in a data-constrained intermediate city. The Loja application shows that open geospatial data can reveal structured spatial relationships among *LST*, street-network conditions, green access, slope, and walkability–heat balance.

The workflow is not intended to replace field-based thermal-comfort studies, pedestrian surveys, or detailed urban-design audits. Its value lies in providing a transparent first diagnostic layer that can help identify where more detailed investigation is needed. This is particularly relevant for intermediate Andean and Latin American cities, where planning decisions often need to be made despite limited local monitoring infrastructure and incomplete official spatial datasets.

5. Conclusions

This study developed and tested a reproducible open-data workflow for examining the spatial relationship between walkability potential and observed surface thermal pressure in Loja, Ecuador. The analysis combined Landsat-derived land surface temperature, OpenStreetMap urban-form indicators, DEM-derived slope, composite heuristic indicators, and spatial autocorrelation across 100 m, 250 m, and 500 m grids. The results show that walkability potential, observed *LST*-based heat intensity, and walkability–heat balance is spatially structured rather than randomly distributed across the retained analytical grid. At the 250 m scale, the heat-intensity clusters were spatially selective, indicating that surface thermal pressure is concentrated in particular areas rather than uniformly distributed across the city. For this case study, the 250 m grid provided the most interpretable balance between local detail and spatial stability, although this scale should not be interpreted as generally optimal.

The main contribution of the study is not a definitive comfort map or a validated model of pedestrian heat exposure. Rather, it is an exploratory diagnostic framework that helps identify where pedestrian-supportive urban form and surface thermal pressure overlap, diverge, or require further investigation. The Walkability–Heat Balance Index should be interpreted as a spatial balance indicator, not as a measure of physiological thermal comfort. Several limitations remain central to interpretation. The thermal component is based on a single Landsat 9 scene and represents date-specific surface thermal pressure. The walkability index relies on open-data proxies and does not include sidewalk quality, crossing safety, landuse mix, shade continuity, pedestrian counts, or perceived safety. Strict QA masking improves reliability but reduces spatial completeness and may introduce data-availability bias. The weighting structure is theoretically informed and should be interpreted cautiously, even with sensitivity testing.

Future research should validate and extend the workflow through multi-date *LST* composites, field-based microclimatic measurements, canopy and shade indicators, network-based accessibility, landuse and street-level morphology data, pedestrian observations, and perception-based thermal-comfort surveys. Under these conditions, the workflow can serve as a transparent first diagnostic layer for data-constrained intermediate cities, supporting more targeted and evidence-informed field investigation and planning analysis.

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