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Visual Assessment of Street-level Thermal Comfort Potential: A Comparative Study of Turin and Detmold

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Abstract

As urban heat intensifies under climate change, understanding which streetscape characteristics make urban environments visually comfortable has become relevant for urban design and heat adaptation planning. This thesis investigates visual thermal comfort potential, or how thermally comfortable a street appears from a photograph, across two European cities with contrasting climatic backgrounds: Turin, Italy (humid subtropical) and Detmold, Germany (oceanic temperate).

A multi-layer attribute selection was developed combining Local Climate Zone (LCZ) classification for point selection, remote sensing indices (LST, NDVI, MNDWI, albedo), and pixel-fraction streetscape attributes from semantic segmentation of street-view imagery. A structured image-rating questionnaire was distributed to 235 residents across ten survey points per city in both cities. Analysis proceeded through inter-rater validation, city-level comfort profiling, respondent-group comparisons across socio-demographic variables, and a machine learning pipeline with SHAP-based variable influence analysis.

Detmold respondents rated the same images more comfortable than Turin respondents, reflecting the role of climatic background in shaping comfort expectations. When streetscape attributes and questionnaire variables were modelled jointly using a random forest, scene composition consistently outweighed respondent profile. Sidewalk share and vegetation share dominated in Detmold; sky share and wall share in Turin. Among the attributes, Vegetation share, sky share, pole share, wall share, and MNDWI were positively associated with comfort in both cities, while LST, road share, person share, and bicycle share reversed direction between cities, indicating context-dependent associations.

The study contributes a replicable cross-city framework linking LCZ classification, environmental attributes, and visual comfort ratings, and demonstrates that the streetscape features driving perceived comfort differ substantially across climatic contexts, with direct implications for thermally responsive street design.

Keywords: Visual thermal comfort potential, Local Climate Zone, street-view imagery, semantic segmentation, remote sensing, SHAP, Turin, Detmold.

List of Abbreviations

Abbreviation	Full Term
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BGI	Blue-Green Infrastructure
CatBoost	Categorical Boosting (machine learning algorithm)
CFD	Computational Fluid Dynamics
CRS	Coordinate Reference System
DN	Digital Number
ENRM	Elastic Net Regularization Model (Lasso + Ridge)
EPSG	European Petroleum Survey Group (coordinate reference system code)
EROS	Earth Resources Observation and Science Center
ETRS89	European Terrestrial Reference System 1989
GADM	Database of Global Administrative Areas
GEE	Google Earth Engine
GSV	Google Street View
GVI	Green View Index
H/W	Height-to-Width ratio
KML	Keyhole Markup Language
KMZ	Keyhole Markup Language (compressed)
KNN	K-Nearest Neighbors (regression)
LCZ	Local Climate Zone
LightGBM	Light Gradient Boosting Machine
LST	Land Surface Temperature
MAE	Mean Absolute Error
ML	Machine Learning
MNDWI	Modified Normalized Difference Water Index
MSE	Mean Squared Error
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infrared
NRW	North Rhine-Westphalia
OA	Overall Accuracy
OLS	Ordinary Least Squares
OTC	Outdoor Thermal Comfort
PET	Physiologically Equivalent Temperature
PICOS	Population, Intervention, Comparator, Outcome, Setting
RGB	Red, Green, Blue (color model)
RMSE	Root Mean Squared Error
RQ	Research Question
RS	Remote Sensing
SD	Standard Deviation
SHAP	SHapley Additive exPlanations
SPEQ	Subjective Perception Evaluation Questionnaire
SVF	Sky View Factor
SVI	Street View Imagery
SVR	Support Vector Regression
SWIR	Short-Wave Infrared
UH	Urban Heat
UHI	Urban Heat Island

USGS	United States Geological Survey
UTCI	Universal Thermal Climate Index
VATA	Visual Assessment of Thermal Affordance
WOS	Web of Science
WUDAPT	World Urban Database and Access Portal Tools
XGBoost	Extreme Gradient Boosting

Table 1. list of abbreviations used in this study. Created by author.

AI Tool Disclosure

In the preparation of this thesis, Grammarly (Grammarly Inc.) was used as a grammar and language editing tool to improve the clarity and correctness of the written text. All academic content, arguments, analyses, and conclusions are entirely the author's own. The use of this tool was limited to linguistic revision and did not involve the generation of any substantive content.

Data Availability

All scripts and code developed for this research are documented and publicly available via the link provided in the Appendix.

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1.1 Background

Urban environments are experiencing intensifying heat stress as a consequence of both global climate change and the Urban Heat Island (UHI) effect (Jabbar et al., 2023; Tong et al., 2021). Research shows by 2050, over 78% of the cities will experience 2.5°C increase in temperature (Yu et al., 2026). During heatwave events, there is also temperature difference in cities that can range from 1–4°C on average to more than 10°C, and its effects are not evenly distributed across urban space: compact, densely built street typologies accumulate more heat than open, vegetated ones (Pappalardo et al., 2023). In this context, the thermal quality of cities has become an important concern for urban planning, public health, and mobility research (Lee et al., 2025).

The thermal conditions experienced by pedestrians at street level are directly shaped by streetscape attributes including vegetation cover, surface materials, sky exposure, and the visual composition of the built environment (Jamei & Rajagopalan, 2019). A widely adopted framework for comparing thermal differences across urban contexts is the Local Climate Zone (LCZ) classification, which organizes urban landscapes into distinct classes defined by their surface cover, morphology, and thermal properties (Oke et al., 2017; Stewart & Oke, 2012). The LCZ classification, produces measurably different local thermal environments, and has been shown to correspond with significant variation in both microclimatic conditions and subjective thermal perception across urban settings (Lam et al., 2023; R. Liu et al., 2026).

Among the physical attributes influencing the thermal conditions in cities, some measurable attributes are: Land Surface Temperature (LST) that has been widely used as the primary indicator of UH stress (C. Hu & Zeng, 2025; Urban et al., 2022), Normalized Difference Vegetation Index (NDVI) that measures vegetation density, and has been shown to reduce thermal load through vegetation-driven shading and evaporation (Larkin et al., 2021), Modified Normalized Difference Water Index (MNDWI) that captures the independent cooling effect of water features and surface moisture (C. Hu & Zeng, 2025), albedo that determines the proportion of incoming solar radiation absorbed and re-emitted as sensible heat within the street canyons (Oke et al., 2017). These remotely sensed data are widely used in studies that examine the influence of physical streetscape attributes on thermal comfort (Hadibasyir & Firdaus, 2022; Kursah, 2023; Sharma et al., 2021).

The physical dimension of street thermal conditions accounts for only part of how people experience and evaluate UH. Microclimatic parameters explain around 50% of the variation in people's subjective assessments of outdoor thermal comfort, and the rest being attributable to psychological adaptation factors including expectations, perceived control, and the visual richness of the environment (Nikolopoulou & Steemers, 2003). To assess the thermal comfort potential of the streets, researchers evaluate it from direct sensory experience and visual assessment that is called "Thermal Affordance". Thermal affordance is the capacity of a streetscape to effect thermal comfort, as visually communicated by the appearance of sky

exposure, shade, vegetation, building enclosure, and surface materials(S. Yang et al., 2025). Understanding which visual attributes of streets drive these visual thermal comfort assessments has direct implications for street design, UH adaptation policy, and the planning of thermally comfortable, walkable cities (Z. Liu et al., 2025; López-Lambas et al., 2021). Adaptation of techniques such as image semantic segmentation, that identifies the existing pixels of different attributes by percentage, helps quantify the visual attributes of streetscapes(Cordts et al., 2016; Hosseini et al., 2022; Z. Wu et al., 2024).

This thesis is across two European cities, Turin (Italy) and Detmold (Germany), to investigate how people visually assess the thermal comfort potential of the streets. The study uses the LCZ classification system as its organizing base for selecting study points. Also, to characterize the thermal environment at each study area, this study employs two complementary layers of environmental attributes. The first layer consists of remote sensing indices such as LST, NDVI, MNDWI, and Albedo. The second layer comprises pixel-level semantic segmentation fractions derived from street-level imagery, which quantify the proportions of sky, vegetation, building, and road surfaces visible from pedestrian height, combining a visual thermal comfort rating questionnaire distributed to residents of both cities.

1.2 Problem Statement

The intensification of UH creates an urgent need to understand which street design attributes make urban environments visually and thermally comfortable for pedestrians(Ben Ratmia et al., 2024; Lai et al., 2025). In analyzing the human Outdoor Thermal Comfort (OTC) within specific urban settings and microclimates, most of the studies about pedestrian or active mobility users' are laid into quantitative analysis such as site measurements and then simulations to understand the effects of different streetscape features (L. Chen et al., 2024; Costa et al., 2024; Ma et al., 2019; Ojha & Mukherjee, 2025; M. Yang et al., 2025; Yin et al., 2022), measuring walkability by mathematical formulas (Zou et al., 2025), applying pedestrian flow simulations (X. Zhang & Ludwig, 2025), and optimization of the pedestrians' thermal comfort by simulations (T. Zhang et al., 2025). These research usually are rich in physical effects, but lack subjective consideration (de Quadros & Mizgier, 2023; Peng et al., 2019).

There are other types of studies that incorporate the subjective features of human thermal sensation by having both quantitative analysis of data on physical parameters (in situ air temperature, mean radiant temperature, direct solar radiation, relative humidity, and wind speed, etc.) and qualitative measurements of psychological parameters (in situ sensation analysis and observations of personal characteristics and preferences)(Cortese et al., 2020; de Quadros & Mizgier, 2023; Peng et al., 2019; Potchter et al., 2022; Shooshtarian et al., 2020; Siqi et al., 2023; Villadiego & Velay-Dabat, 2014; Y. Zhang et al., 2025). The aim of these types of studies is to proof the quantitative results, by the qualitative experiments (Cortese et al., 2020; Peng et al., 2019), that asses the in situ perception rather than long term perception (Urban et al., 2022).

In the studies about the human Outdoor Thermal Comfort in relationship with the LCZs, there are studies about the UH characteristics and mitigation strategies in different LCZs (Costa et al., 2024; Rahmani & Sharifi, 2025) without exploring the human perception, also the relationship between physical attributes of different LCZs with the OTC, and their mitigation strategies with the lack of integrating social aspects or human perception (Abedrabbah et al., 2025; X. P. Chen et al., 2024; G. Xu et al., 2023). About the relationship between LCZ zones and human subjective thermal perception, there are studies that obtain in situ microclimatic data and comparing them with the thermal sensation of people using questionnaire surveys based on ASHRAE standard to understand how meteorological variables such as air temperature, relative humidity, etc. is being perceived by people in different LCZ classes (Das et al., 2020; Lam et al., 2023; Lau, Chung, et al., 2019; Lau, Shi, et al., 2019; H. Zhang et al., 2025). In these research, the thermal sensation perception data is based on brief, instantaneous assessments made while people are moving through the space; so, these methods are not suitable for examining long-term behavioral adaptation or patterns of how people use the space over time (Talhi et al., 2026).

For understanding the perceived thermal perception there is a need of performing research interacting with other human senses such as visual, with a long term perception analysis that can be approached by methods such as street view image ratings (Shoghi et al., 2025; Shooshtarian et al., 2020; Urban et al., 2022).

The present study fills the space between these approaches. It does not measure in situ thermal sensation during exposure; instead, it investigates visual thermal comfort potential or how thermally comfortable a street appears to be from a street-level photograph. This approach, validated by (Cortese et al., 2020; Urban et al., 2022), enables systematic comparison across multiple locations without requiring simultaneous fieldwork, decouples the comfort assessment from momentary weather conditions, and yields direct insight into which visible features of the streetscape drive thermal comfort judgements. Paired with a comprehensive physical attribute dataset collected at case studies, it enables the relationship between what people see and what is physically present to be systematically investigated.

1.3 Research Objectives

Primary Objective: To investigate how people visually assess the street-level thermal comfort potential of street sections in Turin (Italy) and Detmold (Germany), and to identify the streetscape parameters that most strongly shape those visual assessments.

Secondary Objectives:

- Develop and apply a multi-layer attribute collection characterizing the physical and visual profile of two case studies.
- Collect visual thermal comfort ratings via an image-based questionnaire distributed to residents case studies.

1.4 Research Questions

RQ1. How do people visually assess the thermal comfort potential of street sections across cities with different climatic backgrounds?

RQ2. Which streetscape attributes and personal demographic characteristics influence how people visually assess thermal comfort from street images?

1.5 Thesis Structure

This thesis is organized into five chapters, each of them addressing a key aspect of the study:

Chapter 1 – Introduction: Provides the background, problem statement, outlines of the research objectives and questions and the thesis structure.

Chapter 2 – Literature Review: Consists of a comprehensive review of the existing literature, covering key concepts and theoretical frameworks related to Urban Heat and Thermal Comfort.

Chapter 3 – Methodology: Describes the study area, and the rationale of point selections, attribute table collection, and questionnaire design.

Chapter 4 – Results: in this chapter, the results of the attribute table data collection, and the results from questionnaires are presented.

Chapter 5 – Conclusion: this chapter returns to the research questions, consolidates the findings across both cities, and reflects on the broader implications for future urban thermal comfort research and practice.

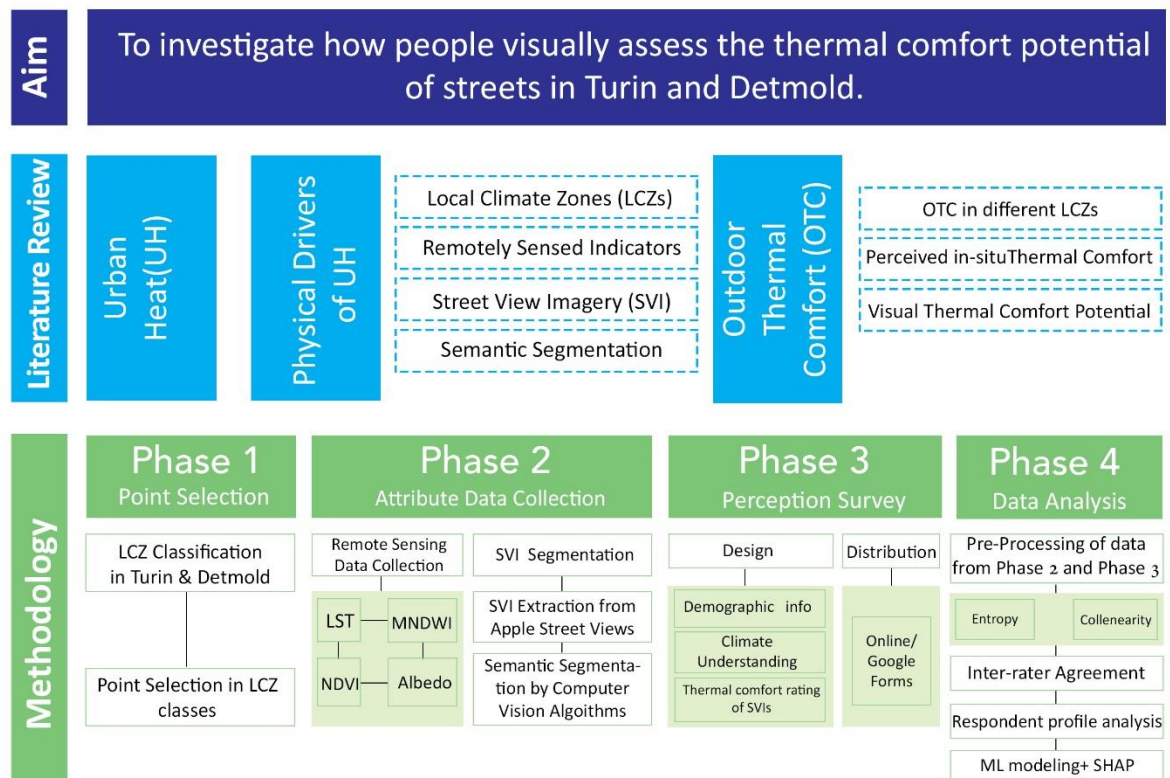


Figure 1. Overview of the thesis structure developed by author.

2. Literature Review process

To find the most relevant research and having a thorough understanding of the existing and ongoing research in this subject, the framework of PICOS was selected to do this literature review. The PICOS (Population, Intervention, Comparator and Outcome, Setting (Schiavenato & Chu, 2021)) framework was originally developed for clinical research to structure questions around a “Problem, Intervention, Comparison, and Outcome” (Richardson et al., 1995). Far from being a rigid clinical tool, PICO offers researchers in different sciences a disciplined way to ensure their questions are specific, comparable, and answerable, the qualities that matter regardless of whether the study design is experimental, descriptive, or mixed-methods (Nishikawa-Pacher, 2022).

In order to do it, the breakdown of PICOS was as follow:

- **P — Population** Who is being studied?
 - “human” OR “women” OR “men” OR “children” OR “elderly” OR “pedestrian” OR “cyclist” OR “active mobility users”
- **I — Intervention / Exposure** What is being examined?
 - “street” OR “road” OR “streetscape preference” OR “street attributes” OR “streetscape attributes” OR “street design” OR “height to width ratio” OR “width to height ratio”
- **C — Comparison** What is being compared?
 - “Climate zone” OR “climatic conditions” OR “Local Climate Zone” OR “LCZ” OR “urban morphology” OR “photo-elicitation” OR “visual assessment” OR “street image”
- **O— Outcome** What is being measured/explored?
 - “thermal comfort” OR “thermal perception” OR “perception” OR “preference” OR “comfort” OR “heat” OR “Thermal comfort potential”
- **S- Setting**
 - “street” OR “streetscape attributes” OR “street design” OR “streetscape” OR “street canyon”

Following this breakdown, the search strings suitable for two databases of Web of Science (WOS) and SCOPUS were written, then, the process of adding or omitting different keywords was done in order to reach the best possible results. After the search, to select the most relevant research, a filtration was implemented, based on which only the research articles, and literature reviews that were in English, open access and written from 2020 onwards. The results were as follows:

Data base	Literature review	Research articles	After Final filtration
WOS	10	80	22
SCOPUS	96	488	45

Table 2. The summary of the sources of the literature review (author)

The systematic search was therefore supplemented by targeted hand-searching and citation tracking, retrieving foundational methodological papers directly relevant to the study design but not captured by the keyword search. This combination of systematic and supplementary searching resulted in a total of 87 sources cited across the chapter, distributed across two thematic sections as described below.

3. Urban Heat (UH)

The intensification of urban heat through climate change and urbanization has made the thermal conditions of street-level environments an increasingly important concern for urban design, public health, and mobility research (Jabbar et al., 2023; Tong et al., 2021). While this study does not directly measure or model the Urban Heat Island effect, the physical factors that drive heat accumulation at street level are directly relevant because they are precisely the attributes that the present study collects and analyses as predictors of perceived visual thermal comfort. Understanding how these physical factors operate, and how they have been characterized in the existing literature, therefore provides the necessary foundation for the attribute data collection applied in this study.

The intensified thermal environment within cities, maximized by the increase of duration of heatwaves, their intensity, and frequency due to global climate change, creates a cascade of negative impacts that changes across social, ecological, and technical systems (Tong et al., 2021). The influence of urban heat is more than simple thermal discomfort, but on critical infrastructure (Dwivedi & Soni, 2024), and social and environmental justice (Pappalardo et al., 2023) where climate change exacerbates existing social inequities and health disparities (Leap et al., 2024). Research shows that racism and climate change are deeply intertwined issues, not separate crises. Their interaction has particularly severe and harmful impacts on marginalized communities (Abi Deivanayagam et al., 2023).

Increasing research indicates a clear and ongoing connection between the city's hottest neighborhoods and the demographic characteristics of their residents. In U.S., a detailed analysis of 20 metropolitan regions quantified this inequality (Dialesandro et al., 2021). This research revealed that, on average, the low-income neighborhoods are 2.2°C (4°F) hotter than the wealthiest ones. In some cities across California, this temperature gap can rise to as much as 3.7°C (7°F), particularly affecting low-income and Latinx communities. This phenomenon is not unique to the U.S.; a study in Padua, Italy, found that the most critical heat-related risk was concentrated in sectors with more low-income households, children, and elderly, where the UH intensity reached 5–8°C higher than rural contexts around (Todeschi et al., 2022).

These equity dimensions mean that the design of thermally comfortable streets is not merely an aesthetic concern but a question of social and environmental justice. This, provides the broader motivation for the present study's investigation of which street visual attributes drive thermal comfort perceptions across different climatic contexts.

4. Physical Drivers of Street-Level Thermal Conditions

A comprehensive body of academic literature identifies several physical factors that drive Street Level Thermal Conditions, among them there are some factors that are more repetitive

that include: Surface materials that lead to reflectivity and absorption of the heat (Q. Chen et al., 2023; Nurfaizah et al., 2025; Tyagi & Danish, 2025). The Street Canyon geometry that defines the amount of the sky that is visible or the Sky View Factor (SVF), and the ratio of height to width (H/W ratio) that identifies the wind flow and heat storage capacities of the street canyons (Esposito et al., 2024; Park et al., 2025; Rana et al., 2025). Another important factors are Vegetation and water existence or Blue-Green Infrastructure (BGI), that lead to permeability, shading and evaporations, all of them lead to cooling effects of the streetscapes (Del Serrone et al., 2022; Kumar et al., 2024; H. Yang & Zeng, 2025).

All these factors can be identified, and measured by different methods and tools:

4.1 Local Climate Zones, A Framework for classifying the forms of the cities

The Local Climate Zone (LCZ) classification system, formally illustrated by Stewart and Oke (2012), supplies a standard framework for describing urban and natural landscape types based on measurable physical and thermal properties. The framework was developed to replace the "urban vs rural" terminology that had made cross-city comparison of thermal measurements unreliable. In this classification there are 17 zone types defined, 10 of them built and 7 natural areas. Each of these classes are defined by specific geometric and surface cover parameters including SVF, H/W ratio, Building, Impervious and Pervious Fractions that are the percentage of these at each class, and Roughness Height, that is the mean height of the building in the class (Stewart & Oke, 2012). Since its introduction, this system has been widely adopted in urban climate research globally (Aslam & Rana, 2022; L. Zhou et al., 2022).

The 10 built LCZ types span a wide range of urban morphologies, from the most compact and densely built to the most open and vegetated. LCZ 1 (compact high-rise) and LCZ 2 (compact mid-rise) represent the densest built forms, characterized by high building fractions (40–70%), low SVF (0.2–0.6), high H/W ratios, and minimal vegetation. In these classes there are deep canyon environments with restricted sky exposure and impaired ventilation (Huang et al., 2023). LCZ 3 (compact low-rise) shares the same high density but at lower building heights. LCZ 4 (open high-rise), LCZ 5 (open mid-rise), and LCZ 6 (open low-rise) represent less dense built forms, lower building fractions (20–40%), higher SVF (0.5–0.8), more pervious surfaces, and greater vegetation presence. In these classes, the urban fabrics are more open (Stewart & Oke, 2012). LCZ 7 (lightweight low-rise) captures informal settlement morphologies. LCZ 8 (large low-rise) and LCZ 9 (sparsely built) represent commercial and suburban typologies with low building fractions and large open areas. LCZ 10 (heavy industry) covers industrial land uses characterized by large heat-generating structures and high impervious cover (Oke et al., 2017; Stewart & Oke, 2012). The seven natural LCZ types (A to G) cover diverse natural land covers providing a complete typological framework applicable globally. Figure 2 derived from (Stewart & Oke, 2012), shows all the classes.

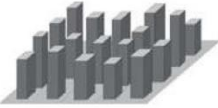
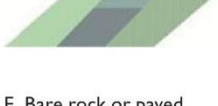
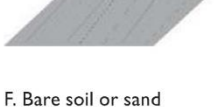
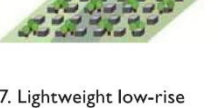
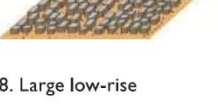
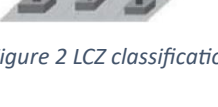
Built types	Definition	Land cover types	Definition
1. Compact high-rise 	Dense mix of tall buildings to tens of stories. Few or no trees. Land cover mostly paved. Concrete, steel, stone, and glass construction materials.	A. Dense trees 	Heavily wooded landscape of deciduous and/or evergreen trees. Land cover mostly pervious (low plants). Zone function is natural forest, tree cultivation, or urban park.
2. Compact midrise 	Dense mix of midrise buildings (3–9 stories). Few or no trees. Land cover mostly paved. Stone, brick, tile, and concrete construction materials.	B. Scattered trees 	Lightly wooded landscape of deciduous and/or evergreen trees. Land cover mostly pervious (low plants). Zone function is natural forest, tree cultivation, or urban park.
3. Compact low-rise 	Dense mix of low-rise buildings (1–3 stories). Few or no trees. Land cover mostly paved. Stone, brick, tile, and concrete construction materials.	C. Bush, scrub 	Open arrangement of bushes, shrubs, and short, woody trees. Land cover mostly pervious (bare soil or sand). Zone function is natural scrubland or agriculture.
4. Open high-rise 	Open arrangement of tall buildings to tens of stories. Abundance of pervious land cover (low plants, scattered trees). Concrete, steel, stone, and glass construction materials.	D. Low plants 	Featureless landscape of grass or herbaceous plants/crops. Few or no trees. Zone function is natural grassland, agriculture, or urban park.
5. Open midrise 	Open arrangement of midrise buildings (3–9 stories). Abundance of pervious land cover (low plants, scattered trees). Concrete, steel, stone, and glass construction materials.	E. Bare rock or paved 	Featureless landscape of rock or paved cover. Few or no trees or plants. Zone function is natural desert (rock) or urban transportation.
6. Open low-rise 	Open arrangement of low-rise buildings (1–3 stories). Abundance of pervious land cover (low plants, scattered trees). Wood, brick, stone, tile, and concrete construction materials.	F. Bare soil or sand 	Featureless landscape of soil or sand cover. Few or no trees or plants. Zone function is natural desert or agriculture.
7. Lightweight low-rise 	Dense mix of single-story buildings. Few or no trees. Land cover mostly hard-packed. Lightweight construction materials (e.g., wood, thatch, corrugated metal).	G. Water 	Large, open water bodies such as seas and lakes, or small bodies such as rivers, reservoirs, and lagoons.
8. Large low-rise 	Open arrangement of large low-rise buildings (1–3 stories). Few or no trees. Land cover mostly paved. Steel, concrete, metal, and stone construction materials.	VARIABLE LAND COVER PROPERTIES	
9. Sparsely built 	Sparse arrangement of small or medium-sized buildings in a natural setting. Abundance of pervious land cover (low plants, scattered trees).	Variable or ephemeral land cover properties that change significantly with synoptic weather patterns, agricultural practices, and/or seasonal cycles.	
10. Heavy industry 	Low-rise and midrise industrial structures (towers, tanks, stacks). Few or no trees. Land cover mostly paved or hard-packed. Metal, steel, and concrete construction materials.	b. bare trees	Leafless deciduous trees (e.g., winter). Increased sky view factor. Reduced albedo.
		s. snow cover	Snow cover >10 cm in depth. Low admittance. High albedo.
		d. dry ground	Parched soil. Low admittance. Large Bowen ratio. Increased albedo.
		w. wet ground	Waterlogged soil. High admittance. Small Bowen ratio. Reduced albedo.

Figure 2 LCZ classification (source: Stewart & Oke, 2012)

Research confirms that these morphological differences produce measurable differences in both physical microclimate and human thermal perception. In a study of sub-tropical high-density Hong Kong that LCZ classes with lower SVF and higher building density produced higher thermal comfort values than more open LCZ types, establishing LCZ type as a reliable

predictor of objective thermal conditions(Lau, Chung, et al., 2019). To extend this to subjective thermal perception in an Australian context, the researchers found that respondents in compact LCZ zones reported systematically lower thermal satisfaction than those in open zones under equivalent meteorological conditions(Lam et al., 2023). This, confirms that morphological differences captured by LCZ classification translate into perceptual differences detectable through questionnaire surveys(Lam et al., 2023). A study of a tropical Indian city, further established that the way urban morphology shapes thermal sensation is not universal but varies depending on the climatic setting of each city (Das et al., 2020).

4.2 Remotely Sensed Indicators of the Urban Thermal Environment

Satellite-derived remote sensing indices have become standard tools to characterize the physical thermal and biophysical environment of cities at neighborhood and street scale(Pani et al., 2026).

Land Surface Temperature (LST), is one of the satellite-based indicator of urban surface heat. In a study in Shanghai, for the heat exposure risk assessment of 400 rail transit station areas, the LST extracted via Google Earth Engine, identified thermally critical street-level zones across a dense urban network (Zou et al., 2025). In a study in Czech, LST values were extracted within 30 m circular buffers around each of the survey points and used them as the objective thermal baseline against which street-level photographic comfort ratings (Urban et al., 2022). In an analysis of urban thermal comfort, it was found that satellite-derived LST is among the most significant predictors of subjective thermal perception scores, confirming the relevance of LST as a variable for perception-based studies(C. Hu & Zeng, 2025).

The Normalized Difference Vegetation Index (NDVI), is the quantity of the active vegetation that is visible to the satellite sensor (Rouse Jr et al., 1973). This index is usually among the environmental predictors of the thermal comfort models in studies(C. Hu & Zeng, 2025). The higher NDVI values consistently associated with lower perceived thermal stress scores(C. Hu & Zeng, 2025). In a study in Ningbo, NDVI was used as the primary indicator of urban green space change, directly linking NDVI decline to rising surface temperatures across the analysis period(H. Yang & Zeng, 2025). In a 56-city study combining satellite data and street view imagery, NDVI was found to be one of the strongest statistical predictors of perceived built environment quality at street level (Larkin et al., 2021).

The Modified Normalized Difference Water Index (MNDWI), that captures surface water and moisture conditions is a satellite-based proxy in the studies of perceived thermal comfort(C. Hu & Zeng, 2025) and land cover change and drainage (Sajjad et al., 2025).

The surfaces albedo, or solar reflectivity of materials, directly governs heat absorption is a fundamental driver of the street-level thermal conditions(X. Zhang et al., 2022). Surfaces with low albedo, like soil and rock, absorb much radiation, resulting in temperature rises that can be up to three times greater than those experienced on high-albedo surfaces like water(Nurfaizah et al., 2025). This physical principle has profound consequences in the built environment. A study utilizing Envi-met simulations, assessed the effect of high-albedo

surfaces on human comfort within a low-rise housing development in India. They discovered that reflective façades led to severe localized heating, resulting in air temperatures rise in the urban canyons formed by the buildings, above 43.7°C, thereby heightening thermal discomfort for pedestrians(Tyagi & Danish, 2025). The stored energy based on the surface albedo, is then released slowly as sensible heat, particularly after sunset, preventing urban areas from cooling down as effectively as their rural counterparts(Tyagi & Danish, 2025). This process is a key contributor to the pronounced nocturnal Urban Heat Island (UHI) effect observed in many cities, including Turin, where the urban-rural temperature differential is often greatest at night, denying the population thermal respite and heat stress(Milelli et al., 2023).

4.3 Streetscape attributes quantified through Street View Imagery (SVI)

In empirical studies concerning pedestrian experiences, urban perception, health, specifically those assessing thermal comfort, bikeability, and walkability, the analysis of streetscape features via Street View Imagery (SVI) has become an established methodological approach(Biljecki & Ito, 2021). The SVIs transformed the possibilities for large-scale, systematic assessment of the built environment's effects on human experience (Ki et al., 2023). Among the main services that provide SVIs are Google Street View (GSV), Apple Street View, Crowdsourced services such as Mapillary and KartaView (Biljecki & Ito, 2021).

Based on a literature review, the data that can be captured from these SVIs can mainly be categorized as follow(Biljecki & Ito, 2021): The spatial infrastructures that can be found by SVIs, such as building types and conditions such as their age(Kraff et al., 2020), detecting the paintings or graffiti on the walls (Novack et al., 2020), control of the road quality (Q. Zhou & Lin, 2019), street furniture such as traffic signs, poles, etc. (Biljecki & Ito, 2021). The Green View Index (GVI) that is the quantified amount of visible greenery visible by the pedestrian (Labib et al., 2021). Analyzing the Thermal Comfort Perception by the amount of sunshine and the sky view factor (SVF) (C.-B. Hu et al., 2020; Nice et al., 2020). The mobility and transportation by investigating the pedestrian crashes in relationship with the road infrastructures (L. Hu et al., 2020), and safety (Cicchino et al., 2020). The walkability of the streets by analyzing different factors such as traffic, aesthetic features, and sidewalk quality (Z. Zhou & Xu, 2020). The Urban Perception analysis based on the streets' quality (C. Wu et al., 2020), perceptual aspects such as wealth, vibrancy, etc. (Min et al., 2019).

In a study, the SVIs were used to introduce and evaluate the concept of "thermal affordance" through the "Visual Assessment of Thermal Affordance (VATA)" framework. By extracting 19 visual-perceptual indicators from street-level imagery, the authors modeled how streetscape features influence human thermal comfort(S. Yang et al., 2025). This methodology provides a scalable, cost-effective alternative to traditional resource-intensive climate monitoring, allowing for high-resolution mapping to guide sustainable urban design and mitigate heat island effects. SVIs are also used to quantify street canyon morphology and investigate its

causal impact on the LST (Z. Liu et al., 2025). Table 2.1. in the appendix, summarizes the literature review conducted for this part, with more detail.

4.4 Semantic Segmentation, A Standard Method for Quantitative Streetscape Analysis

Within SVI-based urban research, semantic segmentation has emerged as the standard method for extracting quantitative streetscape attributes from street-level photographs. Semantic segmentation classifies every pixel of an image into a predefined semantic category such as sky, building, tree, road, vehicle, person, and so on, using deep learning models trained on large annotated urban image datasets (Cordts et al., 2016). The value of this approach is demonstrated in a landmark study to map the sky, building view factors, and tree in a high-density urban environment in Hong Kong (Gong et al., 2018). Semantic segmentation uses learned representations of visual context, texture, shape, and spatial relationships rather than color values alone, that reduces errors (Gong et al., 2018).

One of the most widely used training datasets for urban streetscape segmentation is Cityscapes (19 urban-specific classes derived from European street-level photography). The Cityscapes dataset (Cordts et al., 2016) was compiled from images captured across 50 German and French cities, making its semantic categories directly applicable to the morphological and visual characteristics of European mid-rise urban streets. In a study of thermal affordance in Singapore, the SegFormer-B5 model was finetuned on Cityscapes to extract 19 pixel fraction values as the primary inputs to their thermal comfort prediction model (S. Yang et al., 2025). In a thermal environment mapping study using street view imagery, combined semantic segmentation with in situ measurements across different urban morphologies, demonstrating that segmentation-derived visual attributes can serve as reliable proxies for street-level thermal conditions across diverse urban contexts (Y. Hu et al., 2024). Table 2.2. in the appendix, summarizes the literature review conducted for this part, with more detail.

5. Outdoor Thermal Comfort (OTC)

Thermal comfort is understood as a psychological state in which human experiences subjective satisfaction with their surrounding thermal conditions, as formally established by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) (Ličina et al., 2018). The outdoor thermal comfort is in relation with different factors, such as the solar radiation's variability and intensity, the dynamic nature of wind, the wide range of outdoor activities and clothing (Das et al., 2020; G. Xu et al., 2023).

There are a range of outdoor thermal comfort indices specifically designed for open and semi-open environments. Among the most widely applied are the "Physiologically Equivalent

Temperature (PET)” and the “Universal Thermal Climate Index (UTCI)”. PET expresses the thermal conditions of any given environment in terms of the equivalent air temperature in a standardized reference setting, making it useful for comparing conditions across locations. UTCI, is a model that incorporates a sophisticated representation of human physiology and has the advantage of applicability across all climates, seasons, and scales (Evgenia et al., 2024; Y. Li et al., 2024).

Most studies about pedestrian thermal comfort are structured around quantitative analysis of the effects of streetscape attributes on these outdoor thermal comfort indices through Computational Fluid Dynamics (CFD) simulations beside field measurements. These studies are rich in physical and physiological effects but lack subjective considerations (de Quadros & Mizgier, 2023; Peng et al., 2019). Table 2.3 in the Appendix presents a summary of representative studies reviewed for this section.

5.1 OTC in different LCZs

As the LCZ classification is a decent climatic-basis for studying different zones or neighborhoods in a city, many researchers have adopted it. For example, in the studies about the UH characteristics and mitigation strategies (Costa et al., 2024; Rahmani & Sharifi, 2025), also in the relationship exploration between physical attributes of different LCZs with the OTC, and their mitigation strategies (Abedrabboh et al., 2025; X. P. Chen et al., 2024; G. Xu et al., 2023). In the studies that focus on the human subjective thermal perception, there are studies, that obtain in situ microclimatic data and comparing them with the thermal sensation of people using questionnaire surveys based on ASHRAE standard to understand how meteorological variables such as air temperature, etc. is being perceived by people in different LCZ classes (Das et al., 2020; Lam et al., 2023; Lau, Chung, et al., 2019; Lau, Shi, et al., 2019; H. Zhang et al., 2025). There are also research on the distribution of heat in different LCZ zones using Street View Images using semantic segmentation and mobile in situ climatic measurements (Y. Hu et al., 2024). A summary of studies on LCZ classification and outdoor thermal comfort is in Table 2.4 in the Appendix.

5.2 Perceived, in-situ Thermal Comfort

In order to have a thorough understanding of the thermal comfort and the perception of people about it in a specific time and location, researchers usually incorporate the subjective features of human thermal sensation by having both quantitative analysis of physical parameters (in situ air temperature, relative humidity, mean radiant temperature, direct solar radiation, wind speed) and qualitative measurements of psychological parameters (in situ sensation analysis and observations of personal characteristics, behavior, and preferences) (Cortês et al., 2020; de Quadros & Mizgier, 2023; Peng et al., 2019; Potchter et al., 2022; Shoosharian et al., 2020; Siqi et al., 2023; Villadiego & Velay-Dabat, 2014). The aim of these studies is to complement quantitative findings with qualitative experiments (Cortês et al., 2020; Peng et al., 2019).

A research in urban public spaces across Europe demonstrated that microclimatic parameters, accounted for only approximately 50% of the variation in people's subjective assessments of

thermal comfort(Nikolopoulou & Steemers, 2003). The remaining variation could not be explained by physical measurements alone but was instead associated with psychological adaptation. This study, identified six key dimensions of psychological adaptation: naturalness; expectations (shaped by seasonal norms, prior experience, and cultural context); experience at different environmental stimulation, time scales, time of exposure, and perceived control(Nikolopoulou & Steemers, 2003). Subsequent scholarship built on this framework, confirming that psychological parameters play a structurally important role in outdoor thermal comfort evaluations and that their relative weight varies across cultural and climatic contexts(Shooshtarian et al., 2020).

5.3 Visual Thermal Comfort Potential: Perceived, long term Thermal Comfort

The psychological adaptation literature establishes that thermal comfort is not simply a physiological reaction or response to physical stimuli but a complex perceptual and cognitive construct shaped by expectations, context, and prior experience(Nikolopoulou & Steemers, 2003; Urban et al., 2022; S. Yang et al., 2025). A logical extension of this insight is the concept of thermal affordance that is the inherent capacity of a street environment to influence human thermal comfort, as visually communicated by the physical and spatial attributes of the streetscape, and assessable from a street-level photograph independently of in situ measurement (S. Yang et al., 2025). This concept was operationalized through VATA framework, by recruiting 176 Singapore residents to perform pairwise comparisons of 500 street-level photographs on 20 thermal comfort indicators, and finding that pixel-level visual attributes of the streetscape such as sky fraction, vegetation fraction, and building enclosure, were statistically significant predictors of thermal affordance ratings. Thermal affordance, in this framework, is precisely what a person estimates when they look at a street scene and judge how thermally comfortable it would feel to be present there(S. Yang et al., 2025). This is what is called, long-term thermal comfort perception, or what is called “Visual Thermal Comfort Potential” in the present study (Urban et al., 2022). Visual thermal comfort potential differs from both measured thermal comfort (assessed via physical indices such as PET or UTCI) and experienced thermal comfort (assessed via in situ questionnaire surveys during actual exposure) in a fundamental way: it is based solely on the visual information available in a street-level image(Urban et al., 2022). Respondents evaluate what they can see and from those visual cues interpret how thermally comfortable the environment would feel under specified thermal conditions(Urban et al., 2022; S. Yang et al., 2025). This approach has well-established methodological precedents. In a study across four outdoor spaces in Lisbon, the photographic comparison method was validated as a rigorous approach to outdoor thermal perception surveys. This means that respondents can reliably differentiate between levels of perceived thermal comfort from street photographs and that their rankings correspond meaningfully to the objective physical properties of the depicted environments(Cortezão et al., 2020). In another research, using Google Street View photographs thermal comfort perception was evaluated in Czech cities during heatwaves, demonstrated that respondents can predict heat-related discomfort from street photographs even when explicit

meteorological conditions are not shown (Urban et al., 2022). Table 2.5 in the appendix, contains the detailed information of the studies reviewed for the last two sections.

Table 2 summarizes the main literature that influenced different sections of this research:

Study	Subject	Points taken from it in the present study
(Stewart & Oke, 2012)	Introduced the 17-class Local Climate Zone classification system based on measurable morphological parameters (SVF, building fraction, impervious fraction, roughness height, H/W ratio).	point selection, morphological attribute framework, and cross-city comparison
(Urban et al., 2022)	Used GSV photographs to assess long-term outdoor thermal comfort perception during heatwaves across Czech cities; extracted LST within 30 m circular buffers around each survey point.	the photographic visual rating methodology for the questionnaire; the pairing of RS attributes as objective baseline against visual comfort ratings.
(S. Yang et al., 2025)	Developed the VATA framework using SegFormer-B5/Cityscapes semantic segmentation and a pairwise photographic comparison survey of 176 Singapore respondents.	The theoretical concept of thermal affordance (renamed visual thermal comfort potential in this study); the use of SegFormer-B5 finetuned on Cityscapes
(C. Hu & Zeng, 2025)	Used explainable machine learning to identify satellite-derived environmental attributes (LST, NDVI, MNDWI, albedo) as predictors of subjective thermal perception scores in a Chinese city.	The specific combination of four RS indices (LST, NDVI, MNDWI, albedo) as environmental attributes; the use of MNDWI as a humidity proxy; the framing of RS indices as predictors of perceived comfort.
(Cortezão et al., 2020)	Validated the photo comparison for qualitative outdoor thermal perception surveys across four outdoor spaces in Lisbon; demonstrated that respondents reliably rank photographs by thermal comfort.	Methodological validation for the visual rating approach.
(Nikolopoulou & Steemers, 2003)	Demonstrated in European urban public spaces that physical parameters explain only ~50% of outdoor comfort variation; identified six dimensions of psychological adaptation including expectations and environmental stimulation.	The fundamental theoretical justification for studying visual/perceived thermal comfort rather than relying exclusively on physical thermal indices. The distinction between measured, experienced, and visual thermal comfort.
(Lam & Lau, 2018)	Compared outdoor thermal comfort between Melbourne and Hong Kong; showed that climate-based acclimatization creates systematically different thermal expectations, modulating comfort ratings even at identical objective conditions.	The theoretical justification for the cross-climatic comparative design: Turin vs. Detmold residents bring different thermal expectations.

(Lam et al., 2023)	Used LCZ classification to assess summer thermal perceptions in compact vs. open zones; found that compact LCZ respondents report lower thermal satisfaction under equivalent meteorological conditions.	Direct empirical evidence that morphological LCZ differences translate into subjective comfort differences detectable by questionnaire survey.
(Cordts et al., 2016)	Published the Cityscapes dataset: 19 urban semantic classes derived from street-level imagery across 50 German and French cities.	Cityscapes dataset for Semantic Segmentation.
(Larkin et al., 2021)	Combined GIS, Sentinel-2 satellite data, and GSV images across 56 cities to predict perceived built environment quality; found NDVI among the strongest predictors.	Supports RS data as a valid predictor of perceived street quality including thermal comfort; confirms that cross-city SVI-based analysis is methodologically feasible.

Table 3. Summary of the main literature and their up taking points. (by author)

6. Research Gap and the Positioning of the Present Study

The foregoing review reveals a consistent tension in the existing literature. On one hand, the physical thermal comfort literature has developed sophisticated tools for measuring and modelling the objective thermal conditions of urban streets. Also, these researches have produced substantial evidence about how design variables such as canyon geometry, tree canopy, pavement type, and surface materials influence those conditions(X. P. Chen et al., 2024; Jia et al., 2022; M. Yang et al., 2025). On the other hand the psychological adaptation literature have convincingly demonstrated that objective conditions are insufficient to explain how people actually experience and evaluate urban thermal environments(Nikolopoulou & Steemers, 2003). Perceived comfort depends on a complex interplay of physical, cognitive, and contextual factors that cannot be captured by thermal indices alone(Urban et al., 2022; S. Yang et al., 2025).

Studies that bridge these two domains by linking the visual physical attributes of streets to perceived comfort ratings, remain comparatively rare. Cortesão et al. (2020) validated the photographic comparison method for outdoor thermal perception, but focused on a small number of spaces within a single city. Urban et al. (2022) collected photographic thermal comfort ratings across Czech cities but without an explicit LCZ framework or the multi-layer physical attribute characterization. Yang et al. (2025) linked visual pixel fractions from street photographs to thermal affordance ratings, but within a single climatic context (Singapore) and without pairing visual ratings against physical environmental attributes such as LST, NDVI, MNDWI, and albedo. Studies combining quantitative physical attribute data across multiple matched locations within a comparative cross-city analysis, where both the visual composition of each image and the physical conditions at each location are measured simultaneously, are still rare.

The present study addresses this gap by selecting two European cities with different climate contexts, Turin (Italy), and Detmold (Germany). In each city, the classifying the LCZ in order to provide a base map for selecting study points. then accumulating the physical attributes that drive UH in each point, along with the visual data extracted from SVIs at each point. Finally, gathering people's visual perception through image-rating by survey, to identify the effects of the attribute data and also people's climatic and social backgrounds on their thermal comfort potential perception. The full methodology criteria are discussed in the next chapter.

7. Phase 1: Point Selection

7.1 Overview and Rationale for study area selection

This study is conducted across two European cities of Turin or Torino (Italy), and Detmold (Germany), which were selected to enable a comparative assessment of visual thermal comfort potential across LCZs in contrasting urban and climatic contexts. The two cities differ substantially in terms of urban morphology, population density, and climatic regime, making their pairing particularly suited to investigating whether visual thermal comfort perceptions are consistent across them or not. At the same time, both cities share a mid-latitude European setting, comparable urban fabric typologies (including compact and open residential LCZ types), and relevance to current urban heat adaptation debates, making meaningful cross-city comparison possible.

Table 3 presents a comparative overview of key geographic and demographic characteristics of both cities.

Characteristic	Turin	Detmold
Country	Italy	Germany
Region / State	Piedmont (Piemonte)	North Rhine-Westphalia (NRW)
Administrative status	Metropolitan City of Turin	Administrative seat, Lippe district
Coordinates	45.07° N, 7.67° E	51.94° N, 8.87° E
Elevation (a.s.l.) ¹	~238 m	~130–135 m
Municipal area	~130 km ²	~129 km ²
Population (city proper)	~855,000 (2026)	~74,278 (2024)
Köppen climate class	Cfa (humid subtropical)	Cfb (oceanic / temperate)

Table 4 Comparative overview of study city characteristics. Sources: Wikipedia (2024); Grokipedia (2024); (Beck et al., 2018) for Köppen classification; climate-data.org (Climate-Data.org, 2026) for temperature data.

7.2 Turin, Italy

Geographic and Administrative Context

Turin is a major city in northwestern Italy, situated at the foot of the Western Alps at the confluence of the Po and Dora Riparia rivers, at approximately 45.07° N, 7.67° E, at an elevation of approximately 238 meters above sea level (Wikipedia, 2024). It serves as the capital of the Metropolitan City of Turin and of the Piedmont region. With a municipal area of approximately 130 km² and a city proper population of approximately 855,654 residents as of 2026, Turin is the fourth-largest city in Italy by population (Wikipedia, 2024). The city is home to major higher education institutions including Politecnico di Torino and the University of Turin, and has a long history as an industrial and cultural center, formerly hosting the Italian automotive industry (Pizzolato, 2013).

¹ Above Sea Level

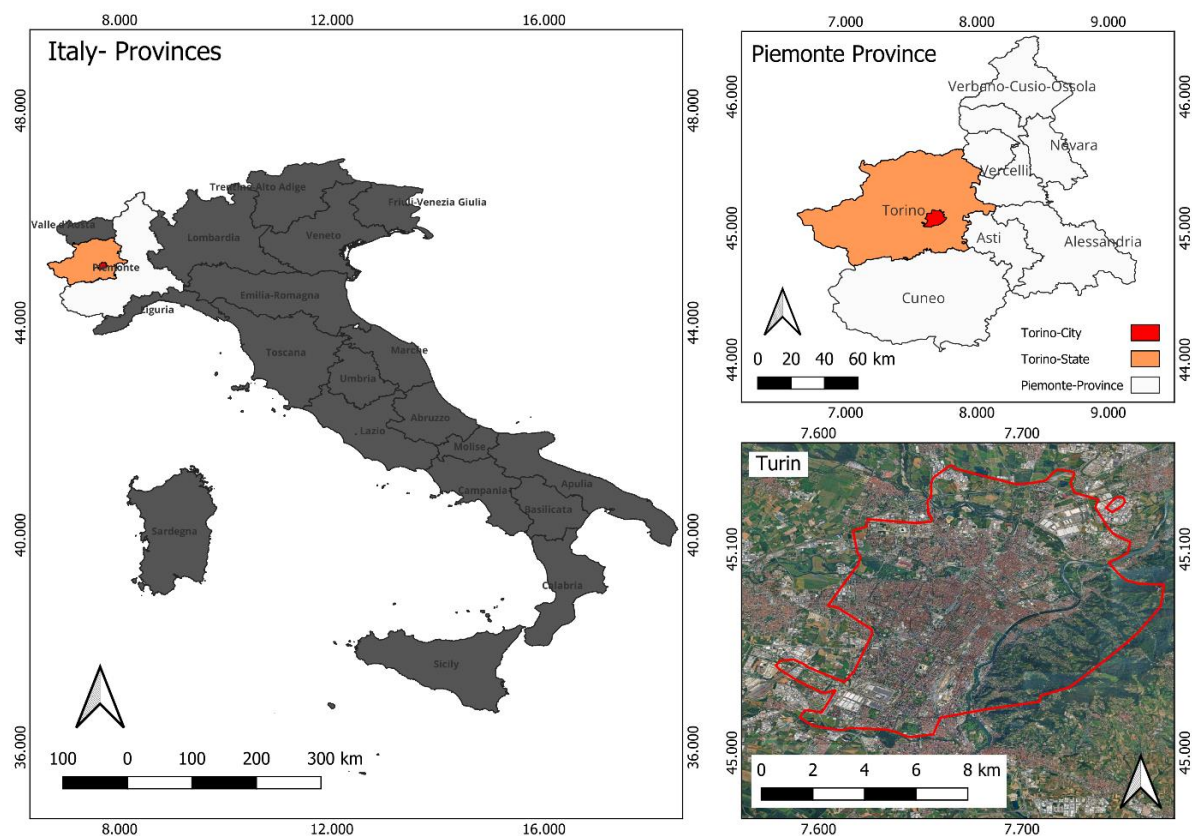


Figure 3. Map of Turin, created by Author in QGIS.

Climate

Turin is classified under the Köppen-Geiger climate system as Cfa (humid subtropical climate) characterized by moderately cold winters and hot, humid summers (Beck et al., 2018; Wikipedia, 2024). The mean annual temperature is approximately 12°C, with July and August being the hottest months and January the coldest (mean minimum ~0°C)(Climate Data, 2026). Annual precipitation averages approximately 1,000 mm, distributed across the year with peaks in spring and autumn(worldweatheronline, 2026b). The position of the city at the edge of the Po Valley, sheltered by the Alps to the west, produces occasional warm and dry föhn wind events in winter and exposes the city to significant urban heat island effects in summer, particularly in its densely built historic core and industrial districts(Melis et al., 2023). Summer mean temperatures during June to August typically range between 22°C and 26°C, making thermal comfort a significant concern for outdoor urban life(worldweatheronline, 2026b).

7.3 Detmold, Germany

Geographic and Administrative Context

Detmold is a medium-sized city in the state of North Rhine-Westphalia (NRW), western Germany, located at approximately 51.94° N, 8.87° E, at an elevation of approximately 130–135 meters above sea level, on the eastern slopes of the Teutoburg Forest (Teutoburger Wald) along the Werre River (Britannica, 2026; Wikipedia, 2026). It serves as the administrative seat of the Lippe district (Kreis Lippe) and of the Regierungsbezirk Detmold(Wikipedia, 2026). With

a municipal area of approximately 129 km² and a population of 74,278 as of 2024 (Grokikipedia, 2026). It is the largest city in the Lippe district and functions as a regional administrative, educational, and cultural center, hosting the Technische Hochschule OWL (TH OWL) campus and the internationally recognized Detmold School of Music (Hochschule für Musik Detmold)(Britannica, 2026).

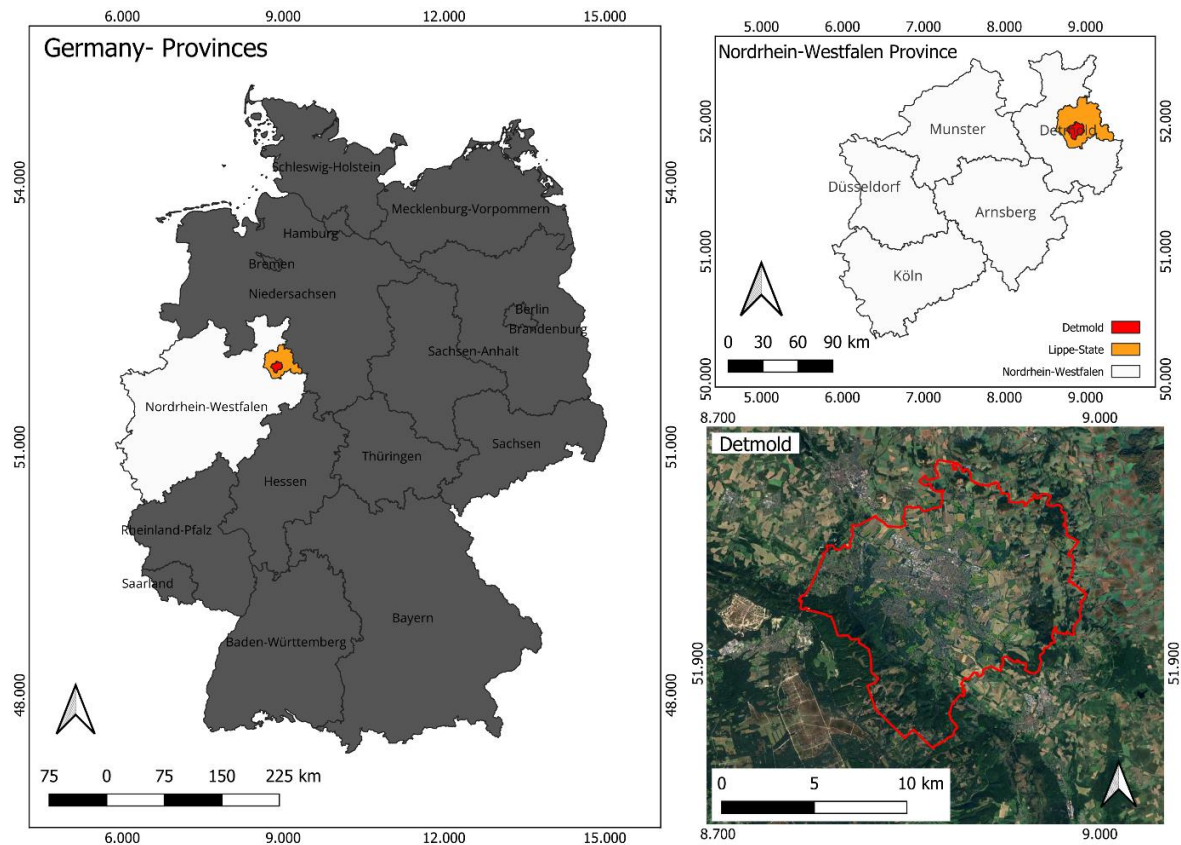


Figure 4. Map of Detmold, created by Author in QGIS.

Climate

Detmold falls under the Köppen-Geiger classification Cfb (oceanic or temperate maritime climate) characterized by mild, wet conditions throughout the year with no pronounced dry season and warm rather than hot summers (Beck et al., 2018). The mean annual temperature is approximately 9–10°C. Summer months (June to August) are typically mild, with mean temperatures of approximately 17–18°C and occasional warm spells reaching above 30°C during heatwave events. Annual precipitation averages approximately 800–900 mm(worldweatheronline, 2026a).

7.4 Comparative Rationale and Study Design Implications

The pairing of Turin and Detmold as study cities is methodologically motivated by their difference in urban scale, population density, and climatic regime. This research design follows the comparative multi-city approach adopted in studies such as (Urban et al., 2022), who conducted parallel thermal perception surveys across two Czech cities with differing climatic

and morphological characteristics, and (Larkin et al., 2021), who examined built environment perceptions across 56 cities varying widely in geographic and climatic context.

The climatic contrast between Turin (Cfa) and Detmold (Cfb) is of particular relevance to this study. It allows investigation of whether visual thermal comfort potential is driven by structural and visual attributes of the streetscape, or whether it is also modulated by climatic grounded expectations and adaptations of the respondents. This comparative dimension adds a cross-climatic generalizability dimension to the findings that would not be achievable in a single-city study.

7.5 LCZ Classification for Detmold, and Turin

Local Climate Zones (LCZ) as introduced in the chapter of literature review, represent a standardized classification system for urban and natural landscapes, developed to improve consistency and comparability in urban climate studies (L. Zhou et al., 2022). The framework was formally introduced by Stewart and Oke (Stewart & Oke, 2012) in response to a fundamental problem in urban climatology: the lack of standardized terminology and clear physical definitions for describing study sites. Prior research commonly used vague descriptors such as "urban" versus "rural" without specifying the actual physical characteristics of measurement locations, making it difficult to compare results across different studies and cities (Stewart & Oke, 2012).

Each zone is characterized by specific thermal, radiative, geometric, and surface cover properties that influence local atmospheric conditions, particularly air temperature (Johnson & Jozdani, 2019). Since its introduction, the LCZ classification has been widely adopted in urban climate research globally and has become the standard framework for urban heat island studies and urban climate investigations (Aslam & Rana, 2022). Table 4 from (Stewart & Oke, 2012), demonstrates the properties of the LCZ classes.

Local climate zone (LCZ)	Sky view factor ^a	Aspect ratio ^b	Building surface fraction ^c	Impervious surface fraction ^d	Pervious surface fraction ^e	Height of roughness elements ^f	Terrain roughness class ^g
LCZ 1 <i>Compact high-rise</i>	0.2–0.4	> 2	40–60	40–60	< 10	> 25	8
LCZ 2 <i>Compact midrise</i>	0.3–0.6	0.75–2	40–70	30–50	< 20	10–25	6–7
LCZ 3 <i>Compact low-rise</i>	0.2–0.6	0.75–1.5	40–70	20–50	< 30	3–10	6
LCZ 4 <i>Open high-rise</i>	0.5–0.7	0.75–1.25	20–40	30–40	30–40	>25	7–8
LCZ 5 <i>Open midrise</i>	0.5–0.8	0.3–0.75	20–40	30–50	20–40	10–25	5–6
LCZ 6 <i>Open low-rise</i>	0.6–0.9	0.3–0.75	20–40	20–50	30–60	3–10	5–6
LCZ 7 <i>Lightweight low-rise</i>	0.2–0.5	1–2	60–90	< 20	<30	2–4	4–5
LCZ 8 <i>Large low-rise</i>	>0.7	0.1–0.3	30–50	40–50	<20	3–10	5
LCZ 9 <i>Sparsely built</i>	> 0.8	0.1–0.25	10–20	< 20	60–80	3–10	5–6
LCZ 10 <i>Heavy industry</i>	0.6–0.9	0.2–0.5	20–30	20–40	40–50	5–15	5–6
LCZ A <i>Dense trees</i>	<0.4	>1	<10	<10	>90	3–30	8
LCZ B <i>Scattered trees</i>	0.5–0.8	0.25–0.75	<10	<10	>90	3–15	5–6
LCZ C <i>Bush, scrub</i>	0.7–0.9	0.25–1.0	<10	<10	>90	<2	4–5
LCZ D <i>Low plants</i>	>0.9	<0.1	<10	<10	>90	<1	3–4
LCZ E <i>Bare rock or paved</i>	>0.9	<0.1	<10	>90	<10	<0.25	1–2
LCZ F <i>Bare soil or sand</i>	>0.9	<0.1	<10	<10	>90	< 0.25	1–2
LCZ G <i>Water</i>	>0.9	<0.1	<10	<10	>90	–	1

^a Ratio of the amount of sky hemisphere visible from ground level to that of an unobstructed hemisphere

^b Mean height-to-width ratio of street canyons (LCZs 1–7), building spacing (LCZs 8–10), and tree spacing (LCZs A–G)

^c Ratio of building plan area to total plan area (%)

^d Ratio of impervious plan area (paved, rock) to total plan area (%)

^e Ratio of pervious plan area (bare soil, vegetation, water) to total plan area (%)

^f Geometric average of building heights (LCZs 1–10) and tree/plant heights (LCZs A–F) (m)

^g Davenport et al.'s (2000) classification of effective terrain roughness (z_0) for city and country landscapes. See Table 5 for class descriptions

Table 5. geometric and surface cover properties of each LCZ class (source: Stewart & Oke, 2012)

The application of LCZ classification to Detmold and Turin was essential for establishing a scientifically rigorous and replicable methodology for survey point selection. The primary objective was to create a classified map of these cities that would serve as a base map for selecting survey points based on their climatic aspects, ensuring systematic representation of the city's diverse urban and natural environments. The classification captures the physical characteristics of the urban fabric such as building density, height, materials, and vegetation

cover, that directly influence local climate conditions and thermal comfort of the case studies. Figure 5, depicts the workflow done by the author for the LCZ classification:

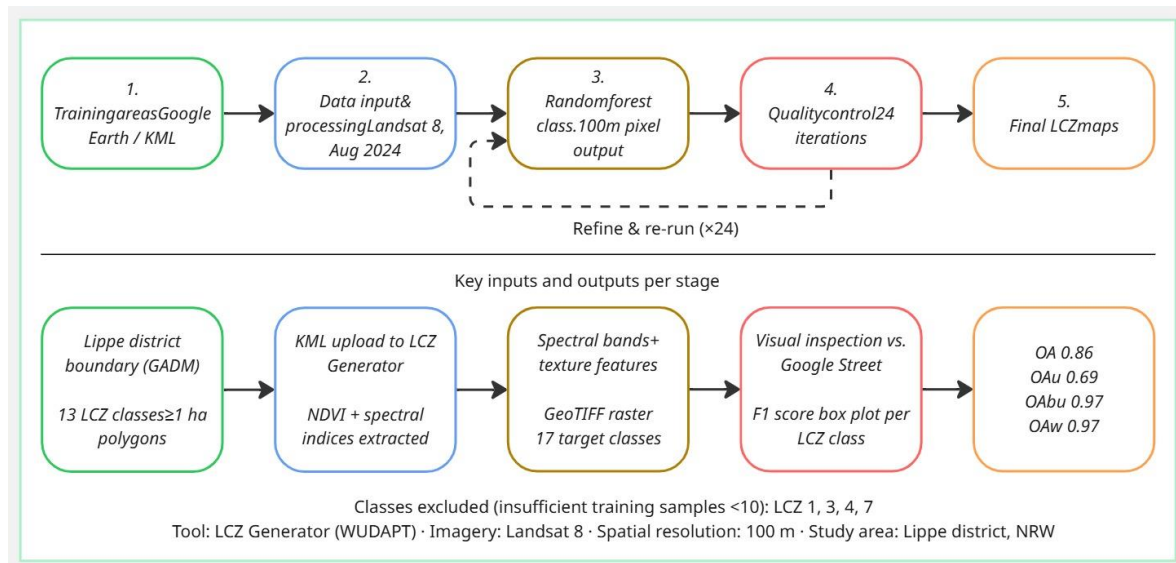


Figure 5 Workflow for the LCZ classification process applied to Detmold and Turin (produced by author).

7.6 LCZ Generator: Tool and Methodology

The classification of LCZ maps was performed using the LCZ Generator, a freely accessible web-based tool developed as part of the World Urban Database and Access Portal Tools (WUDAPT) initiative (Demuzere et al., 2021). The LCZ Generator utilizes a supervised random forest classification algorithm that processes multispectral satellite imagery to identify and map LCZ classes. The classifier is trained on user-defined training areas and uses spectral, textural, and morphological features derived from Landsat imagery to distinguish between different zone types (Demuzere et al., 2021).

The generation of the LCZ map for these two cities followed a systematic workflow:

The first step involved the manual training areas' digitization in Google Earth Pro. For each LCZ class, representative areas were carefully identified and delineated manually, as polygons within and around the city border², in order to have more selection possibilities.

Training areas were selected following WUDAPT guidelines³ to ensure they were:

- Homogeneous examples of the target LCZ class
- Sufficiently large (if possible, minimum 1 hectare, preferably larger)
- Spatially distributed across the study area
- Representative of the typical characteristics of each class

² The SHP data was downloaded from: <https://gadm.org/>

³ <https://www.wudapt.org/digitize-training-areas/>

Figure 6 and Figure 7 show the selected training polygons in Google Earth Pro, and Figure 8 and 9, represent the Examples of the selected samples of each zone in Detmold and Turin:

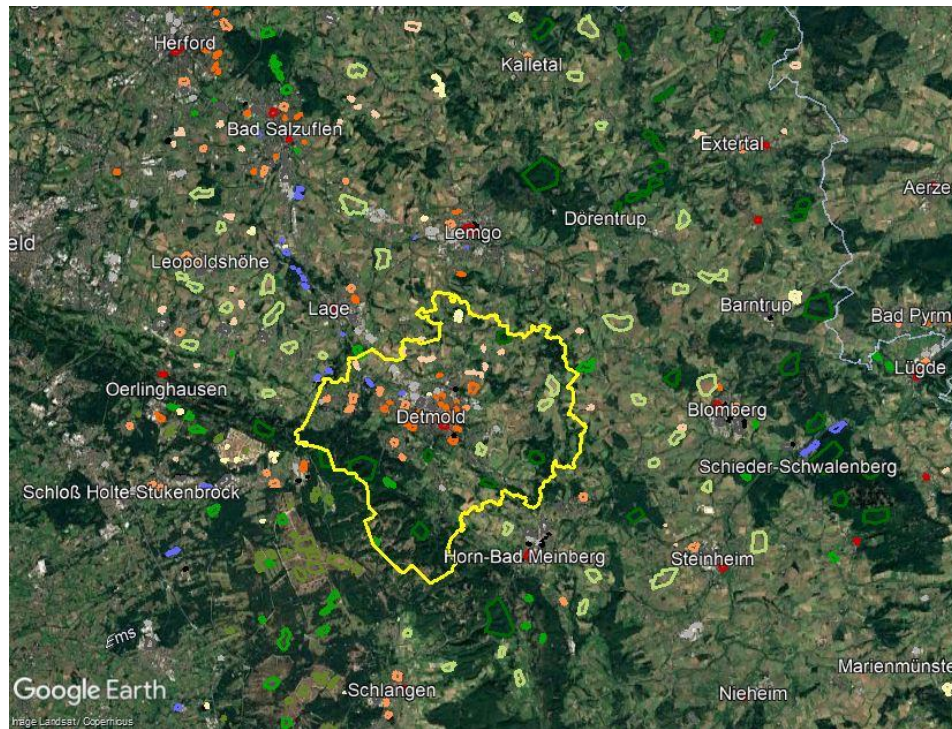


Figure 6. Training areas of Detmold. Colored polygons indicate the digitized LCZ class polygons (produced by author).

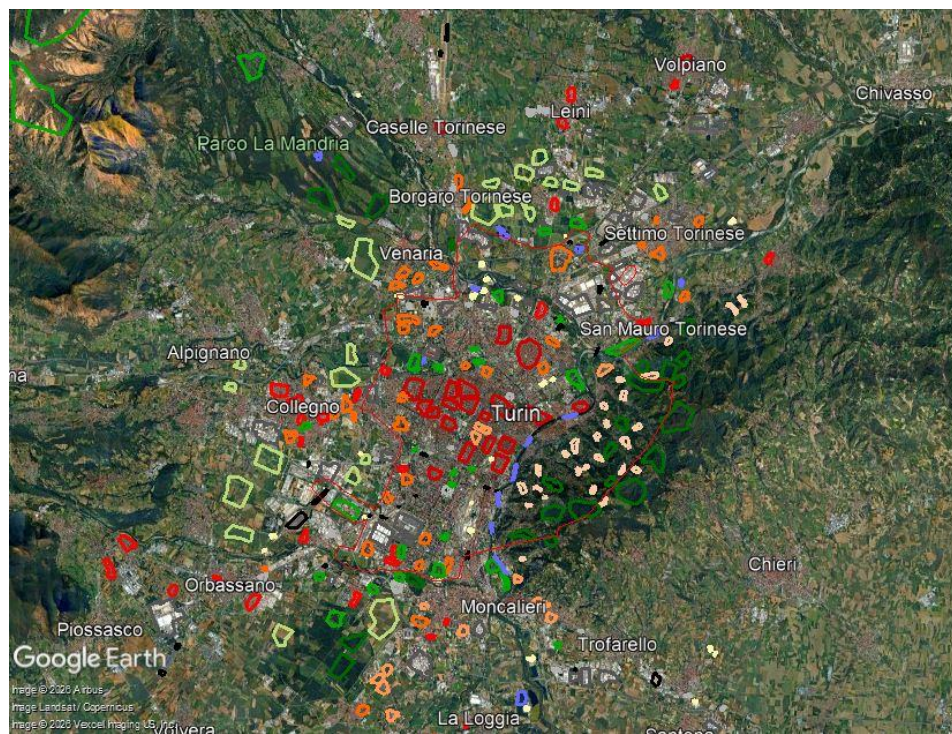


Figure 7. Training area of Turin. Colored polygons indicate the digitized LCZ class polygons (produced by author).



Figure 8. Examples of selected training samples for each LCZ zone in Detmold. Classes 1, 3, 4, and 7 excluded (training samples < 10), produced by author.

				
Class 2- Compact Midrise	Class 3- Compact low-rise	Class 5- Open Midrise	Class 6- Open low-rise	Class 8- Large low-rise
				
Class 9- Sparsely built	Class 10- Heavy industry	Class A- Dense trees	Class B- Scattered trees	Class D- Low Plants
				
Class E- Rock, Paved	Class F- Soil, Sand	Class G- Water		

Figure 9. Examples of selected training samples for each LCZ zone in Turin. Classes 1, 4, 7, and C excluded (training samples < 10), produced by author.

Data Input and Processing

The digitized training areas were uploaded to the LCZ Generator platform⁴ in KML format. The tool retrieved Landsat 8 imagery of the selected date of 27th August 2024 (best possible quality, and less cloud cover) for Detmold and 21st April 2024 for Turin, and computed the necessary spectral indices and texture features for classification.

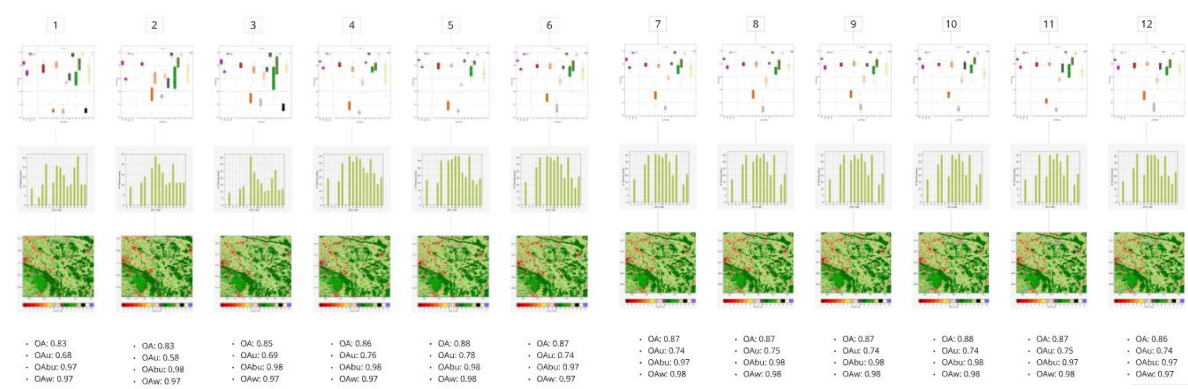
Random Forest Classification

The LCZ Generator's random forest algorithm was trained using the provided training areas and applied across the entire study area. The algorithm considers multiple spectral bands, vegetation indices (such as NDVI), and texture measures to assign each 100m pixel to one of the LCZ classes based on the training data patterns (Demuzere et al., 2021).

Quality Control and Validation

Following the initial classification, the results were visually inspected and compared against high-resolution Google Street images. It should be considered that in order to reach the best accuracy of each class, after the initial classification, the post-processing or refinement was done for 23 more times for Detmold and 9 times for Turin. Turin required fewer refinement iterations (9) than Detmold (23) to achieve satisfactory classification accuracy, likely reflecting the more spectrally distinct urban morphology of the denser Italian city compared to the heterogeneous peri-urban areas of Detmold that led to reaching acceptable results after fewer attempts. These refinements were such as: Minor adjustments to training areas where obvious misclassifications were detected, and the classification was re-run to improve accuracy.

Figures below, shows the outputs of all of the selection and refinement process for Detmold and Turin:



⁴ <https://lcz-generator.rub.de/>

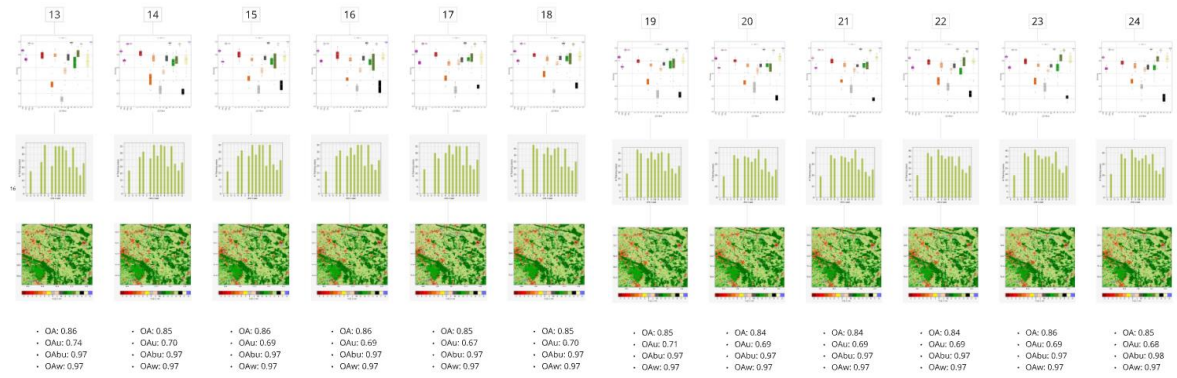


Figure 10. Outputs of all 24 refinement iterations of the LCZ classification process for Detmold(source: author).

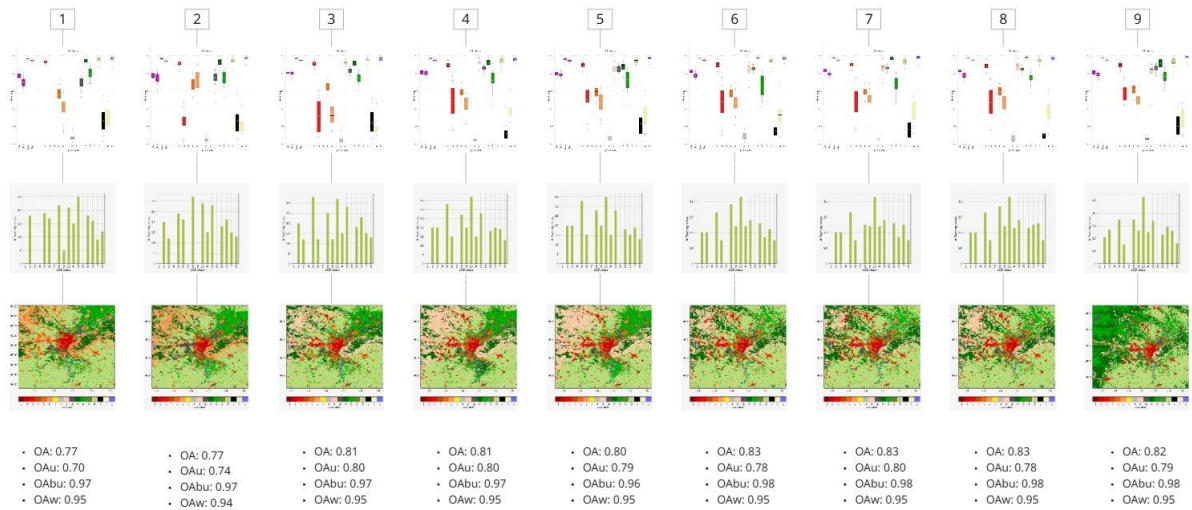


Figure 11. Outputs of all 9 refinement iterations of the LCZ classification process for Turin (source: author).

LCZ Generator Output and Results

The LCZ Generator provides several outputs that support both the use and validation of the classification:

- Classified LCZ map in raster format (GeoTIFF) with 100-meter spatial resolution. Each pixel is assigned to one of the 17 LCZ classes based on the random forest classification:

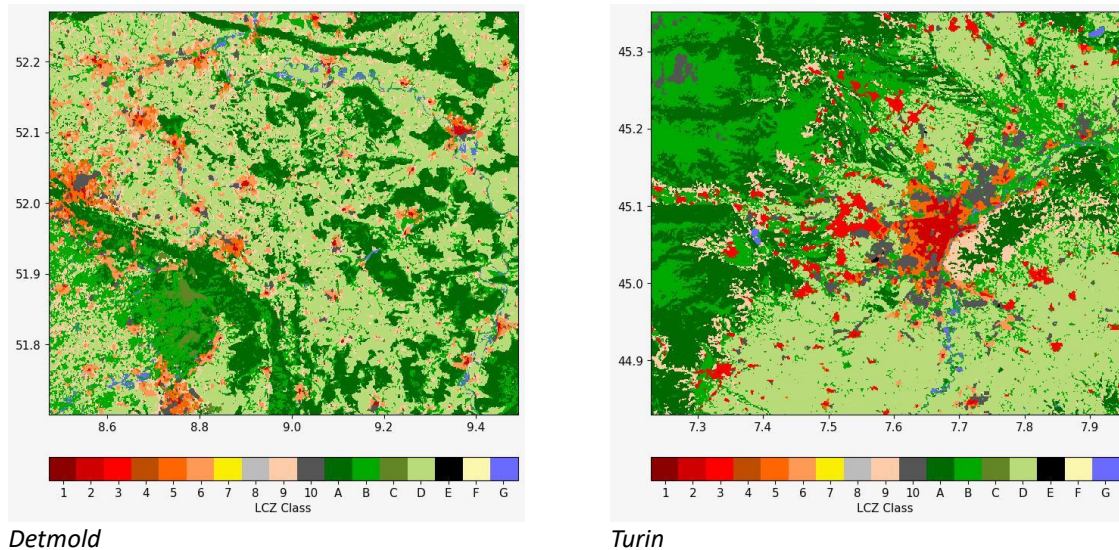


Figure 12. Classified LCZ maps of Detmold (left) and Turin (right), produced by the LCZ Generator (source: author).

Quality Assessment Products: The LCZ generator represents charts that show the accuracy of the generated maps in these charts, the purple box plots refer to the overall accuracy metrics:

- **OA: Overall Accuracy**, this is the general accuracy for all classes combined (both urban and natural).
- **OA_u: Overall Accuracy of Urban classes**, this metric focuses exclusively on LCZ classes 1 through 10 (the built environment).
- **OA_{bu}: Overall Accuracy of Built vs. Natural**, this reflects the model's ability to distinguish any built-up area from any natural area.
- **OA_w: Weighted Overall Accuracy**, this is a metric that accounts for the "degree of error" between similar classes.

Moreover, the other colored boxes show the class-wise F1 metric, based on different LCZ classes. The white dots and black lines represent mean and median respectively, the interquartile boxes show the most frequent accuracy scores, while the whiskers represent the full range of performance, excluding the most extreme 5% outliers on either end (Demuzere et al., 2021). The F1 scores varied considerably across different LCZ classes, reflecting differences in class distinctiveness and training area quality.

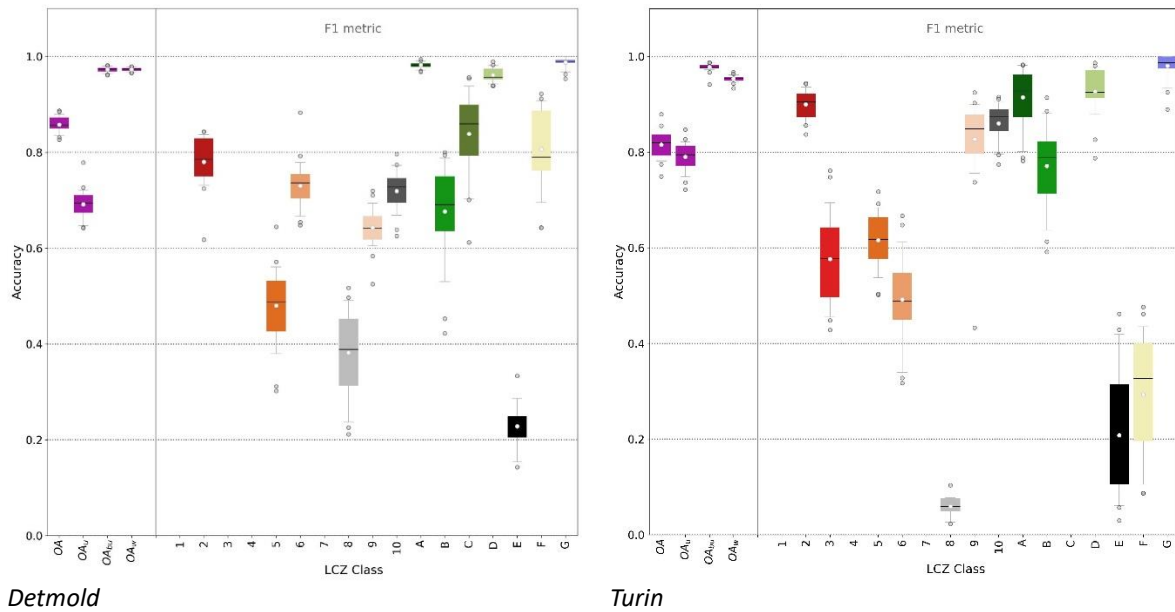


Figure 13. F1 score box plots for LCZ classification accuracy assessment: Detmold (left) and Turin (right), (source: author).

Downloadable Data: One of the data that is given by the LCZ generator is a fact sheet, containing the links to some additional datafiles such as Geotif, Kmz, and Boxplot Figure with Accuracies, also, the information as presented in Figure 9:

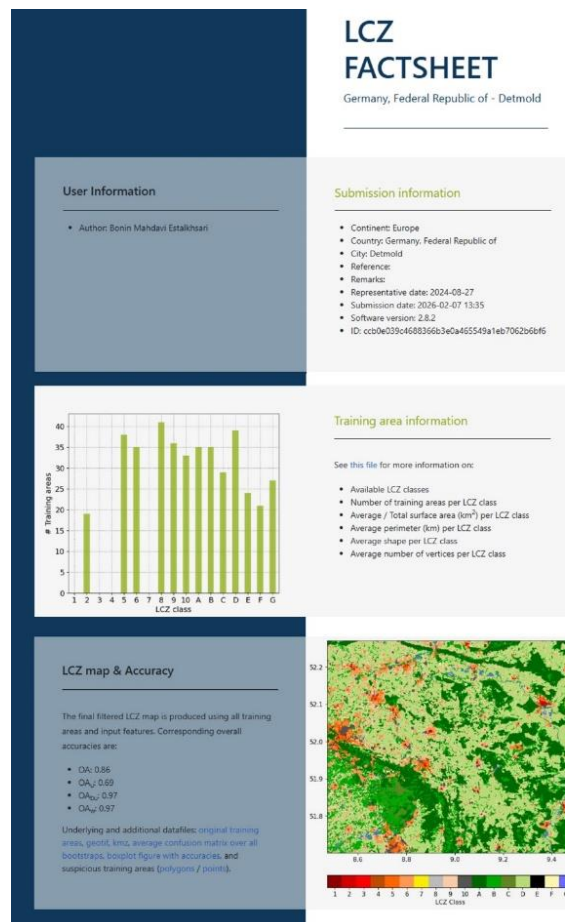


Figure 14. An example of Detmold's LCZ fact sheet. The "Terms of Service" and "Attribution" parts of the fact sheet is omitted here(source: author).

Among all the selection and refinement process, one has been selected with the following accuracies:

City	OA	OA _u	OA _{bu}	OA _w
Detmold	0.86	0.69	0.97	0.97
Turin	0.82	0.79	0.98	0.95

Table 6. Final results of accuracies of the LCZ classification (source: author).

The accuracy metrics demonstrate that the LCZ Generator successfully captured the major urban and natural landscape patterns in Detmold and Turin. The Classified LCZ map and the F1 score box plots of them are demonstrated in figures 7 and 8, respectively.

Processing and Vectorization of LCZ Data in QGIS

The spatial distribution of LCZs was derived from a compressed Keyhole Markup Language (KMZ) raster dataset. The following workflow was implemented within QGIS (Version 3.40.3) to transform the raw imagery into an analytically viable vector format.

Data Import and Pre-processing

The LCZ data, initially formatted as a three-band (RGB) raster KMZ, was imported into the QGIS environment. Because three-band rasters represent visual color rather than categorical data, an RGB to PCT (Paletted) transformation was required. This process utilized the GDAL `rgb2pct` utility to collapse the Red, Green, and Blue bands into a single-band pseudo-colored (indexed) raster. This step is critical to ensure that each unique LCZ color is assigned a discrete integer value (Digital Number, DN) for subsequent vectorization.

Raster-to-Vector Conversion (Polygonization)

The single-band indexed raster was converted into a vector format using the GDAL Polygonize algorithm. This process generated a polygon layer where each feature represents a contiguous group of pixels sharing the same LCZ class ID. To ensure topological integrity, a Fix Geometries operation was performed to resolve any self-intersections or sliver polygons resulting from the raster-to-vector transition.

Attribute Classification and Semantic Enrichment

The resulting attribute table contained raw Digital Numbers (DN) which did not natively correspond to the LCZ nomenclature. A classification schema was applied using the QGIS Field Calculator with a CASE statement. This mapping converted the numeric identifiers into standardized LCZ classes (e.g., LCZ 2: Compact Midrise, LCZ G: Water) as defined by Stewart and Oke (Stewart & Oke, 2012).

Geometric Consolidation (Dissolve)

To simplify the dataset for spatial analysis, a Dissolve operation was executed based on the LCZ_Class attribute. This operation merged all individual parcels belonging to the same category into single multipart features. This reduced the data complexity and facilitated more

efficient area calculations by eliminating redundant internal boundaries within identical zones.

Spatial Clipping and Area Quantification

The global LCZ dataset was clipped to the administrative boundaries of the study area (Turin, and Detmold) using the Vector Clip tool. Following the clip, the geometry of the features was updated to reflect the specific area within the municipal border.

Area calculations were performed using the expression $\$area / 1,000,000$ to convert the output from square meters to square kilometers. To ensure accuracy, these calculations were conducted using a projected coordinate reference system (CRS) appropriate for the region (ETRS89 / UTM zone 32N, EPSG:25832), preserving the metric accuracy of the land-cover extents.

Visualization and Layout

Finally, the dataset was symbolized using the standardized LCZ color palette to maintain international cartographic consistency. Coordinate grids (graticules) and scale bars were integrated within the QGIS Layout Manager to provide spatial context and orientation for the final cartographic outputs.

7.7 The final LCZ map of Detmold

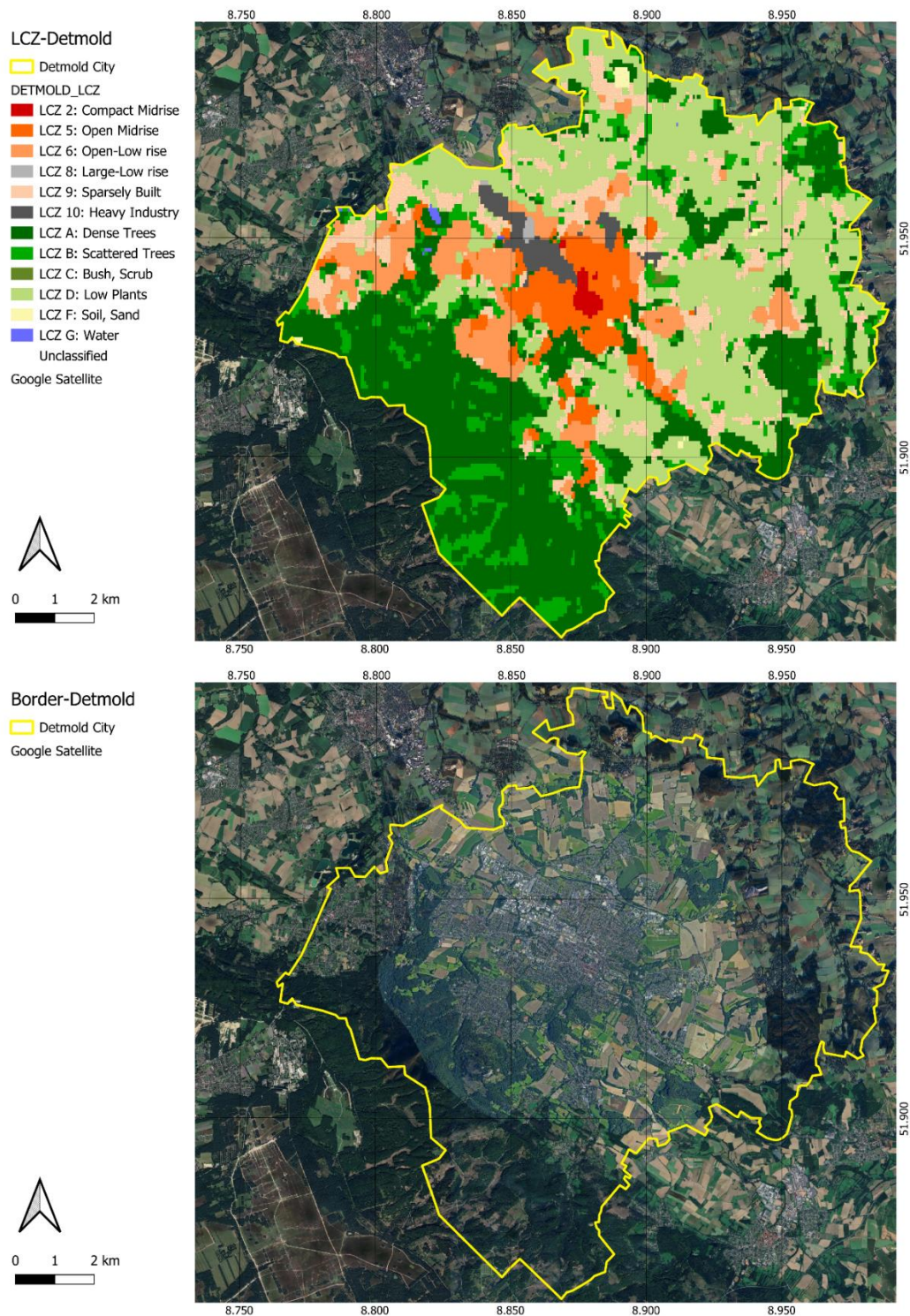


Figure 15. Final LCZ map of Detmold overlaid on satellite imagery (produced by author).

7.8 The final LCZ map of Turin

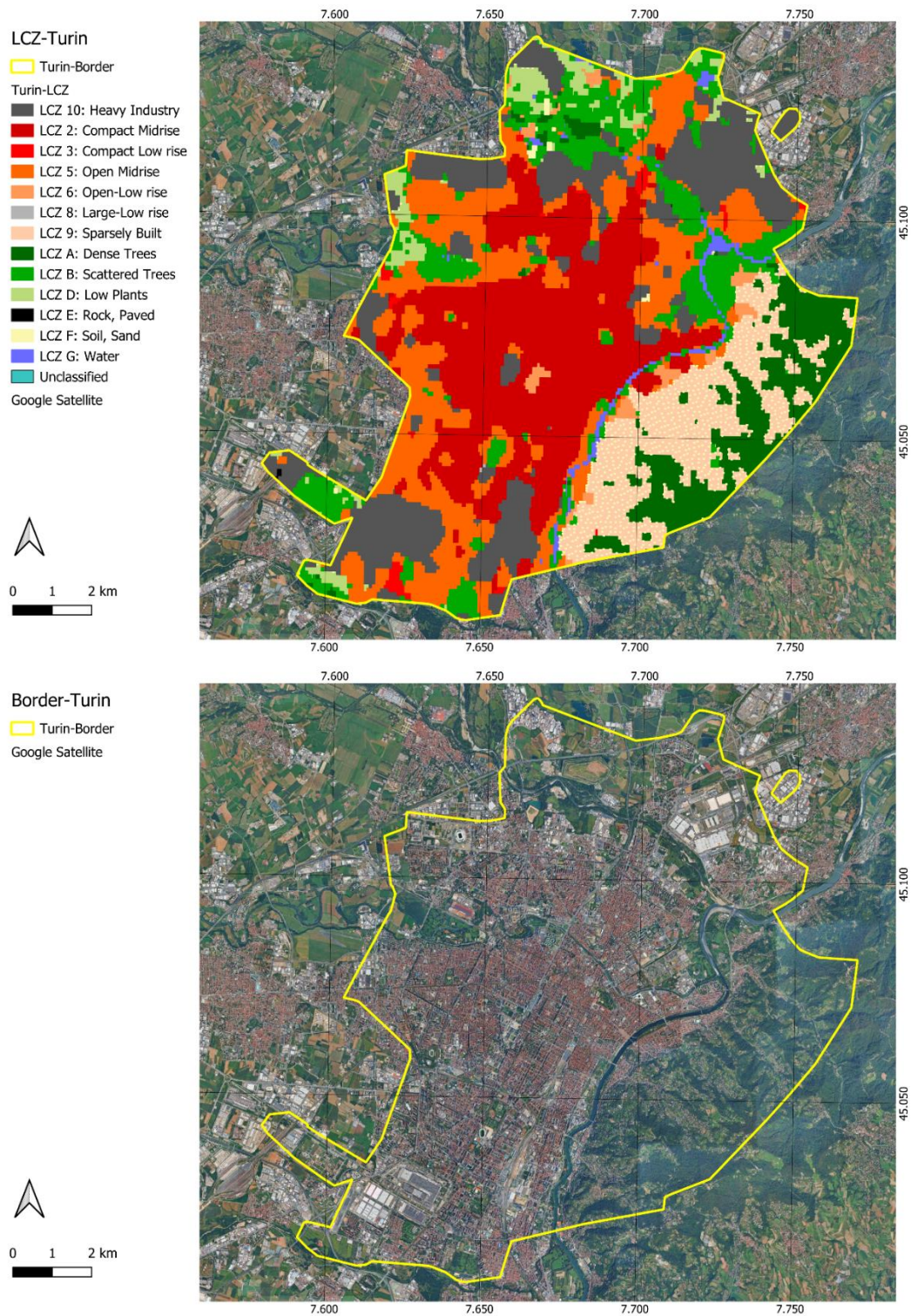


Figure 16. Final LCZ map of Turin overlaid on satellite imagery (produced by author).

7.9 Study Class Selection

In order to select study classes among 6 similar LCZ classes (2,5,6,8,9,10) between Detmold and Turin, the following considerations have been implemented:

- The classes with low accuracy and small areas have been omitted: class 8 (large low-rise)

- Class 9 (sparsely built) have been omitted due to the fact that most of the area within this class in Turin is on the hill side of the city, and this topography is different from the topography of class 9 in Detmold. Moreover, the pictures of the streets with steep would make biases in the perception survey.
- Class 6 (open low-rise) was omitted because the existing patterns of the streets in these classes are totally different between to cities.
- Class 10 (heavy industry) have not been considered since usually the industrial areas of cities are in the surrounding areas of cities to which the usual transportation mode is by automobile, so the survey answers would be biased.

Based on these considerations, two classes of 2 (compact midrise) and 5(open midrise) have been selected, both in midrise classification but with different streetscape attributes and geometries.

7.10 Point Selection in The Study Classes

In the next step, to find the study points within these classes in each city, it was decided to implement a systematic investigation, based on in-place observations and Google Earth pro street views' observations. It was considered to find the settings in the streetscapes that follow the same pattern with the most possible identical streetscape attributes. The patterns are defined as the following:

LCZ class	Point Turin ID	Point Detmold ID	Streetscape Pattern
2	T-1	D-1	Building+ Pedestrian Route+ Parking+ Vehicle Route+ Parking+ Pedestrian Route+ Building
2	T-2	D-2	Building+ Pedestrian Route/Sitting Area+ Vehicle/Pedestrian Route+ Pedestrian Route+ Building
2	T-3	D-3	Building+ Pedestrian Route+ Parking/Vehicle Route+ Vehicle Route+ Parking+ Pedestrian Route+ Building
2	T-4	D-4	Private Greenery+ Pedestrian Route+ Vehicle Route+ Building
2	T-5	D-5	Building+ Pedestrian Route & Scattered Trees+ Vehicle Route+ Parking& Pedestrian Route& Scattered Trees+ Building
5	T-6	D-6	Private Greenery& Building+ Pedestrian Route+ Parking+ Vehicle Route+ Parking+ Pedestrian Route+ Private Greenery& Building
5	T-7	D-7	Private Greenery& Building+ Pedestrian+ Parking+ Vehicle Route+ Parking+ Pedestrian Route+ Building
5	T-8	D-8	Building+ Pedestrian Route+ Parking+ Vehicle Route+ Parking+ Pedestrian Route+ Building
5	T-9	D-9	Public Green Area+ Pedestrian Route+ Parking+ Vehicle Route& Parking+ Pedestrian Route+ Building
5	T-10	D-10	Building+ Pedestrian Route+ Parking& Trees+ Vehicle Route+ Parking& Trees+ Pedestrian Route+ Building

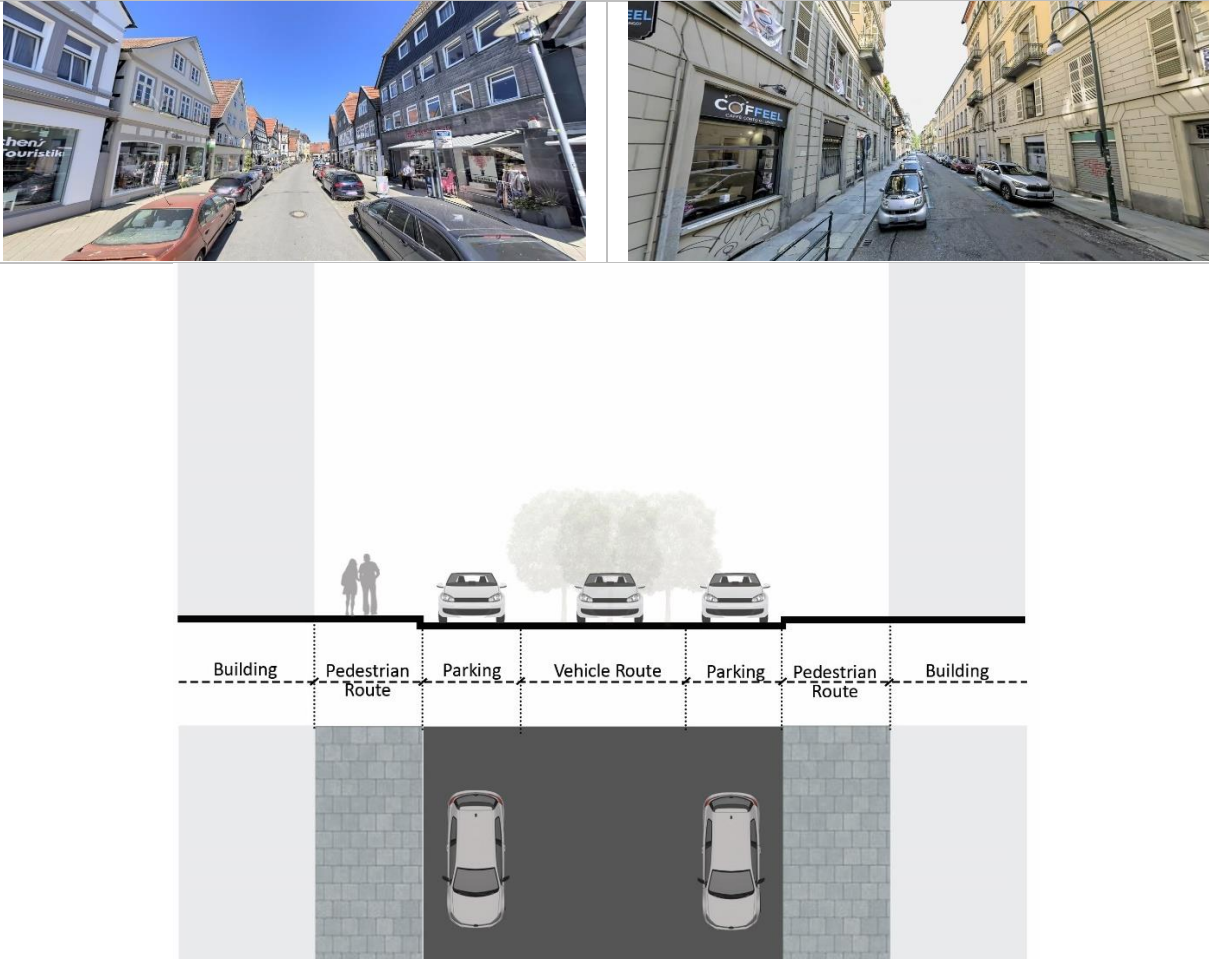
Table 7. Matched streetscape patterns for the 20 survey points across LCZ 2 and LCZ 5 in Turin and Detmold(source: author).

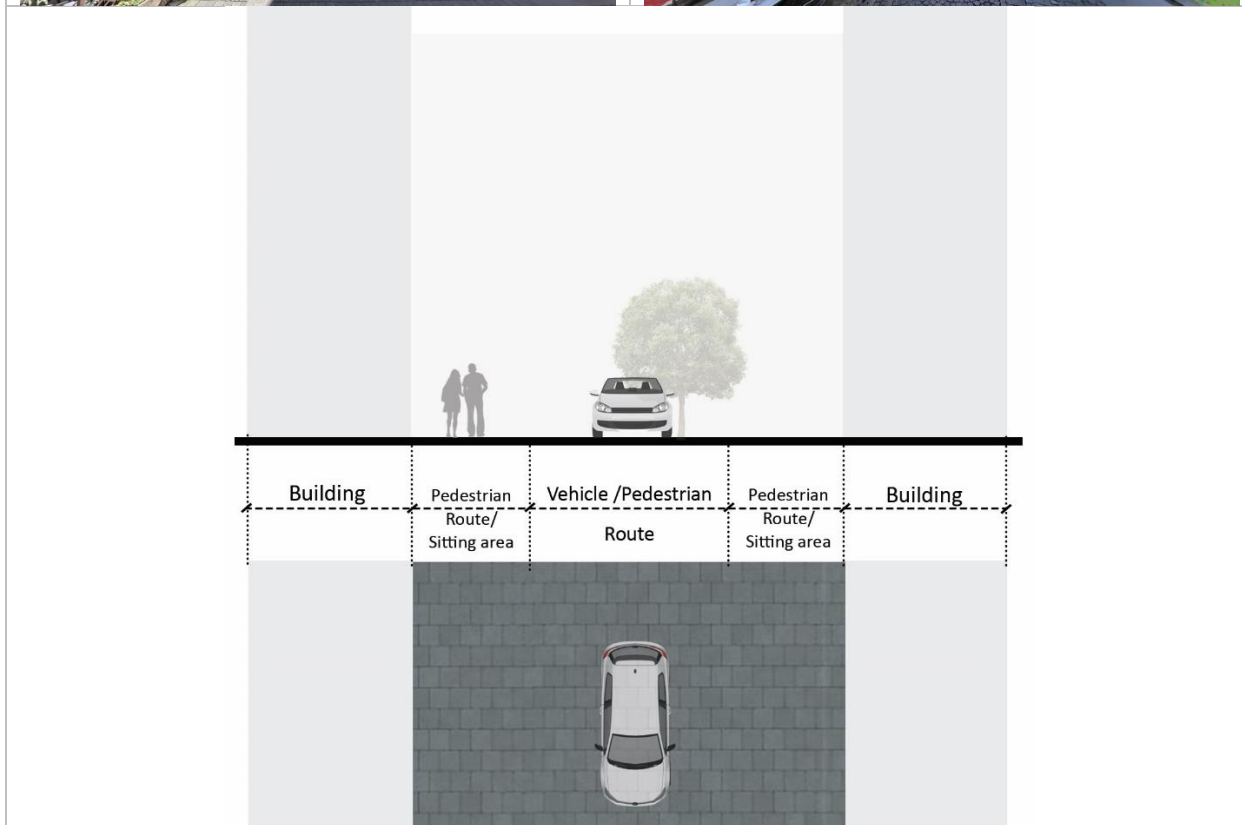
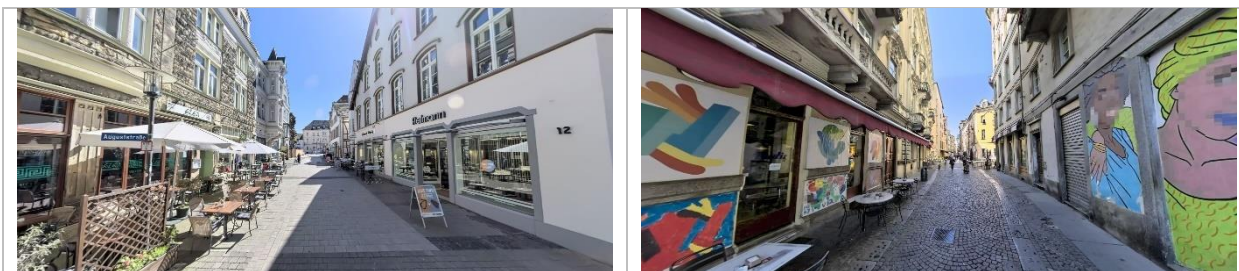
Although there were some limitations, but five points with approximate similarities have been selected within each class in Detmold and Turin. Some of the limitations were as follows:

- In the definitions of classes 2 and 5, the minimum and maximum number of buildings' floors are 3 and 9, respectively. However, in Detmold this number were mostly the minimum but in Turin, it was near the maximum. So, although most of the streetscape attributes have the same pattern, but the height to width ratio in these two cities are so different.
- In some of the patterns, the On-Street Parkings have different orientations in these two cities, but this doesn't influence the existence of these areas.

7.11 LCZ class 2- Point Selection Rationale

Tables 7 and 8 show the diagrams and images dedicated to each of the points and their streetscape patterns:

LCZ CLASS 2	
Detmold	Turin
D-1	T-1
	
D-2	T-2

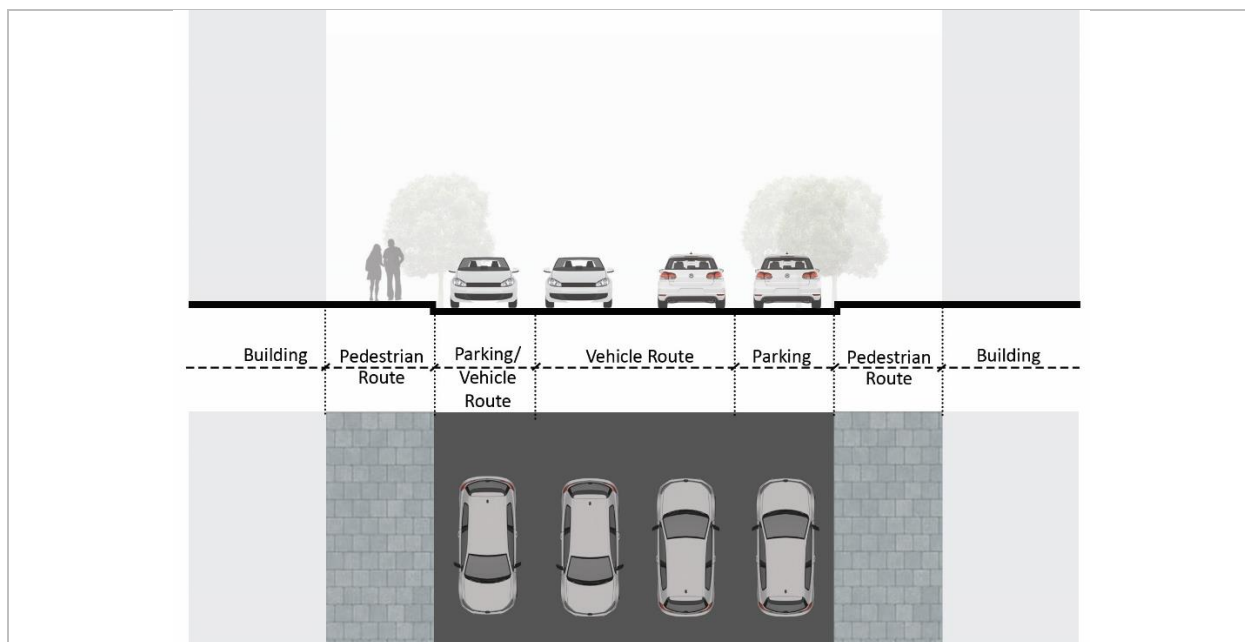


D-3



T-3

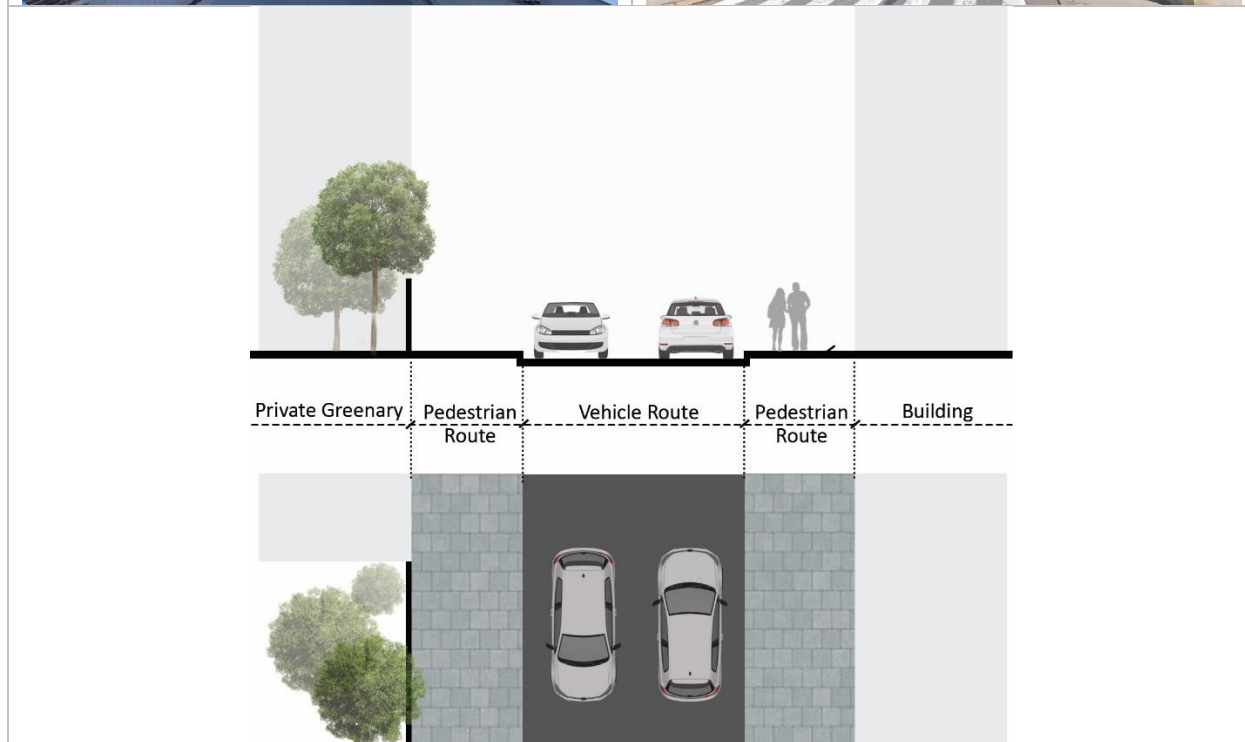




D-4



T-4



D-5

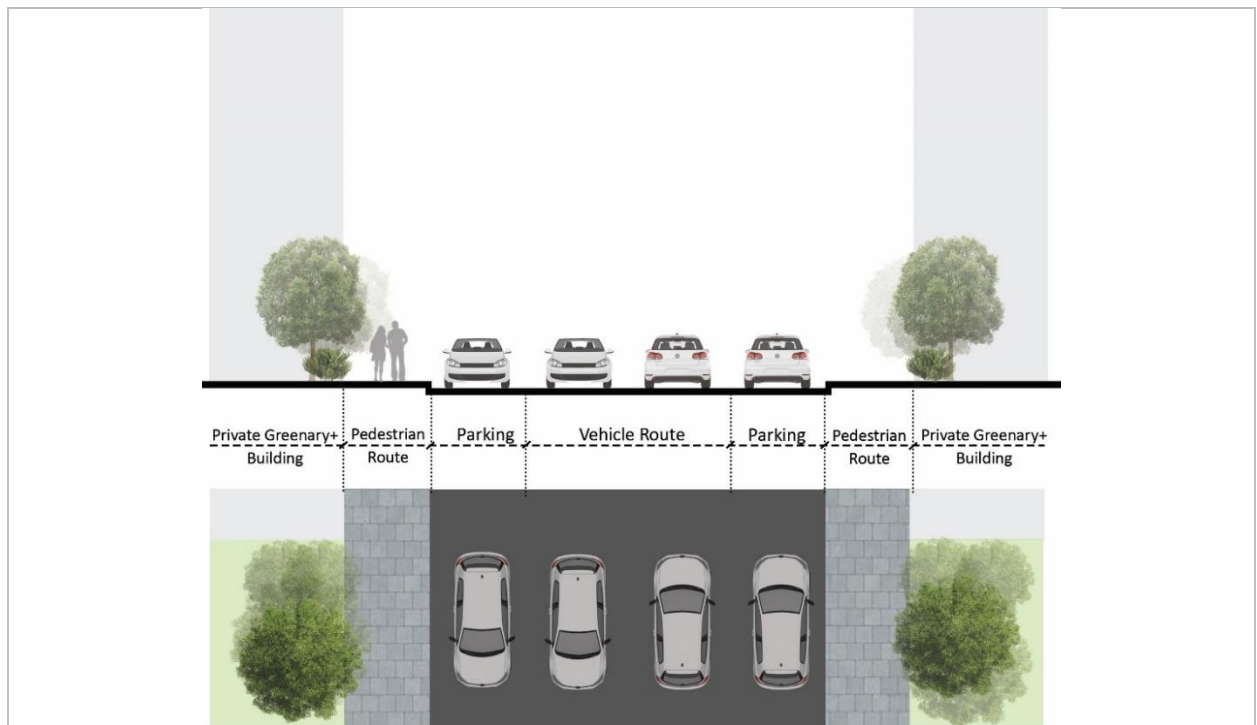
T-5



Table 8. LCZ class 2- Point Selection Rationale (source: author).

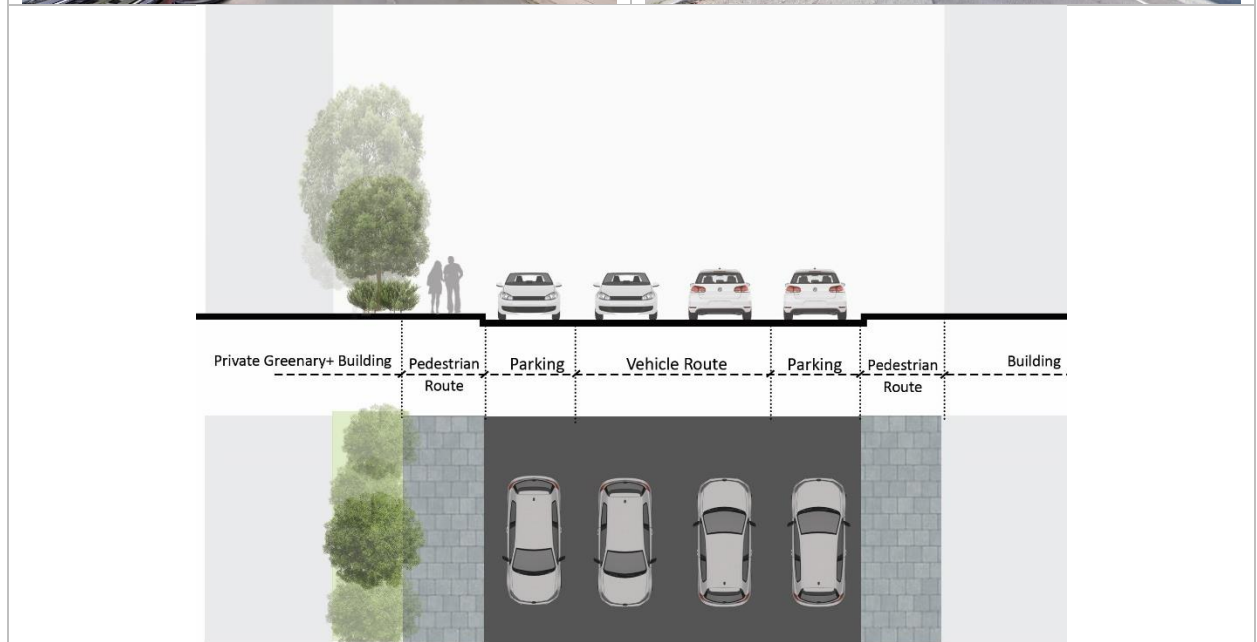
7.12 LCZ class 5- Point Selection Rationale

LCZ CLASS 5	
Detmold D-6	Turin T-6



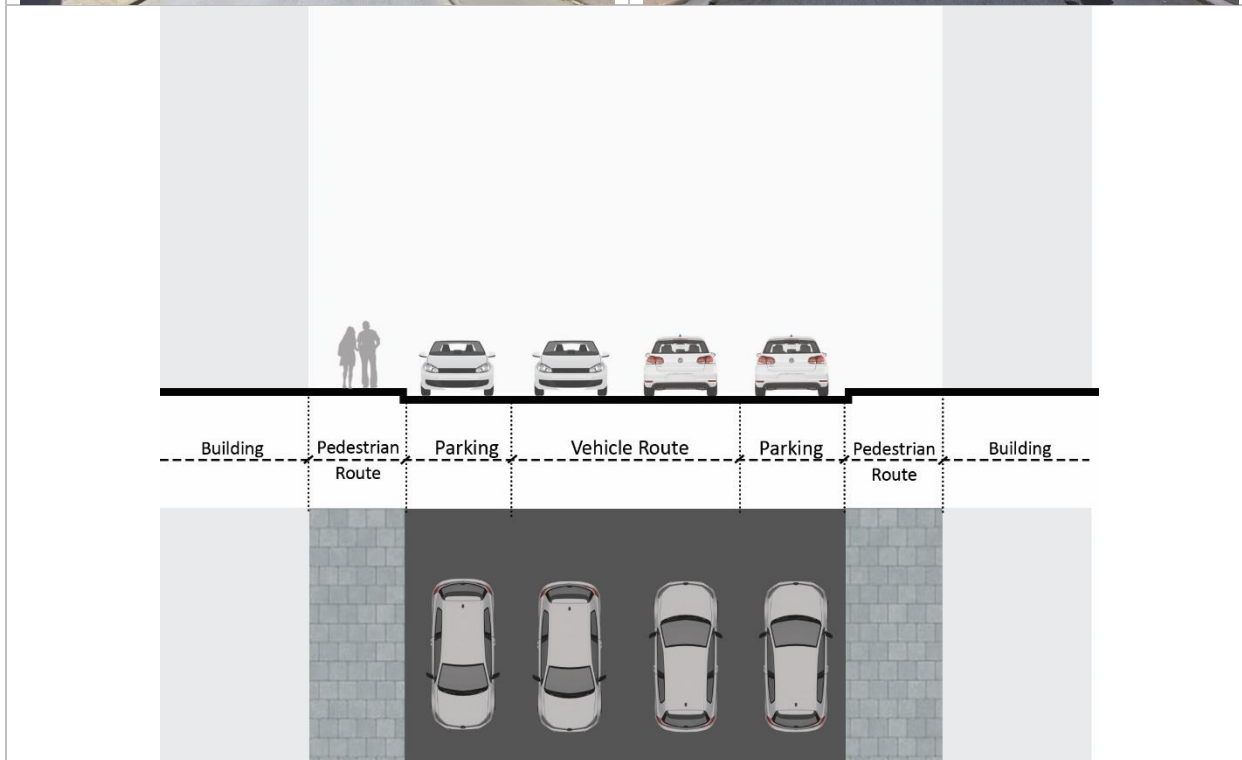
D-7

T-7



D-8

T-8



D-9



T-9



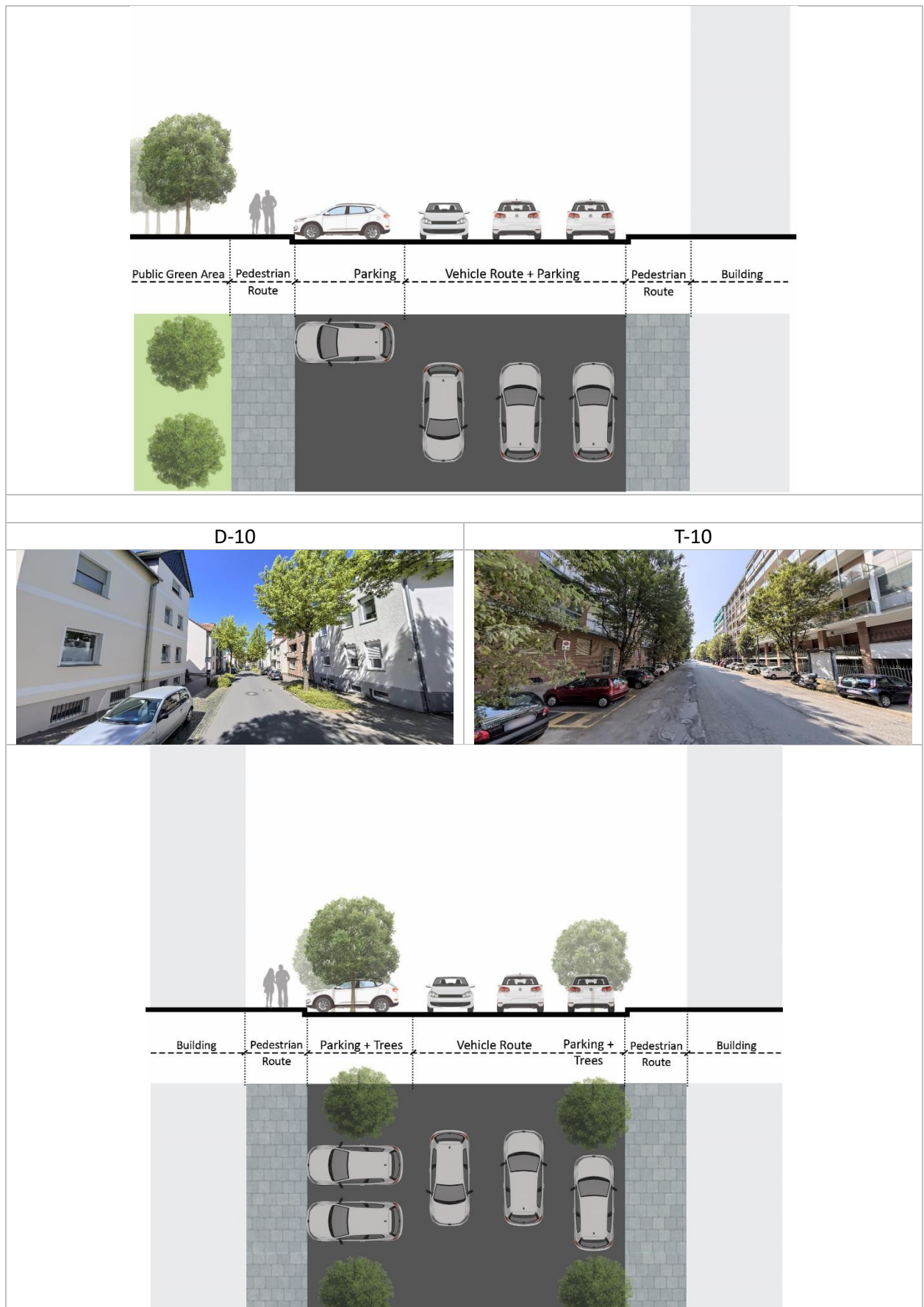


Table 9. LCZ class 5- Point Selection Rationale (source: author).

7.13 Final selected points in each city

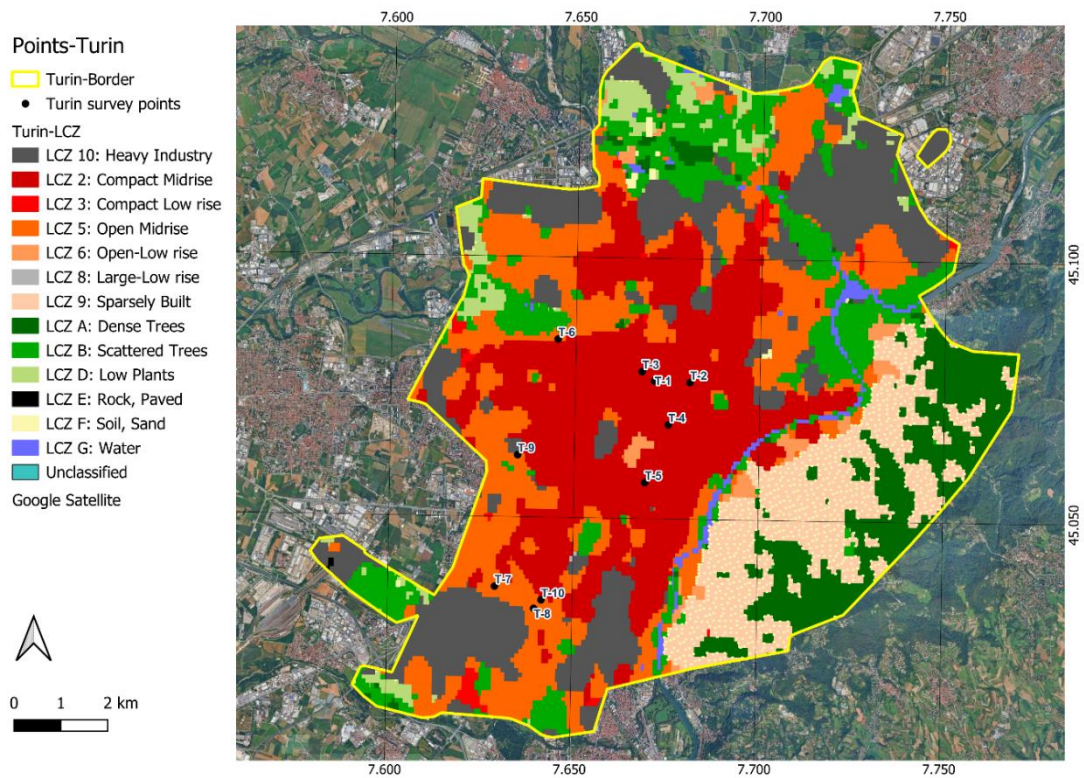


Figure 17. LCZ map of Turin with the 10 selected survey points overlaid (produced by author).

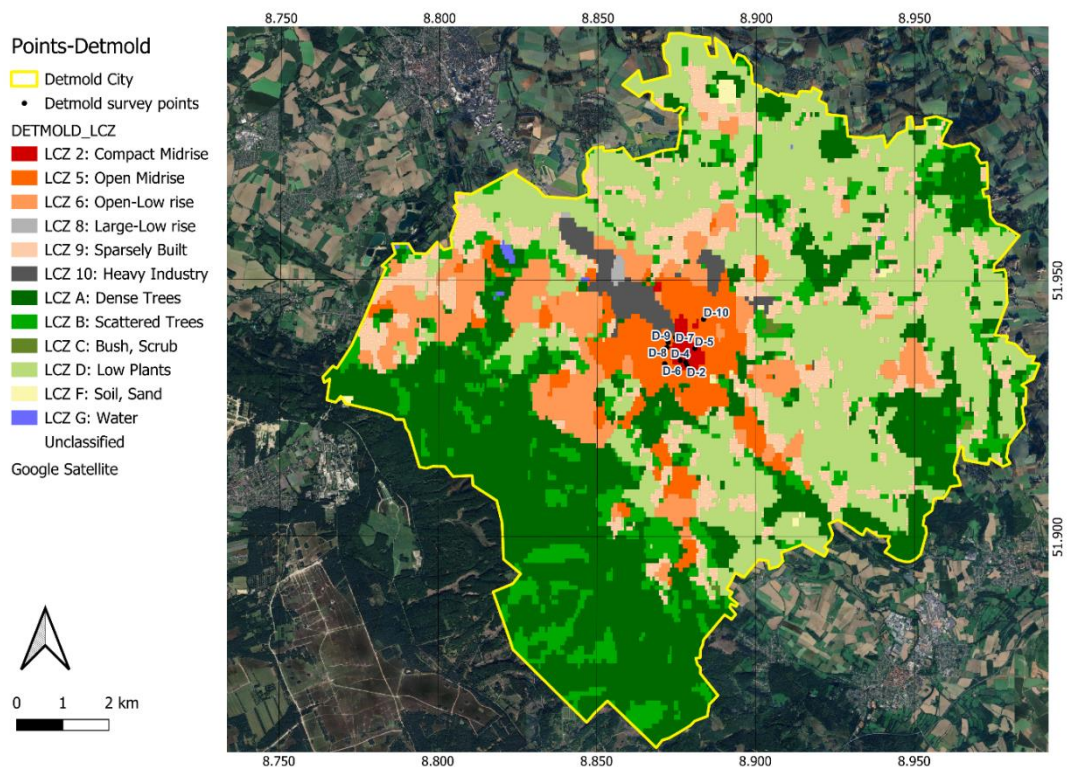


Figure 18. LCZ map of Detmold with the 10 selected survey points overlaid (produced by author).

8. Phase 2: Multi-Layer Attribute Data Collection

This section documents the multi-layer attribute data collection framework developed to characterize each of the 20 street-level points across Local Climate Zones 2 and 5 in Turin and Detmold. The data collection operates on two complementary logics that was derived from the methodology adopted by (S. Yang et al., 2025): a visual composition logic, which quantifies what is seen in the street-level photograph that respondents rated (captured through semantic segmentation of Apple Street View imagery) and a physical environment logic, which quantifies the actual thermal conditions present at each point, regardless of what is visible in any single photograph.

8.1 Justification of the Attribute data selection

The environmental attribute framework developed for this study comprises two layers of data, each capturing a distinct dimension of the streetscape environment at each of the 20 points in Turin and Detmold.

Together a 23-attribute data matrix linking visual perception to measurable urban thermal environment was produced. The collection process proceeded in two sequential layers.

Layer 1 extracts remote sensing environmental attributes: LST, NDVI, MNDWI, and surface albedo, from Landsat 8/9 and Sentinel-2 imagery processed in Google Earth Engine (GEE).

Layer 2 extracts streetscape visual composition attributes of the images that were captured from Apple Street Views, via deep learning semantic segmentation, using SegFormer-B5 trained on the Cityscapes dataset.

The selection of each layer is grounded in a body of established academic literature that has demonstrated its relevance to outdoor thermal comfort and thermal perception at street level that was declared in the chapter of literature review. This section presents the justification for each layer, organized by the type of relationship it establishes with human thermal comfort.

The fundamental premise of this study, that visual assessment of street-level imagery can serve as a valid method for evaluating thermal comfort potential, is directly supported by (S. Yang et al., 2025) who introduced the concept of thermal affordance as the capacity of visual and physical attributes a streetscape to effect thermal comfort. Their VATA method, combining SVI, questionnaire surveys, and physical streetscape attributes including vegetation indices, constitutes the closest methodological parallel to the framework employed in this thesis.

Layer	sources	
Layer 1, Remote Sensing	(Urban et al., 2022)	LST+ SVF+ Visual rating of TC
	(C. Hu & Zeng, 2025)	MNDWI+ LST+ NDVI+ TC
	(Larkin et al., 2021)	Perception Survey+ Semantic Segmentation+ population density+ impervious surfaces+ NDVI
Layer 2, SVI Segmentation		
	(Larkin et al., 2021)	Perception Survey+ Semantic Segmentation+ population density+ impervious surfaces+ NDVI

	(J. Chen et al., 2026)	LCZ+SVF+ BVF+ GVF+ Thermal Variation
	(Lee et al., 2025)	Semantic Segmentation+ Building height+ Building coverage ratio of buildings+ impervious/pervious surfaces+ water surfaces+ air temperature deviation

Table 10. Summary of key references justifying the attribute data selection(source: author) .

8.2 Layer 1, Remote Sensing Environmental Attributes

of the four remote sensing indices in Layer 1 are extracted from satellite imagery processed in GEE. These four indices collectively characterize the physical thermal and biophysical environment at each survey location: LST captures the resultant surface temperature; albedo captures the reflective properties of surface materials; NDVI captures vegetation cover; and MNDWI captures surface water and moisture conditions. Together, they constitute the remote sensing evidence base against which the visual thermal comfort ratings collected through the questionnaire are contextualized and interpreted.

All four indices were extracted at the exact coordinates of each point from single-date satellite acquisitions, selected following a systematic screening of all available Landsat 8/9 and Sentinel-2 scenes over Turin and Detmold for the summer of 2025 (June–August) in Google Earth Engine.

To select the data acquisition dates, only dates on which both cities were covered by the same sensor on the same calendar day were considered eligible. In order to do this, first the full summer 2025 archive was screened, including the main heatwave window of late June to early July and the entire month of August, only two dates met the criterion with acceptable cloud cover for both cities simultaneously: 22 June 2025 for Landsat 8/9, used for LST and Albedo extraction (Turin: 5.87% cloud cover; Detmold: 1.97%), and 12 June 2025 for Sentinel-2, used for NDVI and MNDWI extraction. The 10-day interval between the two sensor dates reflects the independent orbital revisit cycles of the Landsat and Sentinel-2 constellations and is consistent with standard practice in multi-sensor urban remote sensing studies (J. Li & Roy, 2017). Prior to extraction, all scenes were cloud-masked to ensure that extracted values reflect cloud-free observations at every point. Values were then extracted at the exact coordinate of each study point using. Table 10 summarizes the information about data acquisition of each attribute.

Attribute	Satellite / Sensor	Product / Bands	Acquisition date	Resolution
LST	Landsat 8 / Landsat 9	C2 L2 · Band ST_B10 (thermal infrared)	22 June 2025	30 m
Albedo	Landsat 8 / Landsat 9	C2 L2 · SR bands B2, B4, B5, B6, B7	22 June 2025	30 m
NDVI	Sentinel-2 A / B / C	SR Harmonized · B8 (NIR, 842 nm), B4 (Red, 665 nm)	12 June 2025	10 m
MNDWI	Sentinel-2 A / B / C	SR Harmonized · B3 (Green, 560 nm), B11 (SWIR, 1610 nm)	12 June 2025	20 m

Table 11. remote sensing attributes' acquisition sensors, bands, date, and resolution (Source: USGS 2026).

8.2.1 Land Surface Temperature (LST)

LST was retrieved from Landsat 8 and Landsat 9 Collection 2 Level-2 surface temperature products (band ST_B10), accessed through GEE (Abunnasr & Mhawej, 2022). Both sensors were merged into a single collection to maximize scene coverage over the two cities (H. Xu et al., 2024), and acquisition was fixed to 22 June 2025, identified through systematic screening, explained in section 8.2.

The ST_B10 band provides at-surface brightness temperature derived from thermal infrared radiance through atmospheric correction applied at the USGS processing level (Cook, 2014). To convert the raw digital numbers to physical surface temperature, the Collection 2 scaling coefficients were applied (EROS Center, 2020):

$$T_{\text{surface}} = \text{DN} \times 0.00341802 + 149$$

yielding brightness temperature in Kelvin, subsequently converted to degrees Celsius:

$$T^{\circ}\text{C} = T_{\text{K}} - 273.15$$

City-wide LST rasters were produced for visual inspection, while point-level values were extracted at the exact coordinates of each survey location.

8.2.2 Normalized Difference Vegetation Index (NDVI)

NDVI was derived from Sentinel-2 Level-2A Harmonized Surface Reflectance imagery (COPERNICUS/S2_SR_HARMONIZED), accessed via GEE. Sentinel-2 was preferred over Landsat due to its 10 m spatial resolution, which better captures the heterogeneity of urban vegetation that would be missed at Landsat's 30 m resolution (Iqbal et al., 2025; Lefebvre et al., 2016). The acquisition date was fixed at 12 June 2025, following the systematic screening procedure described in Section 8.2.

NDVI was computed from the standard normalized difference of Band 8 (NIR, 842 nm) and Band 4 (Red, 665 nm) (Tucker, 1979):

$$\text{NDVI} = \frac{B8 - B4}{B8 + B4}$$

Values range from -1 to +1, where higher positive values indicate denser vegetation cover (Tucker, 1979). Point-level values were extracted at the exact coordinates of each survey location.

8.2.3 Modified Normalized Difference Water Index (MNDWI)

MNDWI was computed from the Sentinel, the same extraction date of 12 June 2025 was applied as for NDVI.

MNDWI was derived from the same Sentinel-2 Level-2A Harmonized Surface Reflectance scene used for NDVI (COPERNICUS/S2_SR_HARMONIZED), acquired on 12 June 2025.

MNDWI was computed using Band 3 (Green, 560 nm) and Band 11 (SWIR, 1610 nm), following (H. Xu, 2006):

$$\text{MNDWI} = \frac{B3 - B11}{B3 + B11}$$

The SWIR band suppresses the signal from built-up surfaces and soil, which tend to inflate water detection in the original NDWI (McFeeters, 1996), making MNDWI more suitable for urban environments where water bodies are spatially interspersed with impervious surfaces (H. Xu, 2006). Values above zero are generally indicative of open water surfaces. Point-level values were extracted at the exact coordinates of each survey location.

8.2.4 Surface Albedo

Surface albedo was derived from the same Landsat 8/9 Collection 2 Tier 1 Level-2 Surface Reflectance scene acquired on 22 June 2025, used for LST.

Broadband shortwave albedo was estimated from the Landsat visible and near-infrared surface reflectance bands following the empirical narrowband-to-broadband conversion proposed by (Liang, 2001):

$$\alpha = 0.356 \cdot B2 + 0.130 \cdot B4 + 0.373 \cdot B5 + 0.085 \cdot B6 + 0.072 \cdot B7 - 0.0018$$

where B2, B4, B5, B6, and B7 correspond to the blue, red, NIR, SWIR-1, and SWIR-2 bands respectively, each rescaled to physical surface reflectance using the Collection 2 scaling coefficients (EROS Center, 2020). Point-level values were extracted at the exact coordinates of each survey location.

8.3 Layer 2, Streetscape Visual Composition (SVI Semantic Segmentation)

Layer 2 comprises the pixel-level semantic class fractions extracted from the same horizontal street-level Apple Street View images used in the questionnaire survey. For each of the 20 survey points, the Apple Street View image was processed through a deep learning semantic segmentation model to classify every pixel into one of 19 urban scene categories drawn from the Cityscapes dataset taxonomy (Cordts et al., 2016). The resulting pixel fractions that express the percentage of each semantic class, provide a precise, quantitative description of the visual composition of each streetscape image as perceived by survey respondents (Suo & Zhao, 2025; S. Yang et al., 2025).

Segmentation was performed using the NVIDIA SegFormer-B5 model finetuned on the Cityscapes dataset (Cordts et al., 2016), implemented in Python. The Cityscapes training corpus is directly appropriate for this study as it consists of European urban street-level imagery comparable in morphology and perspective to the Turin and Detmold survey images (Cordts et al., 2016). The final images presented in section 10.5 indicate the results of image segmentation over the SVI of each study point, with the percentages of existing visual streetscape attributes at each image.

9. Phase 3: Perception Survey

9.1 Sources of street view images

Street view imagery used in this study was sourced from Apple Street View that is a popular source in this field (Biljecki & Ito, 2021; Hou & Biljecki, 2022). The selection was initially between self-taken photographs or photos from public sources. The final decision was made following a systematic comparison of the two available approaches: availability during the study period, vegetation richness in summer conditions, camera position at human eye-level, location of the camera on a pedestrian route, and temporal alignment between image dates and remote sensing data collection. The comparison revealed that neither approach satisfies all criteria simultaneously. Public sources offer clear advantages in terms of availability and vegetated summer imagery, while self-taken photographs offer greater control over camera height and placement on walking routes. Crucially, neither method guarantees temporal alignment between image dates and remote sensing data a limitation shared by both approaches equally, although all of the study images are taken in summer.

Given this analysis, the decision to proceed with Apple Street View imagery was further justified by two considerations. First, the temporal mismatch between image dates and remote sensing data is a known and documented limitation in the literature, not a methodological flaw unique to this study. (Chiang et al., 2023), (Larkin et al., 2021), and (Urban et al., 2022) all used street view images from dates that differed from their environmental datasets, and explicitly acknowledged this as an accepted limitation. Second, to compensate for the scenario uncertainty introduced by variable image dates, a contextual framing is provided to survey respondents: participants are asked to imagine themselves in each street scene on a hot summer day, regardless of the seasonal appearance of the image. This scenario-based framing is consistent with the approach adopted by (Urban et al., 2022) who found that respondents can reliably predict heat-related discomfort from street photographs even when explicit meteorological conditions are not shown.

	Images from public data sources	Images taken by the researcher
Availability during the study period	yes	no
Vegetation richness during the study period	yes	no
Human eye-level	no	yes
Location of the camera on a walking pass	no	yes
The similarity of the image dates and RS data	no	no
Image dates on the hottest dates of the year	no	no

Table 12. Comparison of image acquisition approaches for street-level visual thermal comfort surveys: public data sources versus self-taken photographs(source: author).

An alternative approach was considered in which the researcher would take their own street photographs at the sampled locations and use generative AI to add summer foliage to trees to control both camera position and seasonal appearance. This method has precedent in the literature: (Ye & Li, 2026) applied a similar approach to convert summer scenes into winter conditions. However, this option was ruled out for two reasons. The fieldwork period did not coincide with full summer vegetation in both study cities, meaning self-taken photographs would have required extensive AI-based modification. Moreover, introducing generative AI into the image dataset at this scale would require a dedicated validation framework to control for AI-induced visual biases which is a process that falls outside the time constraints of the present study. The scenario-framing approach is therefore retained as the more methodologically transparent and time-feasible solution.

9.2 Questionnaire Design Rationale

As no single existing study matches all criteria of the present research, the questionnaire was designed by the author by adapting and synthesizing validated instruments from the literature. For each section and question, the source references and rationale are documented below.

Overall Questionnaire Structure

The decision to organize the questionnaire into thematically distinct sections instead of presenting all questions in a single list, is grounded in the systematic review of OTC questionnaire practice (Y. Li et al., 2025). Usually, the subjective perception evaluation questionnaires (SPEQ) are structured based on three thematic sections: (1) personal data of the respondents, such as the demographic background information about them; (2) place-related parameters such as information about the respondent's living location, thermal history and adaptation; and (3) thermal perception and comfort ratings that is the respondent's subjective assessment of the thermal environment.

The present questionnaire adopts this three-section structure directly. This structure ensures that the questionnaire collects the full range of data required to address all of the research questions while following the established sectioning logic of the OTC literature.

Section 1: Introduction

The introductory section of the questionnaire serves three functions: it contextualizes the research for the participant through a brief “**Scenario Description**”, it fulfils the ethical requirement of informed consent, and it communicates practical instructions. The design of this section is directly modelled on (Vasconcelos et al., 2024) whose questionnaire on the use of urban green spaces by older adults during hot days in Barcelona opens with an explicit climate scenario framing before presenting the study objective, anonymity statement, participation conditions, and a single informed consent checkbox.

The section closes with a single consent item: "Yes, I want to participate." To estimate the more precise time duration, a pilot test was conducted by the 4 people and the estimation of 8-10 minutes was conducted from that.

Section 2: About You

The demographic section draws on the standard "personal details" category established in outdoor thermal comfort questionnaire research. This section covers extraction of data about age, gender, cultural background, and residency status(Shooshtarian et al., 2020; Vasconcelos et al., 2024), education (Peng et al., 2019), job-related information(Shooshtarian & Ridley, 2016).

Section 3: Climate Experience

The climate experience section captures thermal acclimatization and behavioral adaptation of respondents in each city and identify as '**place-related parameters**' and '**thermal adaptive strategies**' that are standard components of outdoor thermal comfort surveys(Y. Li et al., 2025). The individual questions were designed by the author based on the following sources:

Summer Climate Description

Inspired by the neighborhood heat perception question in(Iqbal et al., 2025): "*How hot or cool do you think your neighborhood is during a heatwave compared to the average outdoor temperature for the city?*" The rating scale (Very cool / Mild / Warm / Hot / Very hot) is consistent with climate description scales reviewed in (J. Y. Li et al., 2023; Y. Li et al., 2025)

Heat Adaptation Level

Designed by the author to operationalize the acclimatization construct established by (Lam & Lau, 2018), who demonstrated that long-term acclimatization to local summer climate significantly shapes thermal perception and comfort ratings.

Transport Mode Frequency

Adapted from (Shooshtarian et al., 2020):"*How often do you attend public spaces in the Adelaide metropolitan area? Daily, two-three times/week, once a week, once-twice/month, rarely, never* " and from (Iqbal et al., 2025), who included mobility-related questions in their Berlin heat stress household survey.

Section 4: Street Image Rating

The image rating question is adapted from (Urban et al., 2022), who asked respondents to rate their expected thermal comfort at each Google Street View location using a labelled multi-point scale. The present study adapts the scale from seven points to five points to reduce respondent cognitive load while maintaining sufficient discriminatory power, and

reframes the scenario from “during a heatwave” to “on a hot summer day” to match the LCZ comparative context.

The question wording draws on the following expressions found in the literature:

(Cortês et al., 2020) "*For a typical summer day, 'which of these spaces do you think it might be the most thermally comfortable?' and 'which of these spaces do you think it might be the less thermally comfortable?'*"

(S. Yang et al., 2025): "*Which Street view image do you perceive as having a more comfortable outdoor thermal environment for you?*"

9.3 The overall view of the Questionnaire (English)

The distribution of the questionnaire was both online and in-person presenting the whole idea and passing the QR code. The questionnaire was open From May 1st until 15th of June 2026. Four separate forms had been distributed: (1) Detmold-English, (2) Detmold-German, (3) Turin-English, (4) Turin-Italian. The form below is the English-Detmold version. City-specific items (Q6, Q7, Q9) are adapted accordingly for each version.

9.4 Section 1: Introduction

Visual Assessment of Street-Level Thermal Comfort Potential Across Local Climate Zones

Hot summer days and heatwaves are becoming increasingly frequent in cities across Europe. In mid-August 2025, North Rhine-Westphalia experienced a heatwave with peak temperatures exceeding 34–35°C (Klimaatlas NRW, 2025; DWD, 2025).

The way urban streets look directly shapes how comfortable people feel walking through them. Understanding how people visually assess the thermal comfort potential of street environments is essential for designing more heat-resilient cities.

This questionnaire is part of a master's thesis research project of Bonin Mahdavi Estalkhsari, conducted at Politecnico di Torino (Italy) and Technische Hochschule Ostwestfalen-Lippe (Germany). The main objective of the study is to investigate how people visually assess the thermal comfort potential of urban streets in Turin and Detmold.

The survey takes approximately 8-10 minutes.

Data protection: Your participation is completely voluntary. All data collected in this study will be fully anonymous, no one can be identified from your responses. The data will be used exclusively for scientific research purposes and will not be used for commercial purposes under any circumstances.

IMPORTANT: Please fill out and submit the questionnaire only once. You will see a confirmation message after submission. **Only people who live in, work in, or regularly visit Detmold are asked to complete this version of the questionnaire.**

By continuing with the questionnaire, you are indicating that you have read the above information and that you wish to participate.

Thank you for your help!
Bonin Mahdavi Estalkhsari

1. Informed consent

☐ Yes, I want to participate.

[Reference: Structure adapted from (Vasconcelos et al., 2024); scenario framing consistent with (Urban et al., 2022)]

9.5 Section 2: About You

This section collects basic background information. All responses are anonymous.

Q1. What is your gender?

- ☐ Female
- ☐ Male
- ☐ Prefer not to say
- ☐ Non-Binary

[Reference: (Shooshtarian et al., 2020; Vasconcelos et al., 2024)]

Q2. Age

- ☐ 18–25
- ☐ 26–35
- ☐ 36–45
- ☐ 46–55
- ☐ 56–65
- ☐ Over 65

[Reference: (Peng et al., 2019)]

Q3. Where were you born?

- ☐ In Detmold
- ☐ Elsewhere in North Rhine-Westphalia
- ☐ Elsewhere in Germany
- ☐ Other:

[Reference: (Peng et al., 2019)]

Q4. Highest level of education completed

- ☐ Not higher than high school
- ☐ Vocational training or equivalent (For example: Ausbildung)
- ☐ Bachelor's degree or equivalent
- ☐ Master's degree or equivalent
- ☐ Doctoral degree (PhD) or more
- ☐ Other:

[Reference: Adapted from (Peng et al., 2019)]

Q5. Current occupation

- ☐ Student
- ☐ Employed Full-time
- ☐ Employed Part-time
- ☐ Self-employed
- ☐ Unemployed
- ☐ Retired

[Reference: (Shooshtarian et al., 2020)]

Q5b. Your daily activity mainly take place

- ☐ Indoors (office, classroom, home)
- ☐ Outdoors (construction, agriculture, fieldwork, etc.)
- ☐ Mixed (both indoors and outdoors)

[Reference: adapted from (Shooshtarian, 2015)]

Q6. Relationship to Detmold

- ☐ I live in Detmold
- ☐ I commute to Detmold regularly

[Reference: Designed by author.]

Q7. How long have you lived or regularly visited Detmold?

- ☐ Since birth
- ☐ Less than 1 year
- ☐ 1–3 years
- ☐ 4–10 years
- ☐ More than 10 years

[Reference: Adapted from (Shooshtarian & Ridley, 2016)]

9.6 Section 3: Your Climate Experience

Your Climate Experience

These questions help us understand your personal experience with heat and outdoor thermal comfort.

Q9. Have you ever visited or spent time in Detmold during summer?

- ☐ Yes
- ☐ No

[Reference: Designed by author.]

Q10. How would you describe the summers in Detmold?

- ☐ cool
- ☐ Mild
- ☐ Warm
- ☐ Hot
- ☐ Very hot

[Reference: Adapted from (Iqbal et al., 2025); scale consistent with (J. Y. Li et al., 2023; Y. Li et al., 2025)]

Q11. How well adapted do you feel to summer heat in your city?

- ☐ Not at all adapted
- ☐ Slightly adapted
- ☐ Moderately adapted
- ☐ Well adapted

[Reference: Designed by author; construct based on (Lam & Lau, 2018); acclimatization framework from (Shooshtarian et al., 2020)]

Q12. In summer, do you modify your outdoor routes to avoid heat?

- ☐ Never
- ☐ Sometimes
- ☐ Always

[Reference: Adapted from (Iqbal et al., 2025; Shooshtarian et al., 2020)]

Q13. In summer, how often do you use the following modes of transport outdoors?

Mode of transport	Daily	Sometimes	Never
Walking	☐	☐	☐
Cycling	☐	☐	☐

Public transport	☐	☐	☐
Private car	☐	☐	☐

[Reference: Adapted from(Iqbal et al., 2025; Shooshtarian et al., 2020)]

9.7 Section 4: Street Image Rating

In this section you will see groups of street photographs of Detmold. For each image, imagine yourself walking through that street on a **hot summer day**, and rate how thermally comfortable you would expect to feel based only on what you see.

There are no right or wrong answers — we are interested in your personal visual impression.

Block 1 to 5: images

[Image 1-10]

Q14-Q23. Imagine walking through the street shown in this image on a **hot summer day**. How thermally comfortable or uncomfortable would you expect to feel?

1	2	3	4	5
Very uncomfortable	Uncomfortable	Neutral	Comfortable	Very comfortable
○	○	○	○	○

[Reference: Adapted from (Urban et al., 2022); scale consistent with (S. Yang et al., 2025); photographic method validated by (Cortese et al., 2020)]

(Q14-Q23 are repeated for all Images (same scale, each with its own image).)

Q24. If you have any related comments, please write in this section. (not compulsory)

9.8 Section 5: Thank You

You have completed the survey.

Thank you for your time and contribution to this research.

Your responses will be used exclusively for academic purposes as part of a master's thesis at Politecnico di Torino (Italy) and Technische Hochschule Ostwestfalen-Lippe (Germany). If you have any questions about this study, feel free to contact:

Bonin

Mahdavi

Estalkhsari

bonin.mahdaviestalkhsari@studenti.polito.it

10. Phase 4: Data Analysis

The data analysis phase was structured around the two main research questions, RQ1 and RQ2. The first one is concerning how people visually assess the thermal comfort potential of street sections across the two cities and social groups, and the second concerning which streetscape and personal demographic attributes are associated with those assessments. Throughout the analysis, visual thermal comfort rating is treated as the perceptual outcome: respondents judged whether they would feel comfortable walking through a given street scene on a hot summer day, and the analysis links those judgements to characteristics of the built environment and the profiles of the individuals making them.

The following diagram explains the process of data analysis:

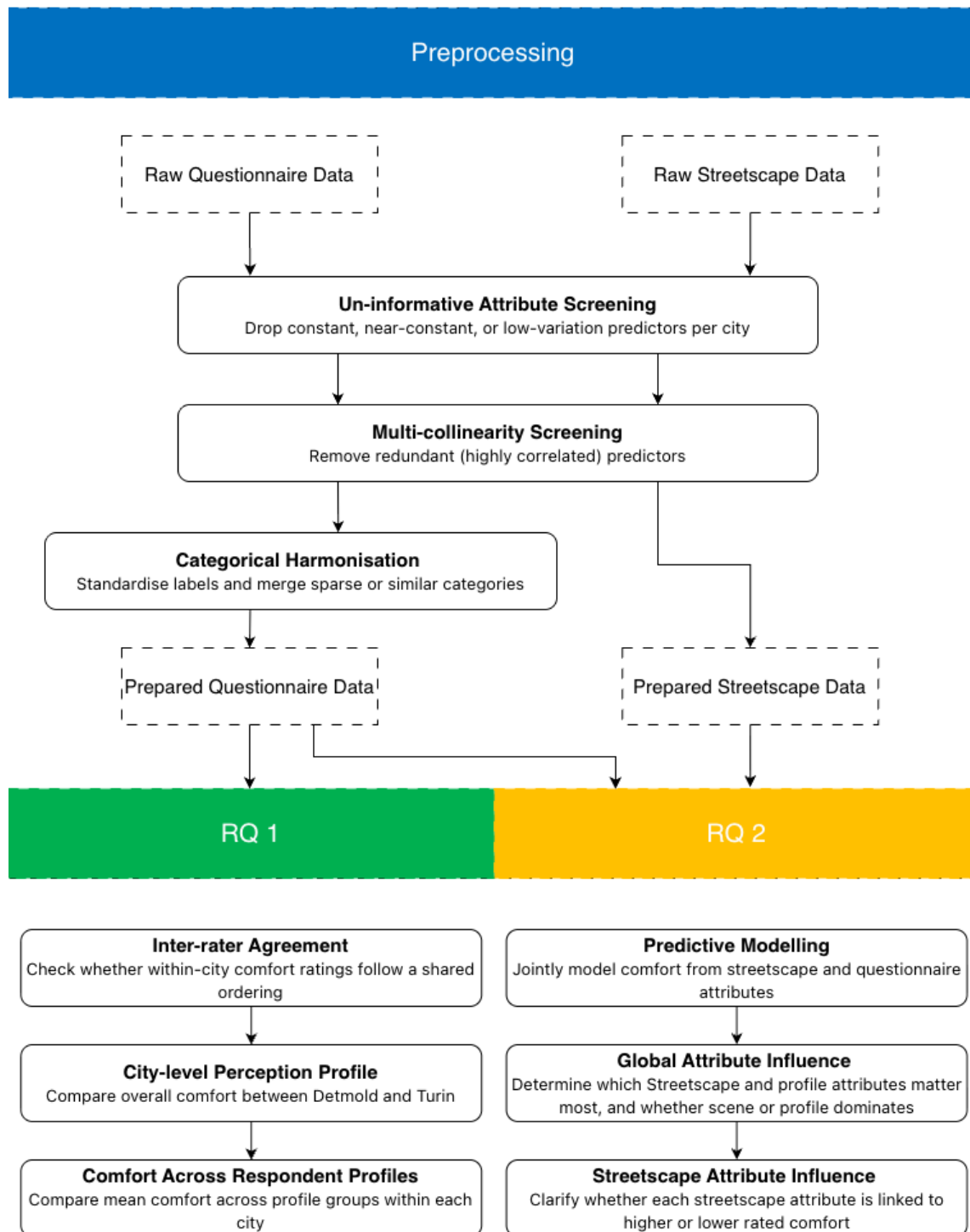


Figure 19. Data analysis workflow. created by author.

10.1 Step 1: Pre-processing

After the data was gathered from the attribute tables and surveys, two preparatory procedures were applied to the datasets: a screening of uninformative attributes, and the multi-collinearity screening. The aim is to reduce the un-necessary attributes, and continue analysis with the ones that have more information and influence. The same statistical logic is

used for both data sources and the methodology for this step was adopted from (Urban et al., 2022).

Uninformative Attributes Screening

Some streetscape attributes were not informative enough for the analysis, because they barely change across the twenty survey points. For example, in the SVI semantic segmentation results, some street-view elements recorded value of zero at every survey points. To avoid carrying empty or near-empty columns into later steps, each attribute in the attribute table is screened using Shannon entropy, which summarizes how evenly values are distributed across points (Shannon, 1948). Attributes with very low entropy are constant and are dropped (Zhu et al., 2026).

The rules of screening the data differ slightly between the data taken from attribute table that are numeric compositions, and the questionnaire data that are categorical respondent profiles and non-numeric (Zuur et al., 2010). Attributes or survey variables removed in a city are excluded from that city's collinearity screen and final data analysis. All screening procedures were implemented in Python using the following libraries: pandas, matplotlib, numpy, seaborn, scipy, scikit-learn.

Attribute table screening:

1. **Constant:** when there are fewer than two distinct values across the study points (Zuur et al., 2010). For instance, an attribute that records a value of zero at every one of the twenty survey points in both cities.
2. **Near-absent:** for attributes having fewer than three non-zero points out of ten (Zuur et al., 2010). For example, the attribute that records a non-zero value at only one of the study points in both cities.
3. **Low normalized Shannon entropy:** attributes whose value distribution remains effectively uniform or single-level even when not constant ($H_{\text{norm}} < 0.50$) (Larkin et al., 2021). For example, the attributes that their non-zero values are concentrated at a single point, leaving the remaining points at or near zero.

Questionnaire data Screening (Zuur et al., 2010):

1. **Constant:** category with only a single response. For example, if a response category such as "prefer not to say" received only a single response across the entire sample, it cannot be used for group-level comparison and is removed.
2. **Near-constant:** modal category fields for at least 95% of valid answers. For instance, when one category captures more than 95% of valid answers, the field provides virtually no variation and is therefore removed.

3. **Low normalized Shannon entropy:** the fields with too little response diversity to support within-city profile comparison ($H_{\text{norm}} < 0.50$). as an example, a transport mode where nearly all respondents selected "never", would be flagged by the entropy screen and excluded.

b) Multi-collinearity screening of the Attribute Table

Streetscape and questionnaire datasets often contain multiple measures of the same underlying quality, for example, vegetation visible in a street-view image and a vegetation index from remote sensing (NDVI). In order to prevent having overlapping attributes, the multicollinearity analysis was done, as it is a usual data cleaning approach while dealing with multi-variable data (Yoo et al., 2014). When predictors are highly correlated, regression coefficients become unstable and physical interpretation is obscured (Dormann et al., 2013). Pairwise correlation screening is one of the most widely used pre-modelling diagnostics (Dormann et al., 2013). Moreover, threshold-based exclusion performs as an elaborate remedy in many applied settings, with the threshold or $|r|$ between 0.4 and 0.85 chosen according to field, sample size, and analytical goal (Dormann et al., 2013).

Spearman's ρ is used throughout because street-view fractions are percentage based and constrained, and questionnaire fields are ordinal or nominal categories (Zhu et al., 2026). Separate correlation matrices were computed for the streetscape attribute table and the questionnaire dataset in each city using Python (pandas and scipy.stats), reporting every unique variable pair sorted by $|\rho|$. For each city, all unique attribute pairs were considered, given by

$$\binom{n}{2} = \frac{n(n-1)}{2}$$

where n is the number of surviving attributes.

For flagging correlated pairs, two city-specific thresholds were applied: $|\rho| > 0.7$ for streetscape attributes and $|\rho| > 0.8$ for questionnaire variables. The stricter threshold for questionnaire types of variables is recommended for calibrating cut-offs to the degree of expected predictor overlap (Dormann et al., 2013), and is consistent with the $|r| \gtrsim 0.8$ threshold commonly adopted in survey-based regression (Hair et al., 2019).

Then, flagged pairs were examined iteratively rather than in a single pass, because collinearity is a network property (Dormann et al., 2013). This means that one attribute can appear in several flagged links simultaneously, and removing a single member of one pair may leave hub attributes that still exceed the threshold with multiple remaining partners (Dormann et al., 2013).

At each iteration, the attribute participating in the largest number of remaining flagged pairs and overlapping most clearly with a retained indicator of the same streetscape quality was removed first. This process was repeated until no flagged correlations remained among the

surviving attributes, or until further removal would have compromised the interpretability of the streetscape representation.

To ensure comparability across cities, attributes dropped in one city were also excluded from the other, producing a shared modelling set for the subsequent analysis.

c) Multi-collinearity screening of the Questionnaire data

The same pairwise Spearman procedure was applied to questionnaire covariates within each city, using only fields that passed the variation screening stage. Categories were ordinally encoded where a natural order exists, such as age bands, education levels, and transport frequency scales. Nominal categorical fields such as gender or city relationship were assigned numeric codes solely to enable computation of the correlation matrix; no ordinal meaning is implied by these codes (Hair et al., 2019).

Pairs exceeding threshold of $|p| > 0.8$ were flagged for review, because socio-demographic variables can correlate moderately without measuring the same underlying construct (Dormann et al., 2013). For instance, age and education or age and occupation are related but conceptually distinct. Unlike streetscape attributes, where two indices may capture virtually identical physical properties, questionnaire variables are not expected to reach that degree of redundancy. Moreover, a higher threshold reduces the risk of unnecessarily dropping informative predictors (Dormann et al., 2013; Hair et al., 2019).

10.2 Step 2: Inter-rater Agreement (Validity Check)

As each respondent rated the same set of streetscape images, it must first be established whether comfort judgments reflect a shared perceptual ordering or an arbitrary use of the ordinal scale. Aggregating ratings into city-level profiles is justified only if respondents tend to rank the same scenes as more or less comfortable (Urban et al., 2022).

As the visual comfort assessment was collected on a five-point ordinal scale, for such data, Spearman's rank correlation is appropriate, as it measures whether two respondents preserve the same relative ordering of scenes without requiring identical absolute scores (Spearman, 1987). Pairs in which one respondent assigned the same rating to every image were excluded, as zero within-person variation cannot be correlated meaningfully with any other response pattern (Urban et al., 2022).

Two agreement checks were conducted:

- At the city level, pairwise Spearman ρ was computed among respondents who completed all ten image ratings, comparing each pair's full ten-image comfort profile. A summary statistic reports the number of pairs analyzed and the central tendency and spread of ρ .
- At the image level, where profile-level correlation is not defined, pairwise ordinal agreement was instead scored for each respondent pair as $1 - |a - b| / 4$, on the 1–5

scale, where a and b are the two respondents' ratings for the same image. 1 indicates identical ratings and 0 indicates maximum disagreement. The same summary statistics were computed per image.

10.3 Step 3: City-level Comfort Rating Summary

Before examining subgroup differences, all comfort ratings within each city are pooled to establish a city-wide mean rating, which serves as the baseline reference for all subsequent respondent-profile comparisons. Therefore, each city is represented by its full set of ratings across all images and all respondents. For each city, the mean rating, standard deviation, and distribution across the five-point scale are reported and compared directly between the two cities.

This step serves two purposes: First, it establishes whether one city tends to be judged as more or less thermally comfortable than the other overall, independent of which respondent groups are being compared (Iqbal et al., 2025; Larkin et al., 2021). Second, it produces the city-wide average rating that is used as the reference baseline in Step 4. The "Difference from Average Rating" column in each respondent-profile comparison table reflects each category's deviation from this city-level mean. The city-level summary is therefore not a standalone finding but a necessary anchor for interpreting all subsequent group-based contrasts.

10.4 Step 4: Comfort ratings comparison across respondent profiles

A- priori Category Harmonization

Respondent profile comparisons are based on category means that aggregate relatively few responses per cell. When response categories are numerous and unevenly populated, some groups contain only a handful of respondents, for instance, only 8 among 116 respondents select the age of 36-45. Means computed from such sparse cells are statistically unstable that means small changes in individual ratings can shift the group average markedly, and are difficult to interpret as representative of a broader population segment (Favero et al., 2023). Highly skewed category distributions also reduce the informational value of descriptive comparisons: a profile figure dominated by one or two large bars alongside several very thin bars conveys little beyond sampling imbalance rather than systematic comfort differentiation (Urban et al., 2022).

For these reasons, response categories were reviewed before comfort outcomes were examined, using the full survey sample collected for this study. Adjacent or similar options were merged where doing so (i) redistributed respondents into more balanced groups, (ii) avoided reliance on cells with very low counts, and (iii) preserved the interpretable contrasts that the questionnaire design intended to capture. Deciding category boundaries before examining comfort outcomes prevents the risk of merging groups simply because their means happen to look similar in this dataset. Comparable outdoor-comfort syntheses likewise treat socio-demographic grouping as a design decision informed by sample composition and field context, rather than as an iterative optimization against the outcome (Chen et al., 2022).

As a result, non-binary gender respondents were excluded from profile analyses rather than merged into another category, as the resulting cell size ($n = 1$ in Detmold) could not support a meaningful group mean or permit a defensible comparison with other gender categories.

The following harmonization rules were applied:

- Gender: non-binary respondents excluded.
- Age: 46–55, 56–65, and over 65 merged into Over 46; younger bands retained separately.
- Birthplace: in-city and in-region merged.
- Education: high school merged with vocational training; master's merged with PhD.
- Occupation: retired merged with unemployed; full-time merged with part-time and self-employed.
- Daily activity: mixed (indoors and outdoors) merged with outdoors.
- Time in city: less than 1 year merged with 1–3 years; more than 10 years merged with since birth.

All other retained questionnaire fields kept their original response categories.

Computing and Interpreting Mean Comfort Scores

Mean comfort is measured on a five-point ordinal scale, where higher values indicate that respondents expected to feel thermally more comfortable walking through the streetscape shown, and lower values indicate less comfortable expectations (Urban et al., 2022; Zhu et al., 2026). For each variable that retained from preprocessing, mean comfort was computed as the respondent-level average across all ten image ratings, then aggregated by category within each city. Detmold and Turin each contribute fifteen profile fields following the variation screening and collinearity review described in Sections 10.1. An overview figure presents all variables as sub-panels, with Detmold and Turin shown side by side in the results section.

Each comparison table reports mean comfort by category and includes Difference from Average Rating as a descriptive reference column.

For ordinal comfort data, magnitude should be weighed alongside sample size and city context, as small shifts on the order of 0.01–0.05 points are difficult to interpret as substantively meaningful (Favero et al., 2023).

The following working bands are applied throughout the process (Favero et al., 2023):

Contrast magnitude	Interpretation
< 0.10	Negligible
0.10 – 0.25	Modest
≥ 0.25	Pronounced

Table 13. Interpretation bands for comfort rating contrast magnitude (source: Favero et al., 2023).

10.5 Step 5: Predictive Modelling and Variable Influence Analysis

The second research question asks which streetscape attributes and respondent-profile variables are most strongly associated with visually assessed thermal comfort when both are considered jointly. Addressing this requires moving beyond the descriptive, variable-by-variable comparisons of Step 4 toward a framework that can capture the combined influence of streetscape and demographic predictors on comfort ratings. To this end, a machine learning modelling pipeline is adopted, followed by a SHAP-based variable influence analysis.

This analysis uses harmonized survey and attribute data from preprocessing: twelve streetscape predictors after variation and collinearity screening, and fifteen questionnaire fields per city. It builds on the within-city rating comparability established in RQ1.

- **Design:** Models are estimated separately for Detmold and Turin. Each city has distinct streetscape images, climate context, and sample composition; separate estimation avoids confounding place-specific visual cues with predictor effects. Questionnaire categories are harmonized with the same a-priori rules as RQ1.
- **Scale:** visual thermal comfort is measured on a five-point ordinal scale (1 = very uncomfortable, 5 = very comfortable). Ratings are treated as numeric outcomes for regression, following descriptive practice in the thermal-comfort literature (Favero et al., 2023). Higher observed ratings, higher predicted values, and positive mean SHAP values all indicate greater expected thermal comfort.

The analysis proceeds in two stages. In the first stage, nine candidate machine learning models are compared following Yang et al. (2025), evaluated on a respondent-level test set, and the best-performing model is retained for each city. In the second stage, SHAP values are computed for the retained model, a random forest in both Detmold and Turin, to explain variable influence at two levels. global mean SHAP values are reported first to contrast the overall contribution of streetscape attributes against questionnaire fields, followed by signed mean SHAP values for streetscape attributes alone to reveal the direction of each predictor's effect on comfort ratings. Results are presented as tables accompanied by grouped bar charts, consistent with reporting conventions in comparable outdoor comfort and streetscape perception studies (Guo et al., 2024; Lee et al., 2025; Zhu et al., 2026).

Predictive Modelling

Comfort ratings are modelled from the harmonized questionnaire variables and screened streetscape attributes retained after pre-processing. Because each respondent rated up to ten city-specific images, the analysis unit is one respondent–image pair (Urban et al., 2022). Within each city, respondents are randomly assigned to a training set (75%) or a held-out test set (25%) by respondent identifier. So, this ensures that all ratings from the same individual remain in a single fold and that information leakage across images from the same respondent is avoided.

Nine machine learning models are evaluated with ordinary least squares (OLS) included as an interpretable baseline: decision tree, k-nearest neighbors (KNN), support vector regression (SVR), elastic net (ENRM), LightGBM, random forest, XGBoost, CatBoost, and OLS. All transformations applied to questionnaire fields and continuous streetscape attributes are fitted on the training data only and then applied to the test set, to prevent data leakage. Tunable models are optimized on the training split via random search (Guo et al., 2024). OLS requires no hyperparameter tuning. Performance is evaluated on the held-out test set using mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and adjusted R^2 , all reported on the original 1–5 comfort scale. The model achieving the lowest test MAE in each city is retained as the sole model carried forward to the SHAP analysis.

Variable Influence Analysis (SHAP)

The retained model from previous Section (random forest in both Detmold and Turin) is explained using SHapley Additive exPlanations (Lundberg & Lee, 2017). For each respondent–image observation, SHAP assigns a contribution to every input predictor such that contributions sum to the model prediction relative to a baseline expectation. Averaging these contributions across observations yields mean SHAP values that indicate whether a feature tends to push predicted comfort upward or downward, and by how much. A tree explainer, appropriate for random forest models, is used for computation (Guo et al., 2024; Lundberg & Lee, 2017). The tree explainer is applied to a random subsample of up to 500 respondent–image observations from each city's held-out test set, so that influence rankings reflect model behavior on unseen data only.

Following reporting conventions in outdoor comfort and streetscape perception studies (Guo et al., 2024; C. Hu & Zeng, 2025; Zhu et al., 2026), the analysis adopts a two-step structure. In Step 1, mean absolute SHAP values (mean $|\text{SHAP}|$) are reported for all predictors jointly (twelve streetscape attributes and fifteen questionnaire fields per city) with each questionnaire variable represented by a single mean $|\text{SHAP}|$ value averaged across its response categories. A block-level summary then contrasts the aggregate influence of streetscape attributes against questionnaire fields within each city, directly addressing the joint-predictor question posed by RQ2. In Step 2, signed mean SHAP values are reported for streetscape attributes only, indicating whether each attribute is associated with higher or lower predicted comfort: a positive mean SHAP indicates association with greater comfort on the 1–5 scale, and a negative value indicates association with lower comfort.

Throughout, findings describe model-based attributions derived from the random forest and should not be interpreted as verified causal effects on human thermal perception (Lenzholzer & de Vries, 2020).

- **Step 1: Global Importance (Mean $|\text{SHAP}|$)**

This step compares the relative influence of twelve streetscape attributes and fifteen harmonized questionnaire fields by reporting mean absolute SHAP values (mean $|\text{SHAP}|$) for

each predictor. Each questionnaire variable is represented by a single mean $|\text{SHAP}|$ value averaged across its response categories, consistent with the variable-level reporting in RQ1, so that streetscape and respondent-profile predictors can be compared on equal footing. A higher mean $|\text{SHAP}|$ value indicates that the random forest assigns greater weight to that variable when predicting comfort ratings on the held-out test subsample.

- **Step 2: Directional Influence of Streetscape Attributes (Signed Mean SHAP)**

In the second step, signed mean SHAP values are reported for the twelve retained streetscape attributes only. Unlike mean $|\text{SHAP}|$, which measures the magnitude of a predictor's influence regardless of direction, signed mean SHAP indicates whether each attribute is associated with higher or lower predicted comfort on the 1–5 scale. A positive value indicates that the attribute tends to push predictions toward greater comfort; a negative value indicates the opposite. Questionnaire fields are excluded from this step, as the focus shifts from the relative weight of predictor groups to the directional role of individual scene-level characteristics in each city.

Chapter five: Results

11. The results of the Attribute Data collection

This section presents the results of the multi-layer attribute data collection framework applied to all 20 street-level survey locations in Turin and Detmold.

11.1 Layer 1, Remote Sensing Environmental Attributes

As explained in the section 8.2, the following dates, satellites and bands were selected for Remote Sensing data acquisitions:

Attribute	Satellite / Sensor	Acquisition date	Resolution
LST	Landsat 8 / Landsat 9	22 June 2025	30 m
Albedo	Landsat 8 / Landsat 9	22 June 2025	30 m
NDVI	Sentinel-2 A / B / C	12 June 2025	10 m
MNDWI	Sentinel-2 A / B / C	12 June 2025	20 m

Table 14. Remote Sensing data acquisition information (source: USGS,2026)

Figures 19 to 26 show these RS attribute data thoroughly.

LST

LST was derived from the Landsat 8 and Landsat 9⁵, accessed via GEE. Both Landsat 8 and Landsat 9 were included in the collection to maximize scene coverage(H. Xu et al., 2024) over both cities on the selected date that is fixed at 22 June 2025, as the date with the most acceptable cloud-cover in both of the two cities. Figure 19 and 20 show the LST at the selected date in both cities.

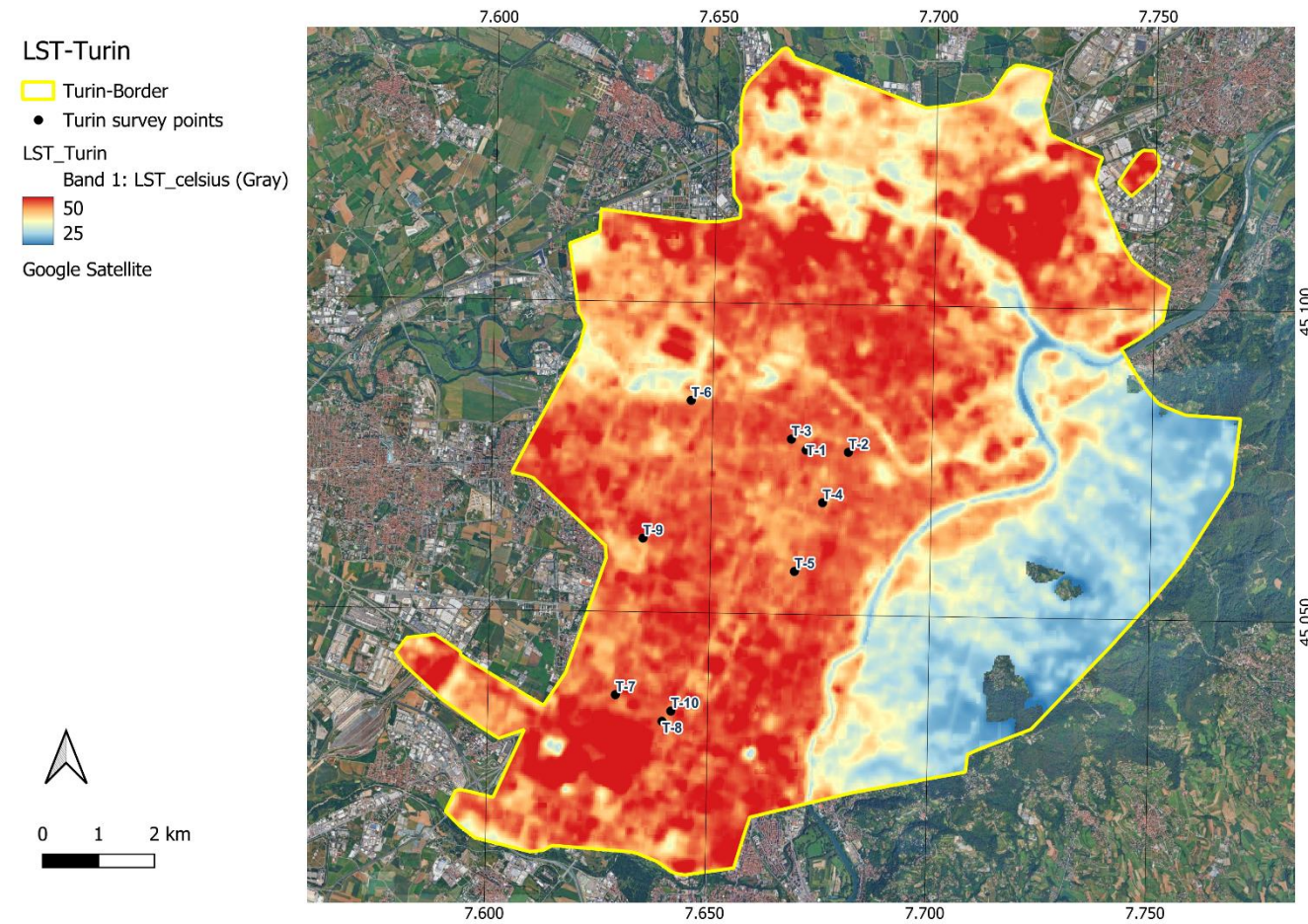


Figure 20. LST map of Turin(produced by author)

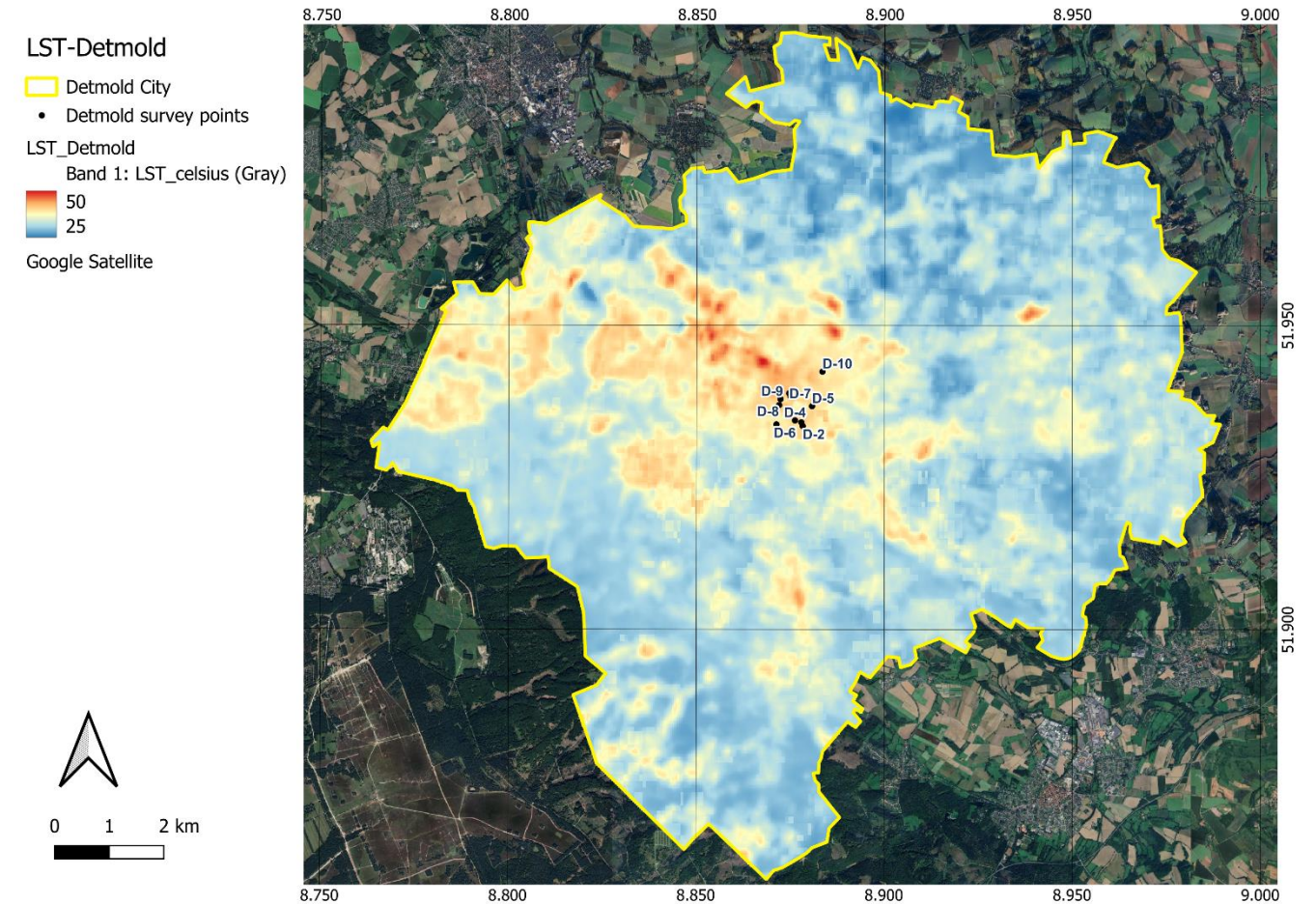


Figure 21. LST map of Detmold (produced by author)

As it is visible from the maps, Turin's points are warmer than Detmold's, with city means of approximately 46.2°C and 40.7°C respectively that is a gap of around 5.5°C that reflects the climatic contrast between the two cities. Within each city, variation is moderate (Detmold: 38.92°C at D-10 to 42.27°C at D-7; Turin: 43.5°C at T-6 to 48.03°C at T-3), with cooler values generally corresponding to points with greater vegetation cover and more open urban fabric.

⁵ ST_B10 thermal infrared band of Landsat 8 and Landsat 9 Collection 2, Tier 1, Level-2 Surface Temperature products.

NDVI

NDVI was derived from Sentinel-2⁶ because in comparison to Landsat with 30m spatial resolution, Sentinel has a 10 m resolution and captures the fine-grained heterogeneity of urban vegetation that would be missed or blurred at Landsat's 30 m resolution (Iqbal et al., 2025; Lefebvre et al., 2016). The extraction date was fixed at 12 June 2025 as the only date on which both Turin and Detmold were simultaneously covered by a cloud-free scene.

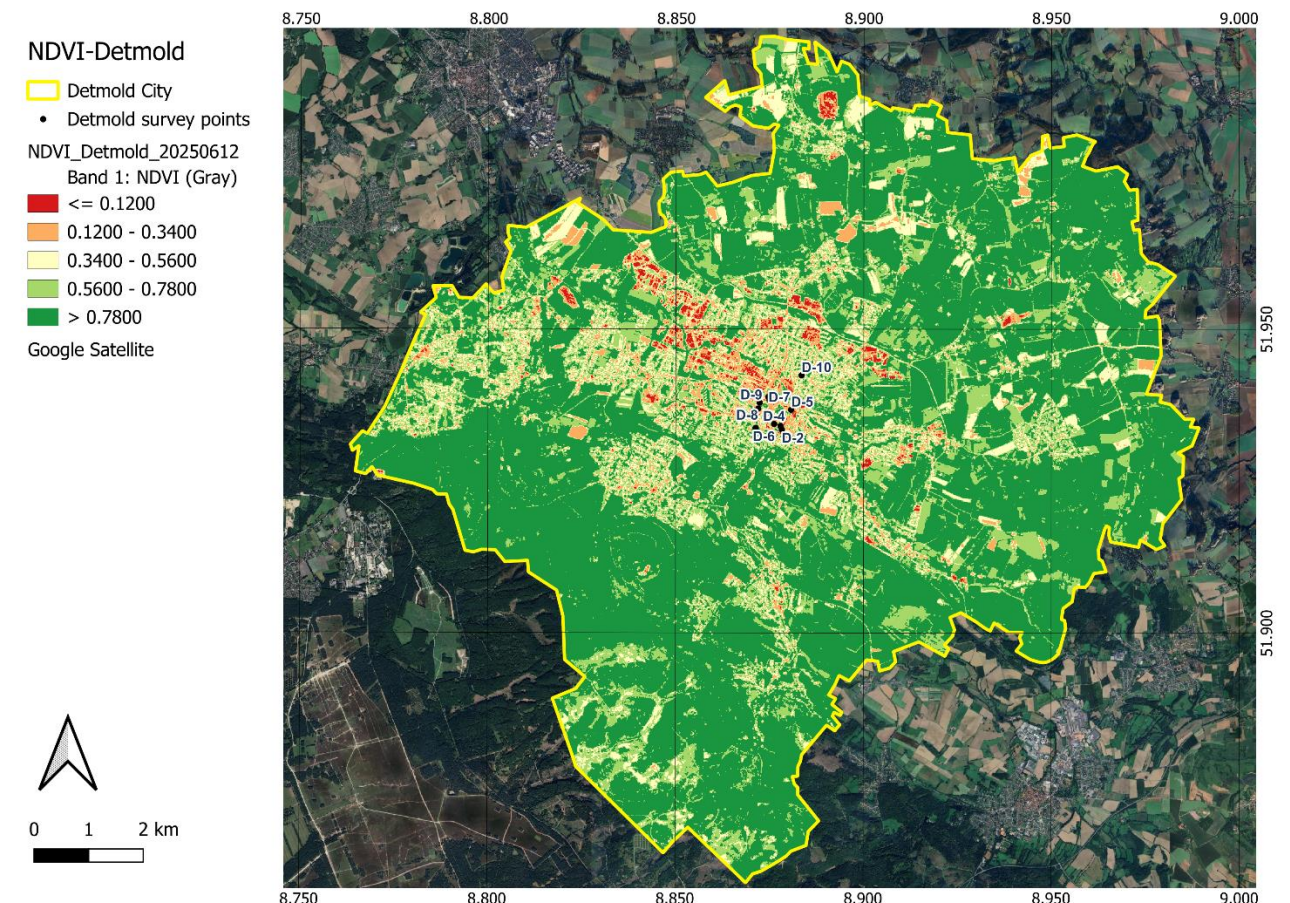
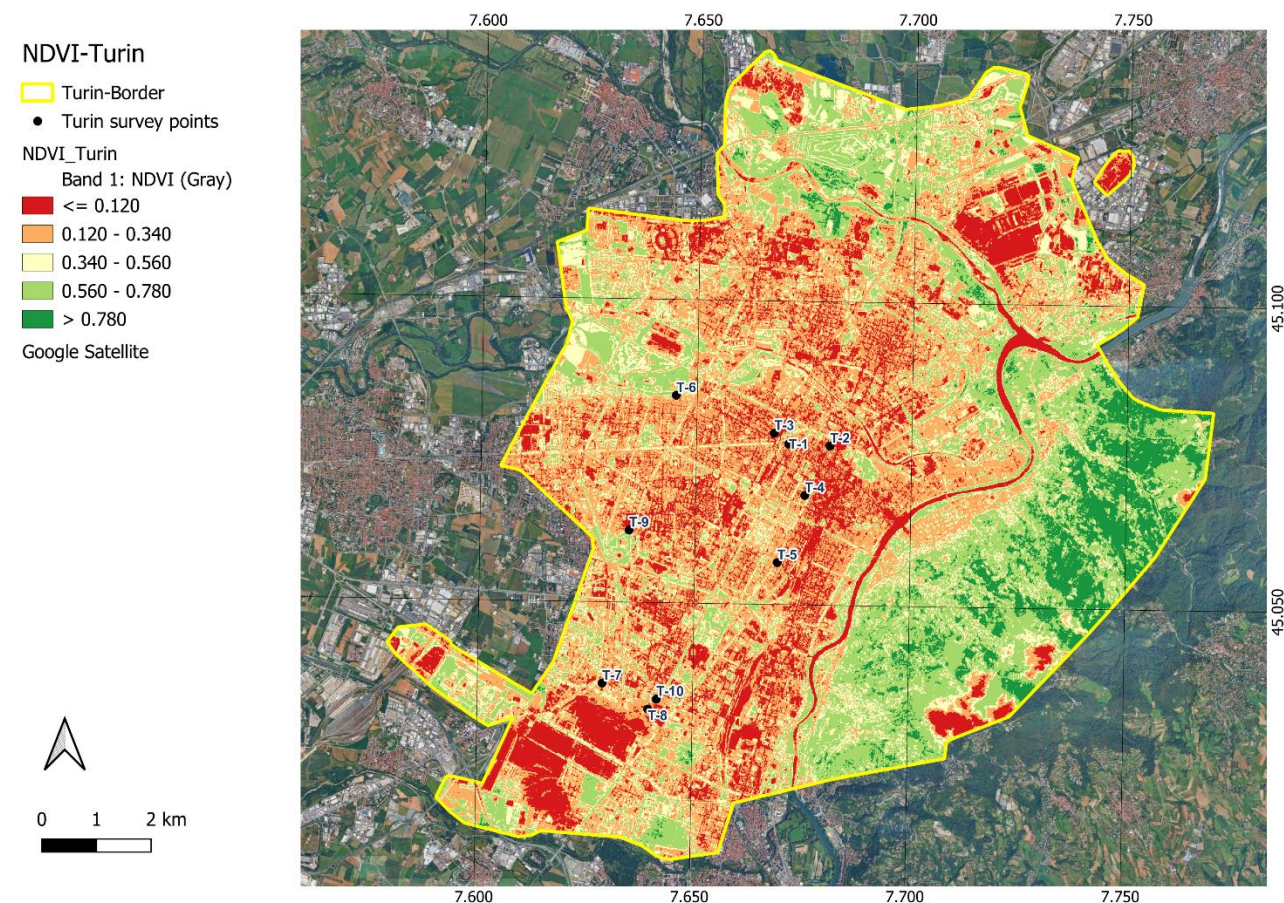


Figure 22. NDVI maps for Turin. Color scale: dark green = high vegetation density; pale yellow = bare/sealed surfaces. (produced by the author).

Figure 23. NDVI maps for Detmold. Color scale: dark green = high vegetation density; pale yellow = bare/sealed surfaces. (produced by the author)

Based on the results, Detmold points are on average greener (mean ≈ 0.287) than Turin (mean ≈ 0.215), though within-city variation is large in both cases. The lowest values in both cities belong to dense LCZ 2 points with minimal greenery (D-3: 0.114; T-3: 0.097), while the highest cluster in LCZ 5 locations with more open fabric and tree canopy (D-10: 0.535; T-6: 0.349).

⁶ Level-2A Harmonized Surface Reflectance imagery (COPERNICUS/S2_SR_HARMONIZED) using the standard normalized difference of Band 8 (NIR, 842 nm) and Band 4 (Red, 665 nm): $NDVI = (B8 - B4) / (B8 + B4)$.

MNDWI

MNDWI was computed from the Sentinel, the same extraction date of 12 June 2025 was applied as for NDVI.

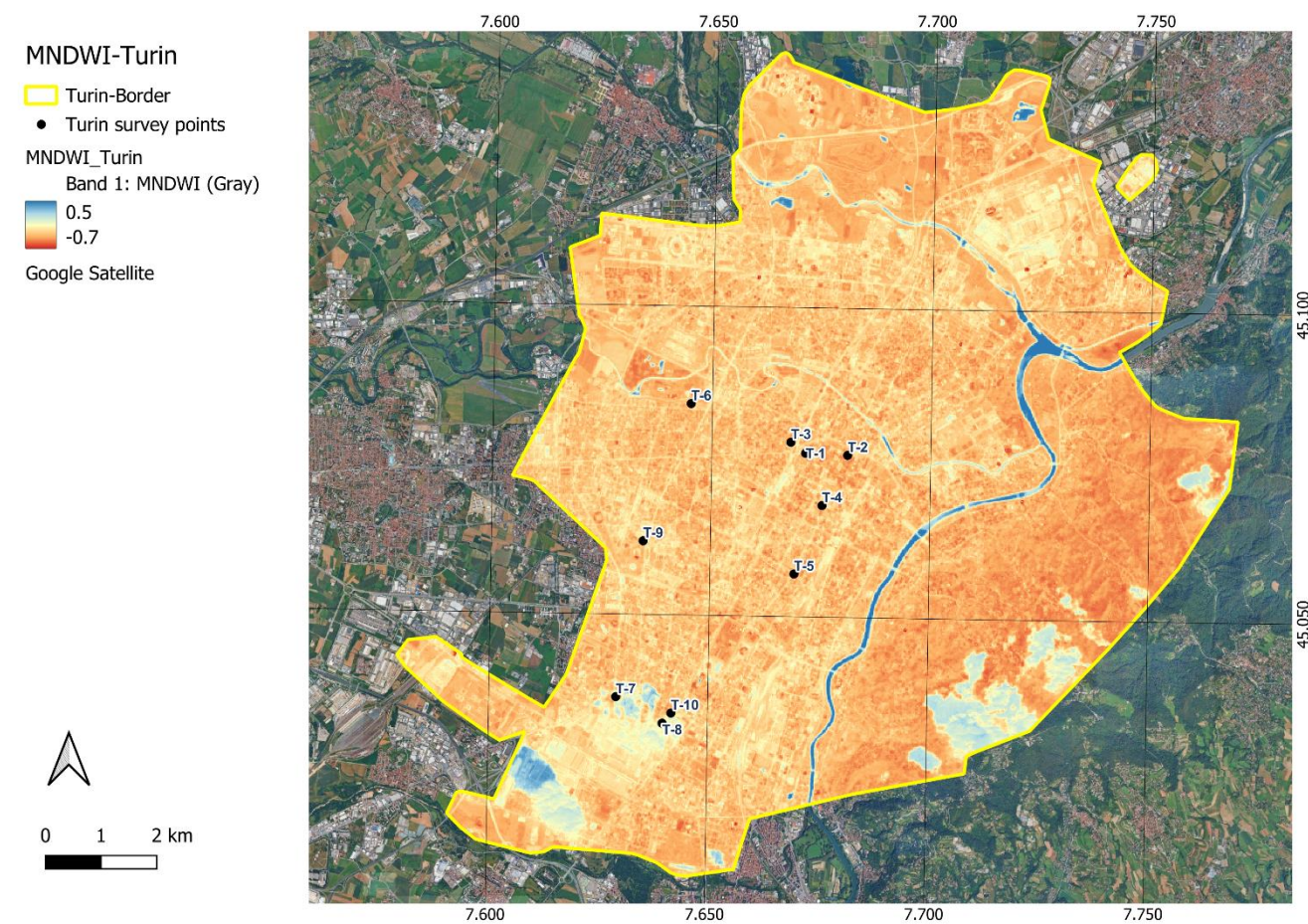


Figure 24. MNDWI maps for Turin, with binary water mask overlay ($MNDWI > 0 = \text{blue}$). (produced by author)

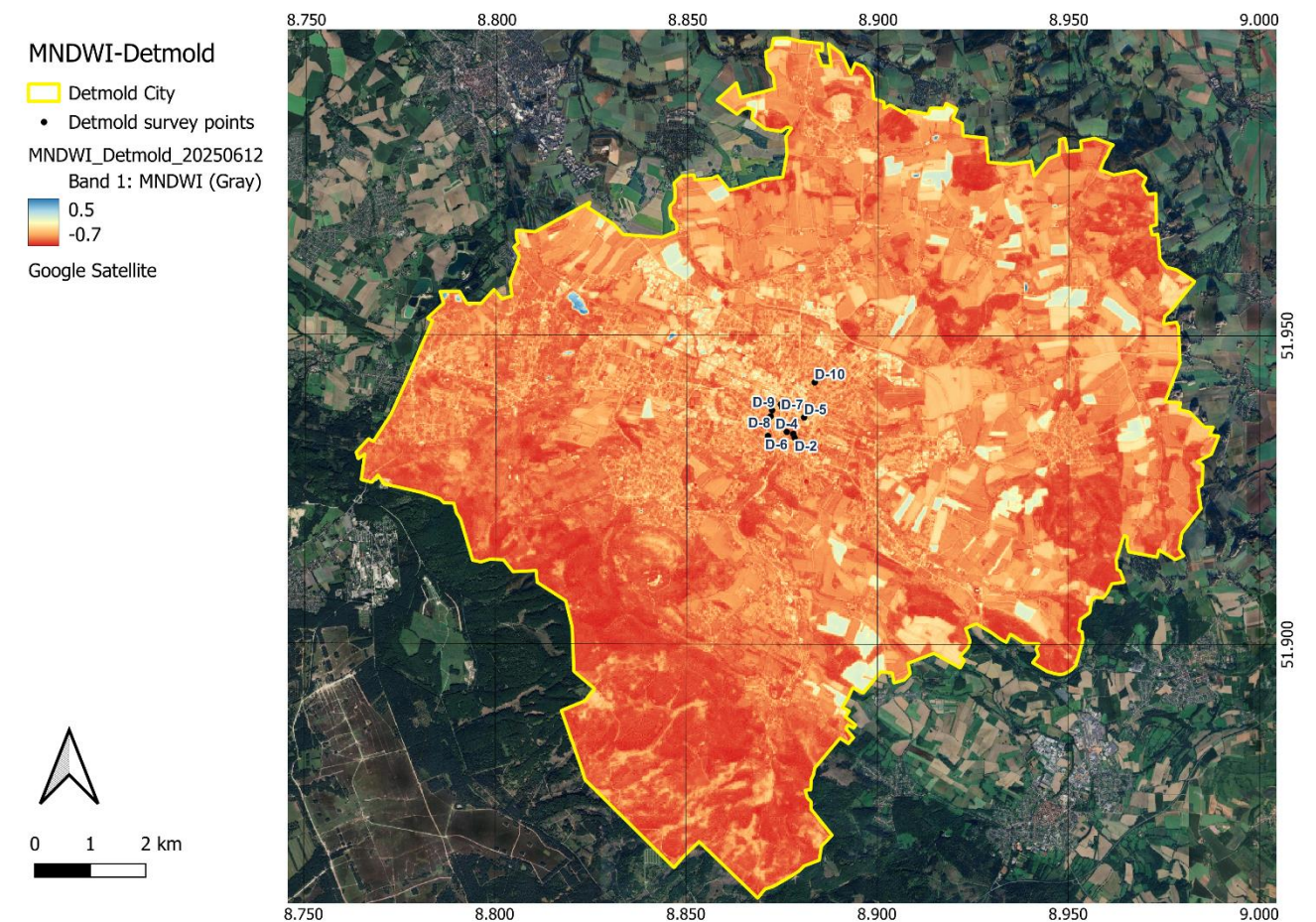


Figure 25. MNDWI maps for Detmold with binary water mask overlay ($MNDWI > 0 = \text{blue}$). (produced by author).

All 20 points return negative MNDWI values, confirming the absence of surface water at every location. The variation across points reflects differences in surface moisture and imperviousness rather than standing water. City means are not very similar (Detmold: -0.361 ; Turin: -0.253), with the most negative values in both cities corresponding to points dominated by sealed surfaces and dense building cover.

Surface Albedo

Albedo was computed from the Landsat 8/9⁷ scenes, and the extraction date was fixed at 22 June 2025, the same scene used for LST. Then, the values were extracted at the exact coordinate of each study point.

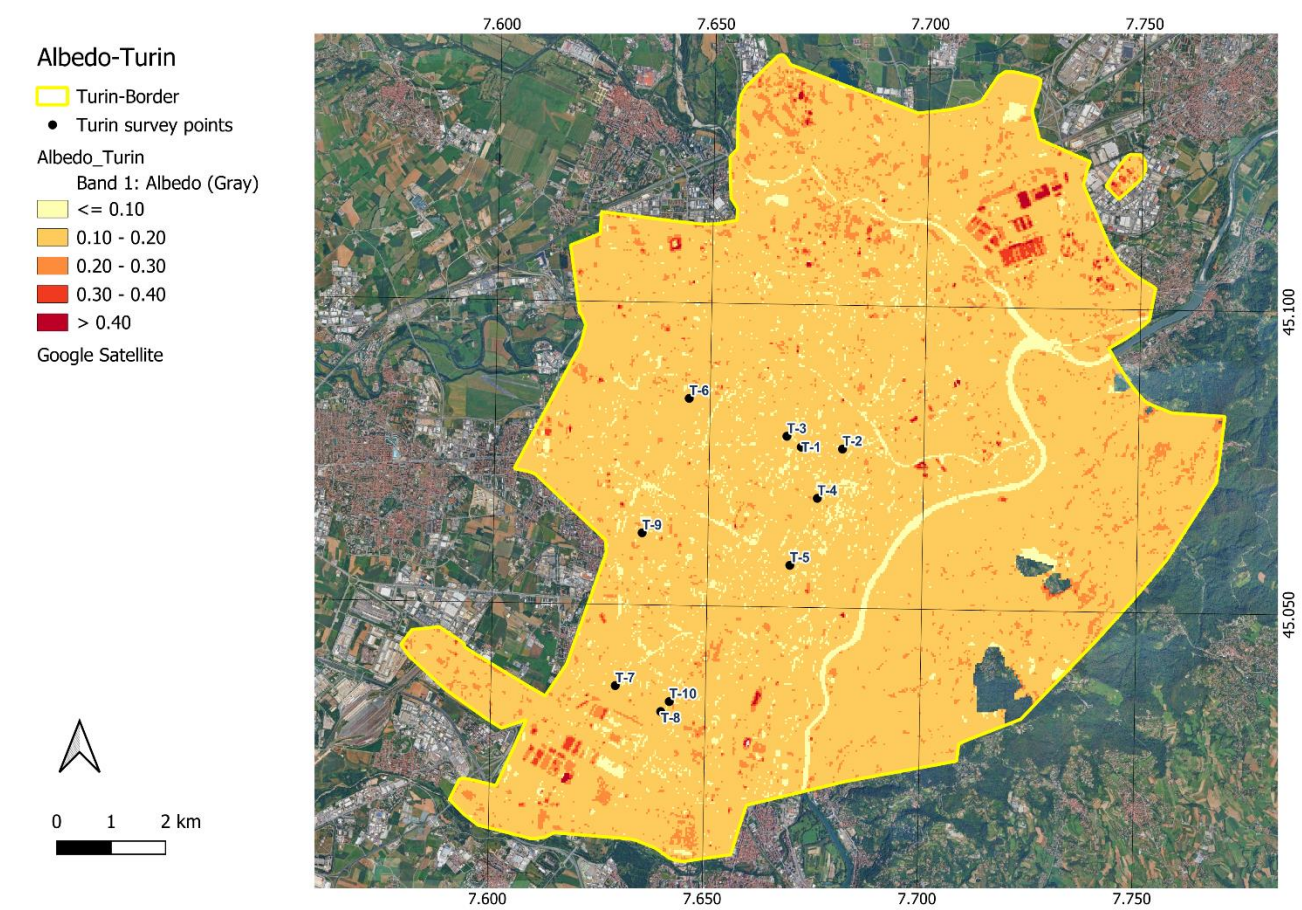


Figure 26. surface albedo maps for Turin. Color scale: dark = high albedo; light = low albedo. (produced by author).

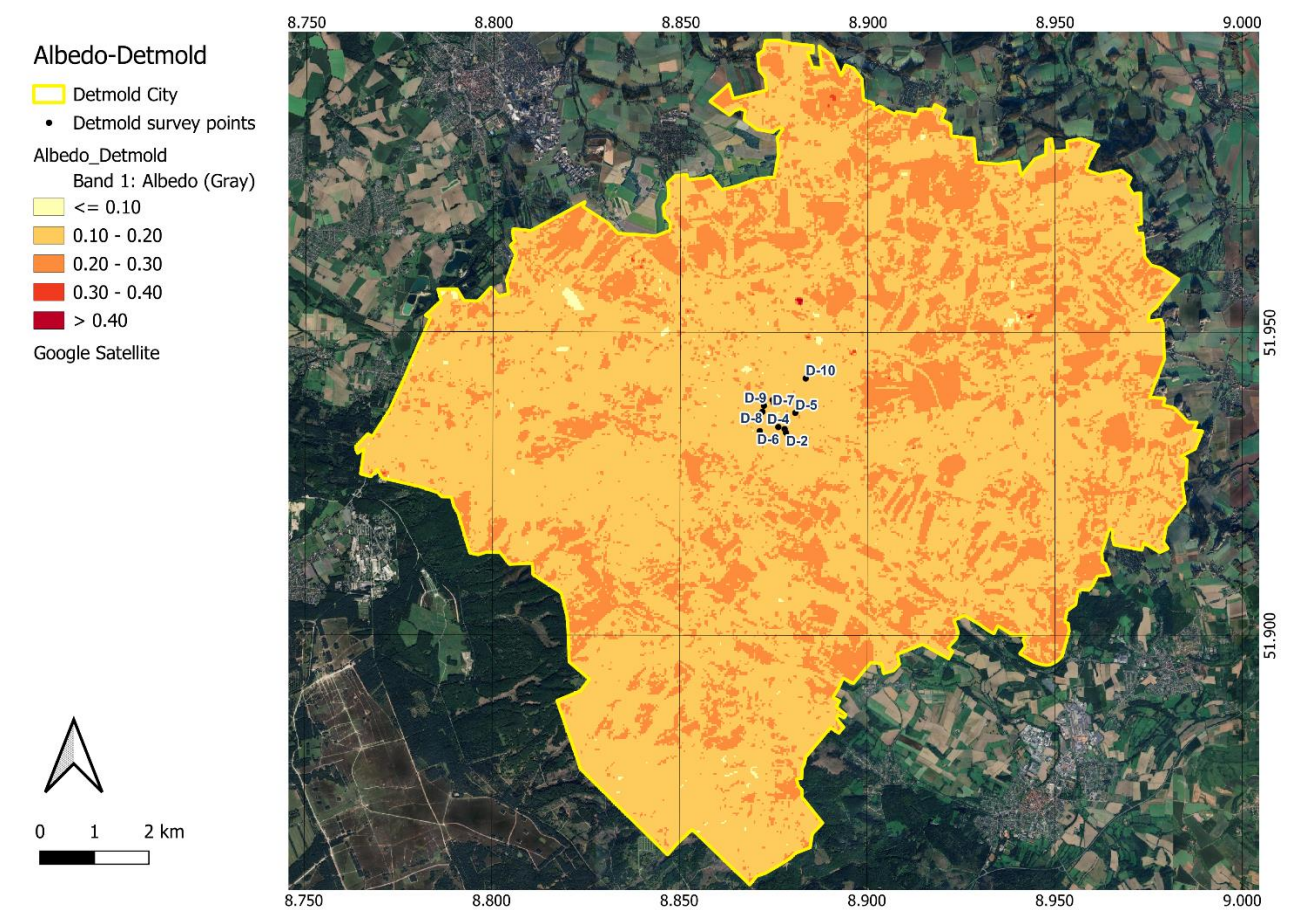


Figure 27. surface albedo map for Detmold). Color scale: dark = high albedo; light = low albedo. (produced by author).

Surface reflectivity is nearly identical between cities (both means $\approx 0.123\text{--}0.124$), indicating comparable material composition across the selected LCZ types. Within-city variation is small, with slightly lower values at points where dark asphalt and road surfaces dominate, and slightly higher values where lighter-toned building materials or mixed surfaces are more present.

⁷ Collection 2, Tier 1, Level-2 Surface Reflectance

11.2 Layer 2, Streetscape Visual Composition (SVI Semantic Segmentation)

Layer 2 quantifies the visual composition of each of the 20 study points’ images through semantic segmentation using SegFormer-B5 finetuned on the Cityscapes dataset (19 classes). Figures within table 14, represent the results of the Semantic Segmentation at each of the study points.

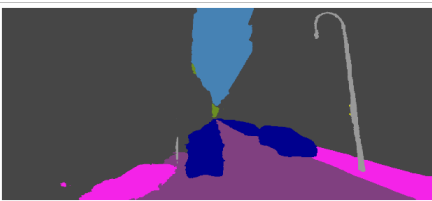
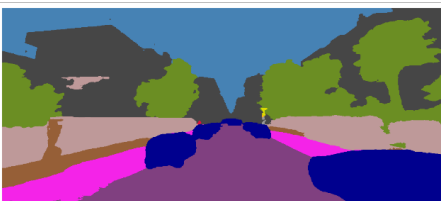
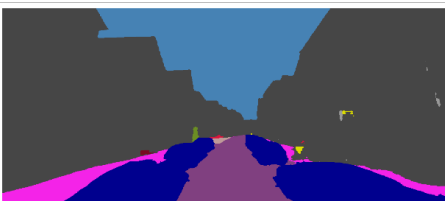
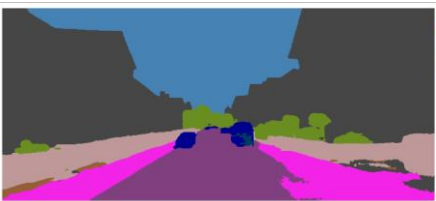
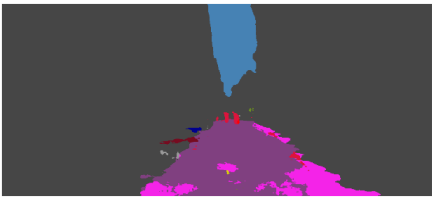
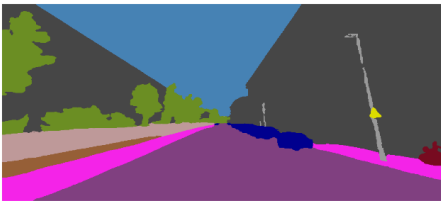
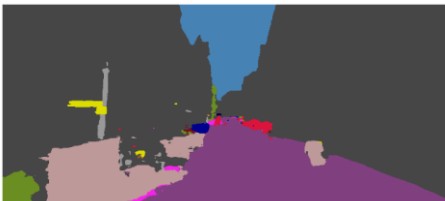
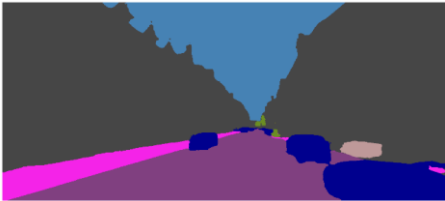
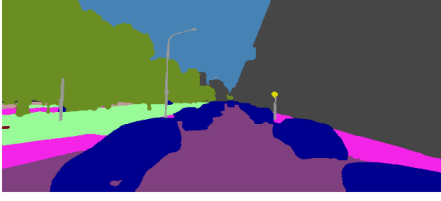
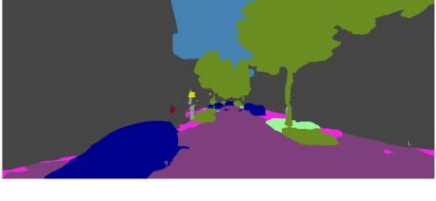
T-1		T-6		D-1		D-6	
T-2		T-7		D-2		D-7	
T-3		T-8		D-3		D-8	
T-4		T-9		D-4		D-9	
T-5		T-10		D-5		D-10	

Table 15. Semantic segmentation maps of all 20 questionnaire stimulus images using SegFormer-B5 finetuned on Cityscapes. (produced by author)

Building coverage: Turin points are dominated by buildings to a greater degree than Detmold, with several LCZ 2 points exceeding 70–80% building share (T-2: 83.5%, T-1: 73%). Detmold's points are more moderate, rarely exceeding 70% (D-8: 70.6% being the exception). Vegetation share: Detmold shows notably higher vegetation presence, with several points exceeding 15–34% (D-7: 34%, D-9: 35.5%). Turin's vegetation share is generally lower and more concentrated in LCZ 5 points (T-4: 20.7%, T-5: 20.7%), while most LCZ 2 Turin points show near-zero vegetation. Sky share: Sky exposure is generally low across both cities, reflecting the midrise character of both LCZ classes. However, Detmold tends to show slightly more sky visibility (D-5: 20%, D-6: 19.2%) compared to Turin's LCZ 2 points, where sky share frequently falls below 6%. Road share: Road coverage is comparable across both cities, typically ranging between 10–22%. T-10 records the highest value overall (24.2%), and both cities show higher road shares at LCZ 5 points with parking and wider carriageways. Car share: Car presence in the streetscape is markedly higher in Turin's LCZ 2 points (T-3: 12.5%, T-5: 4.3%) compared to equivalent Detmold points, where car share is often near zero. This likely reflects differences in on-street parking density and traffic volume between the two cities. Person and bicycle share: Both attributes are near-zero across almost all points in both cities, reflecting the static nature of the Apple Street View imagery rather than actual pedestrian or cycling activity levels.

11.3 The final attribute table

The final result of the attribute data collection, is a table with the representative numbers of each attribute layer, per study point. Table 16, indicates these data:

Points D1 to D10 represent the points in Detmold, and T1 to T10, the points in Turin.

Point Identifiers				Layer 1- RS / GIS				Layer 2- SVI Pixel %																		
Point ID	LCZ Class	LATITUDE	LONGITUDE	LST	NDVI	Albedo	MNDWI	Road (%)	Sidewalk (%)	Building (%)	Wall (%)	Fence (%)	Pole (%)	Traffic light (%)	Traffic sign (%)	Vegetation (%)	Terrain (%)	Sky (%)	Person (%)	Rider (%)	Car (%)	Truck (%)	Bus (%)	Train (%)	Motorcycle (%)	Bicycle (%)
D-1	LCZ 2	51.934063°	8.877855°	41.26	0.173	0.133	-0.514	6.39%	3.72%	60.48%	0.00%	0.07%	0.06%	0.00%	0.07%	0.07%	0.00%	14.77%	0.03%	0.00%	14.28%	0.00%	0.00%	0.00%	0.00%	0.05%
D-2	LCZ 2	51.933468°	8.878225°	40.85	0.326	0.128	-0.416	16.22%	0.35%	66.93%	0.01%	7.79%	0.52%	0.00%	0.37%	1.37%	0.00%	5.86%	0.37%	0.00%	0.17%	0.01%	0.00%	0.00%	0.00%	0.05%
D-3	LCZ 2	51.938360°	8.874952°	41.87	0.114	0.092	-0.239	14.44%	4.21%	59.42%	0.00%	0.63%	0.00%	0.00%	0.00%	0.13%	0.00%	14.08%	0.00%	0.00%	7.08%	0.00%	0.00%	0.00%	0.00%	0.00%
D-4	LCZ 2	51.934386°	8.876176°	40.19	0.358	0.134	-0.305	14.63%	2.13%	49.66%	0.01%	6.02%	0.08%	0.01%	0.04%	15.95%	0.00%	11.27%	0.06%	0.00%	0.05%	0.00%	0.00%	0.00%	0.00%	0.10%
D-5	LCZ 2	51.936731°	8.880699°	40.97	0.262	0.132	-0.297	17.50%	11.47%	26.35%	0.29%	0.00%	0.65%	0.01%	0.09%	21.51%	0.00%	19.96%	0.13%	0.35%	0.50%	0.00%	0.00%	0.00%	0.00%	1.20%
D-6	LCZ 5	51.933729°	8.871238°	39.01	0.35	0.147	-0.284	10.55%	9.56%	46.08%	0.61%	9.53%	0.01%	0.00%	0.00%	3.46%	0.00%	19.16%	0.00%	0.00%	0.91%	0.00%	0.14%	0.00%	0.00%	0.00%
D-7	LCZ 5	51.938840°	8.874629°	42.27	0.357	0.112	-0.273	11.15%	3.89%	30.36%	0.00%	0.00%	0.00%	0.00%	0.00%	33.99%	0.12%	10.59%	0.00%	0.00%	9.89%	0.00%	0.00%	0.00%	0.00%	0.00%
D-8	LCZ 5	51.936912°	8.871946°	40.76	0.158	0.119	-0.473	16.49%	3.47%	70.64%	0.00%	0.01%	0.10%	0.00%	0.00%	0.20%	0.00%	9.06%	0.02%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
D-9	LCZ 5	51.937898°	8.872323°	40.49	0.233	0.112	-0.213	17.72%	0.38%	35.52%	0.00%	0.01%	0.07%	0.00%	0.00%	35.51%	2.72%	5.69%	0.05%	0.00%	2.28%	0.00%	0.00%	0.00%	0.00%	0.05%
D-10	LCZ 5	51.942415°	8.883467°	38.92	0.535	0.126	-0.596	15.16%	0.84%	54.17%	0.00%	0.00%	0.13%	0.00%	0.04%	16.51%	0.45%	6.45%	0.00%	0.00%	6.21%	0.00%	0.00%	0.00%	0.00%	0.04%
T-1	LCZ 2	45.076483°	7.671397°	47.06	0.215	0.108	-0.364	11.07%	5.19%	73.00%	0.00%	0.00%	1.14%	0.00%	0.00%	0.11%	0.00%	5.37%	0.00%	0.00%	4.12%	0.00%	0.00%	0.00%	0.00%	0.00%
T-2	LCZ 2	45.076255°	7.681017°	47.02	0.135	0.109	-0.313	8.94%	3.13%	83.49%	0.00%	0.00%	0.05%	0.00%	0.01%	0.01%	0.00%	3.92%	0.24%	0.01%	0.06%	0.00%	0.00%	0.00%	0.00%	0.14%
T-3	LCZ 2	45.078224°	7.668007°	48.03	0.097	0.118	-0.335	14.29%	0.16%	65.67%	0.00%	0.00%	0.00%	0.00%	0.00%	0.07%	0.00%	7.33%	0.00%	0.00%	12.48%	0.00%	0.00%	0.00%	0.00%	0.00%
T-4	LCZ 2	45.068065°	7.675337°	46.49	0.28	0.134	-0.328	13.20%	8.20%	49.40%	0.39%	0.00%	1.84%	0.00%	0.50%	20.68%	0.00%	5.46%	0.20%	0.00%	0.13%	0.00%	0.00%	0.00%	0.00%	0.00%
T-5	LCZ 2	45.056925°	7.669180°	45.38	0.291	0.116	-0.167	22.33%	8.54%	35.99%	0.00%	0.00%	0.48%	0.00%	0.41%	20.74%	0.09%	4.78%	2.34%	0.00%	4.30%	0.00%	0.00%	0.00%	0.00%	0.00%
T-6	LCZ 5	45.084215°	7.645104°	43.5	0.349	0.14	-0.3	13.32%	5.59%	20.03%	3.09%	11.22%	0.02%	0.00%	0.03%	17.90%	0.00%	18.45%	0.01%	0.00%	10.32%	0.00%	0.00%	0.00%	0.00%	0.00%
T-7	LCZ 5	45.036601°	7.628983°	47.29	0.14	0.124	-0.135	20.36%	6.05%	39.99%	1.70%	4.03%	0.56%	0.00%	0.09%	7.84%	0.00%	17.76%	0.00%	0.00%	1.16%	0.00%	0.00%	0.00%	0.00%	0.46%
T-8	LCZ 5	45.032440°	7.639669°	46.62	0.158	0.122	-0.186	17.39%	8.29%	59.57%	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%	0.00%	5.54%	0.00%	0.00%	9.17%	0.00%	0.00%	0.00%	0.00%	0.00%
T-9	LCZ 5	45.061891°	7.634647°	43.99	0.176	0.134	-0.333	14.29%	4.64%	30.79%	0.00%	0.17%	0.47%	0.00%	0.03%	19.20%	4.72%	11.62%	0.00%	0.00%	14.06%	0.00%	0.00%	0.00%	0.00%	0.02%
T-10	LCZ 5	45.034104°	7.641627°	46.09	0.312	0.121	-0.301	24.23%	0.01%	21.14%	0.00%	0.00%	0.13%	0.00%	0.08%	39.00%	0.30%	4.51%	0.00%	0.00%	10.11%	0.00%	0.00%	0.00%	0.49%	0.00%

Table 16. The final attribute table. source: author

11.4 The final questionnaire

Figure 27 is the copy of the English version survey of Detmold, from Google Forms:

[illegible]

Figure 28. the final survey overview. Source: author.

11.5 Survey Results

In this section the raw results of the surveys will be presented, considering the total respondent number of respondents in Turin 119 and in Detmold, 116. To clean the raw data of the two versions of surveys each city, all of the responds were put together in English. The tables 16 to 26 will identify the responds, by each survey question.

Q1: Gender

Label	Turin Count	Turin %	Detmold Count	Detmold %
Female	64	53.8%	77	66.4%
Male	55	46.2%	38	32.8%
Non-binary	0	0.0%	1	0.9%
TOTAL	119	100.0%	116	100.0%

Table 17. raw survey data, Gender. source: survey by author.

Based on the answers, in both cities the number of female respondents is more than the male one and it is more than half of the total respondents of each city. Moreover, the number of non-binary people in Turin is zero and in Detmold, one.

Q2: Age Groups

Label	Turin Count	Turin %	Detmold Count	Detmold %
18–25	23	19.3%	61	52.6%
26–35	70	58.8%	34	29.3%
36–45	15	12.6%	8	6.9%
46–55	5	4.2%	8	6.9%
56–65	4	3.4%	5	4.3%
65+	2	1.7%	0	0.0%
TOTAL	119	100.0%	116	100.0%

Table 18. raw survey data, Age. source: survey by author.

The dominant age groups in Turin are 26-35 with 58.8% and in Detmold 18-25 with 52.6%, however both of these age groups in both cities aggregate the highest numbers of respondents. So, the greatest number of respondents in both cities are between 18 to 35 years old.

Q3: Place of Birth

Label	Turin Count	Turin %	Detmold Count	Detmold %
In this city	21	17.6%	8	6.9%
In this region	5	4.2%	47	40.5%
In this country	26	21.8%	32	27.6%
Other place	67	56.3%	29	25.0%
TOTAL	119	100.0%	116	100.0%

Table 19. raw survey data, Place of Birth. source: survey by author.

In Turin most of the respondents were born in other places rather than Italy, with the percentage of 56.3%, while in Detmold 40.5% of the respondents were from the region of North Rhine-Westphalia

and 25% were born outside Germany. The number of respondents from the same city of the survey were 21 (17.6%) in Turin, and 8 (6.9%) in Detmold.

Q4: Education Level

Label	Turin Count	Turin %	Detmold Count	Detmold %
High school	7	5.9%	52	44.8%
Vocational	2	1.7%	13	11.2%
Bachelor's	34	28.6%	28	24.1%
Master's	63	52.1%	23	19.8%
PhD	13	10.9%	0	0.0%
TOTAL	119	100.0%	116	100.0%

Table 20. raw survey data, Education Level. source: survey by author.

The Highest level of education completed in the respondents of Detmold were 52 (44.8%) in high school, while this number in Turin dedicates to Master's with 63 (52.1%). 10.9% of the Turin respondents were PhD groups while this percentage in Detmold was zero. In the category of bachelor's, this percentage in both cities is nearly the same with 28.6% and 24.1% for Turin and Detmold, respectively.

Q5: Occupation

Label	Turin Count	Turin %	Detmold Count	Detmold %
Student	57	47.9%	85	73.3%
Full-time	32	26.9%	20	17.2%
Part-time	5	4.2%	8	6.9%
Self-employed	15	12.6%	1	0.9%
Retired	3	2.5%	2	1.7%
Unemployed	7	5.9%	0	0.0%
TOTAL	119	100.0%	116	100.0%

Table 21.. raw survey data, Occupation. source: survey by author.

In both of the cities the highest percentage of the respondents were students with 47.9% and 73.3% in Turin and Detmold, respectively. Then, again in both cities the percentage of Full-time employed respondents dedicated higher than other categories with 26.9% in Turin and 17.2% in Detmold. One of the most important numbers was 12.6% in the self-employed category for Turin, while in this category in Detmold the percentage is 0.9% or just one person. Other categories in both cities have less than 10 respondents.

Q6: Daily Activity Pattern

Label	Turin Count	Turin %	Detmold Count	Detmold %
Mostly indoors	87	73.1%	92	79.3%
Mostly outdoors	3	2.5%	1	0.9%
Mix of both	29	24.4%	23	19.8%
TOTAL	119	100.0%	116	100.0%

Table 22. raw survey data, Daily activity pattern. source: survey by author.

In both of the cities the highest percentage of respondents have indoor activities, with 73.1% in Turin and 79.3% in Detmold. The next category that dedicates high percentage is mix of indoor and outdoor

activities with 24.4% and 19.8% for Turin and Detmold, respectively. Totally less than 5 people in both cities have solely outdoor activities.

Q7: Relationship to City

Label	Turin Count	Turin %	Detmold Count	Detmold %
Resident	110	91.6%	72	62.1%
Commuter	9	7.6%	44	37.9%
TOTAL	119	100.0%	116	100.0%

Table 23. raw survey data, Relationship to the city. source: survey by author.

In this section, 91.6% of the respondents in Turin were also residents of it and only 7.6% were commuters, that means commuting for work or study on a regular basis. While in Detmold 37.9% were commuters and 62.1% were residents of the city.

Q8: Time of the relationship with the city

Label	Turin Count	Turin %	Detmold Count	Detmold %
< 1 year	15	12.6%	18	15.5%
1–3 years	46	38.7%	56	48.3%
4–10 years	38	31.9%	21	18.1%
> 10 years	10	8.4%	13	11.2%
Since birth	10	8.4%	8	6.9%
TOTAL	119	100.0%	116	100.0%

Table 24. raw survey data, Time of the relationship with the city. source: survey by author.

Most of the respondents in both cities were living or commuting there between one and three years, 38.7% in Turin and 48.3% in Detmold. Also, the people who had their relationship with the city between 4 and 10 years dedicated high percentage 31.9%, and 18.1% for Turin and Detmold, respectively. However, the number of people who had their relationship with the study cities since birth is lowest in both cities.

Q9: Level of Heat Adaptation

Label	Turin Count	Turin %	Detmold Count	Detmold %
No adaptation	39	32.8%	6	5.2%
Slight	47	39.5%	37	31.9%
Moderate	28	23.5%	52	44.8%
Well adapted	5	4.2%	21	18.1%
TOTAL	119	100.0%	116	100.0%

Table 25. raw survey data, Level of heat adaptation. source: survey by author.

In the answer to this question, most of the people in Turin were slightly adapted and not adapted to the level of heat, with the percentage of 39.5% and 32.8%, respectively, and only 4.2% of the respondents were well adapted to it. While in Detmold, most of the respondents were moderately adapted to the heat 44.8%, 31.9% were slightly adapted and 18.1% were well adapted. So, this shows that people in Detmold consider themselves more adapted to the heat in their city.

Q10: Route Modification Due to Heat

Label	Turin Count	Turin %	Detmold Count	Detmold %
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Never	5	4.2%	32	27.6%
Sometimes	59	49.6%	70	60.3%
Always	55	46.2%	14	12.1%
TOTAL	119	100.0%	116	100.0%

Table 26. raw survey data, Route Modification due to the Heat. source: survey by author.

In both of the cities, the percentage of people who sometimes modify their routes due to the heat is higher with 49.6% in Turin and 60.3% in Detmold. While, 46.2% of the people in Turin always change their routes due to the heat, and in Detmold this percentage is 12.1%. in Detmold 27.6% of the people never modify their routes due to the heat but in Turin only 4.2% never does it.

Q10: Mode of Transport Frequency

Turin (n=119)					
Mode	Never	Monthly	Sometimes	Weekly	Daily
Walking	6.7%	0.0%	44.5%	0.0%	48.7%
Cycling	54.6%	0.0%	33.6%	0.0%	11.8%
Public Transport	9.2%	0.0%	44.5%	0.0%	46.2%
Car	68.1%	0.0%	18.5%	0.0%	13.4%

Table 27. raw survey data, different modes of transportation frequency-Turin. source: survey by author.

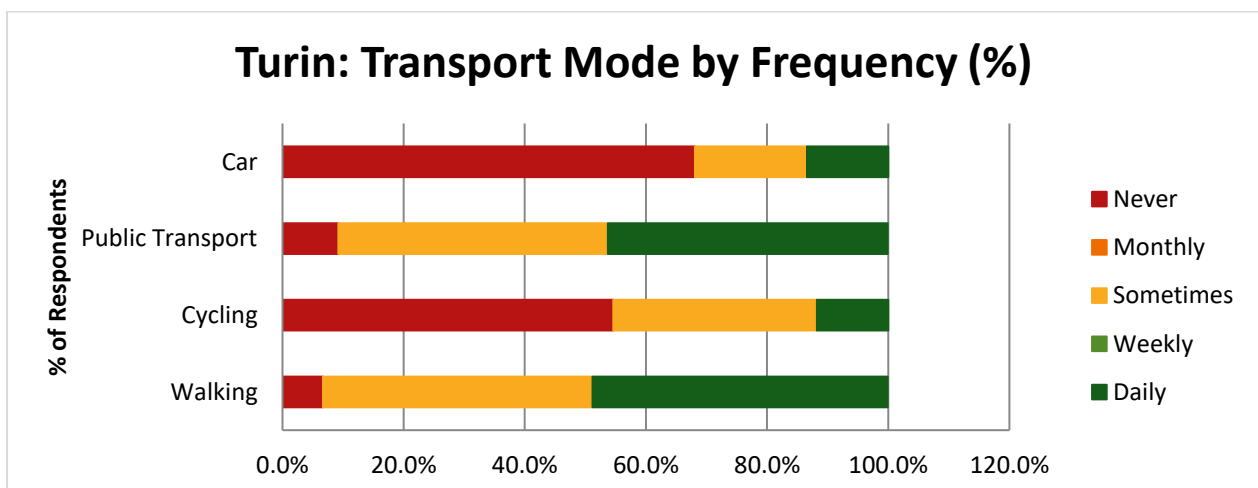


Figure 29. Raw survey data of the Transportation mode by frequency-Turin. source: survey by author.

Detmold (n=116)					
Mode	Never	Monthly	Sometimes	Weekly	Daily
Walking	0.0%	0.0%	39.7%	0.0%	60.3%
Cycling	44.0%	0.9%	36.2%	0.0%	19.0%
Public Transport	36.2%	0.0%	50.0%	0.9%	12.9%
Car	34.5%	0.9%	49.1%	0.0%	15.5%

Table 28. raw survey data, different modes of transportation frequency-Detmold. source: survey by author.

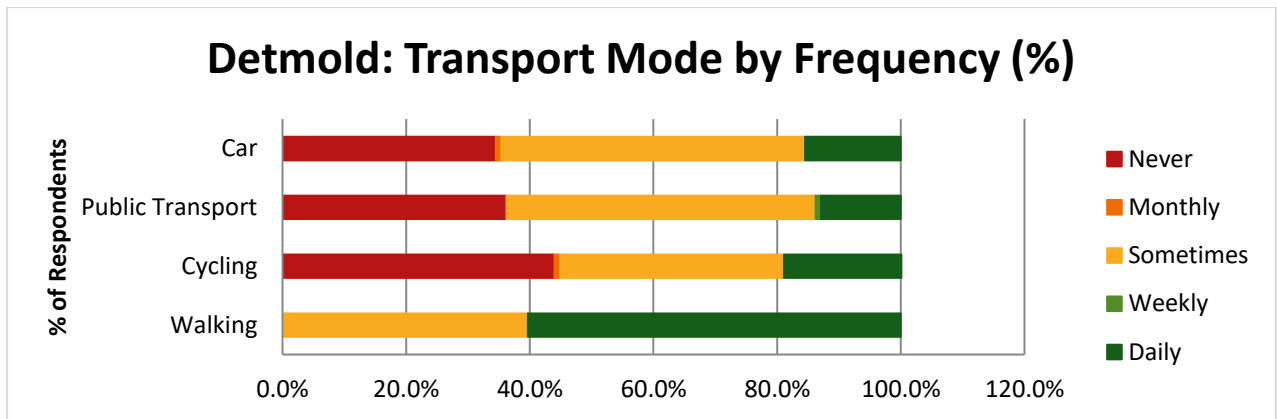


Figure 30. Raw survey data of the Transportation mode by frequency-Detmold. source: survey by author.

Among all modes of transportation, walking was the most used mode in both cities. Daily walking was 60.3% in Detmold respondents and 48.7% in Turin, with 39.7% and 44.5% respectively indicating occasional use or sometimes usage. In Detmold none of the respondents reported the never walking, while in Turin 6.7% never do walking as a transportation mode.

Cycling patterns were more different between the two cities. In Turin, the majority of respondents never do cycle (54.6%), while daily cycling was only 11.8%. Detmold showed higher cycling engagement, with 19.0% daily and 44.0% reporting never, shows a stronger cycling culture in Detmold.

Public transport use exhibited the most visible difference between the two cities. As in Turin, 46.2% of respondents used public transport on a daily basis, while only 12.9% in Detmold, where 36.2% reported never using it. This pattern may represent the differences in urban scale and public transit infrastructure of the two cities.

Car use was lower in Turin, where 68.1% of respondents reported never using a car, compared to 34.5% in Detmold. Sometimes usage of the cars was more usual among Detmold respondents (49.1%), while daily car use was similarly low in both cities (Turin 13.4%, Detmold 15.5%).

11.6 The results of data pre-processing

The pre-processing of the Attribute table data

Remote-sensing indicators and street-view pixel fractions pass through the three-stage screening procedure of constant, near-absent, and normalized Shannon entropy rules as mentioned in the methodology section.

Among the total of 23 streetscape attributes initially extracted, 17 were retained in each city following the screening procedure. The attributes that were excluded: the train category that was constant across all survey points in both cities, five street-view classes (truck, bus, motorcycle, rider, and traffic light) were removed as near-absent or near-constant due to their

negligible occurrence across survey points. And finally, the normalized Shannon entropy screen confirmed that all retained attributes have sufficient distributional diversity (minimum $H_{\text{norm}} \approx 0.68$), and no further exclusions were required at this stage. The removed and remained attributes are listed in the following table.

Layer	Attribute	Applied Rule to Turin	Applied rule to Detmold
RS / GIS	Albedo	Kept	Kept
RS / GIS	LST(°C)	Kept	Kept
RS / GIS	MNDWI	Kept	Kept
RS / GIS	NDVI	Kept	Kept
SVI Pixel %	Bicycle (%)	Kept	Kept
SVI Pixel %	Building (%)	Kept	Kept
SVI Pixel %	Bus (%)	Constant, Near absent, Low entropy	Near absent, Low entropy
SVI Pixel %	Car (%)	Kept	Kept
SVI Pixel %	Fence (%)	Kept	Kept
SVI Pixel %	Motorcycle (%)	Near absent, Low entropy	Constant, Near absent, Low entropy
SVI Pixel %	Person (%)	Kept	Kept
SVI Pixel %	Pole (%)	Kept	Kept
SVI Pixel %	Rider (%)	Near absent, Low entropy	Near absent, Low entropy
SVI Pixel %	Road (%)	Kept	Kept
SVI Pixel %	Sidewalk (%)	Kept	Kept
SVI Pixel %	Sky (%)	Kept	Kept
SVI Pixel %	Terrain (%)	Kept	Kept
SVI Pixel %	Traffic light (%)	Constant, Near absent, Low entropy	Near absent
SVI Pixel %	Traffic sign (%)	Kept	Kept
SVI Pixel %	Train (%)	Constant, Near absent, Low entropy	Constant, Near absent, Low entropy
SVI Pixel %	Truck (%)	Constant, Near absent, Low entropy	Near absent, Low entropy
SVI Pixel %	Vegetation (%)	Kept	Kept
SVI Pixel %	Wall (%)	Kept	Kept

Table 29. The results of the pre-processing of the Attribute table data. source: author

The pre-processing of the Survey data

Respondent-profile fields are screened on the Detmold and Turin surveys. The answers pass through the constant, near-constant ($\geq 95\%$ modal category), and $H_{\text{norm}} < 0.5$ rules described in the methodology.

The questionnaire screening retained fifteen variables in each city. Only one field was removed that was the summer visit of the questioned city on the basis of low normalized Shannon entropy. The near-uniform distribution of yes responses (92% in Detmold, 94% in Turin) provided insufficient variation to support within-city profile comparisons. All remaining questionnaire variables, including gender, occupation, city relationship, daily activity pattern, and transport modes, passed both the near-constant and entropy thresholds and were carried forward to the subsequent analysis. The following table indicates the removed and remained variables in this stage:

Group	Attribute	Applied Rule to Turin	Applied rule to Detmold
Demographics	Gender	Kept	Kept
Demographics	Age	Kept	Kept
Demographics	Birthplace	Kept	Kept
Demographics	Education	Kept	Kept
Demographics	Occupation	Kept	Kept
Demographics	Daily activity	Kept	Kept
Demographics	City relationship	Kept	Kept
Demographics	Time in city	Kept	Kept
Summer & adaptation	Summer visit	Low entropy	Low entropy
Summer & adaptation	Summer description	Kept	Kept
Summer & adaptation	Heat adaptation	Kept	Kept
Summer & adaptation	Modify routes for heat	Kept	Kept
Travel behavior	Transport (walking)	Kept	Kept
Travel behavior	Transport (cycling)	Kept	Kept
Travel behavior	Transport (public)	Kept	Kept
Travel behavior	Transport (car)	Kept	Kept

Table 30. The results of the pre-processing of the survey data. source: author

11.7 The results of multi-collinearity screening

Attribute table

Spearman correlation matrices were computed across all 136 unique pairs among the 17 attributes in each city. Eight pairs in Detmold and nine in Turin exceeded the $|p| > 0.7$ threshold and were flagged for iterative review (Larkin et al., 2021). The strongest flagged associations in Detmold involved sidewalk and sky ($p \approx 0.90$), bicycle and person ($p \approx 0.84$), and building and vegetation share ($p \approx 0.81$). In Turin, the highest correlations were observed between fence and sky ($p \approx 0.81$), LST and NDVI ($p \approx 0.78$), and building and LST ($p \approx 0.77$).

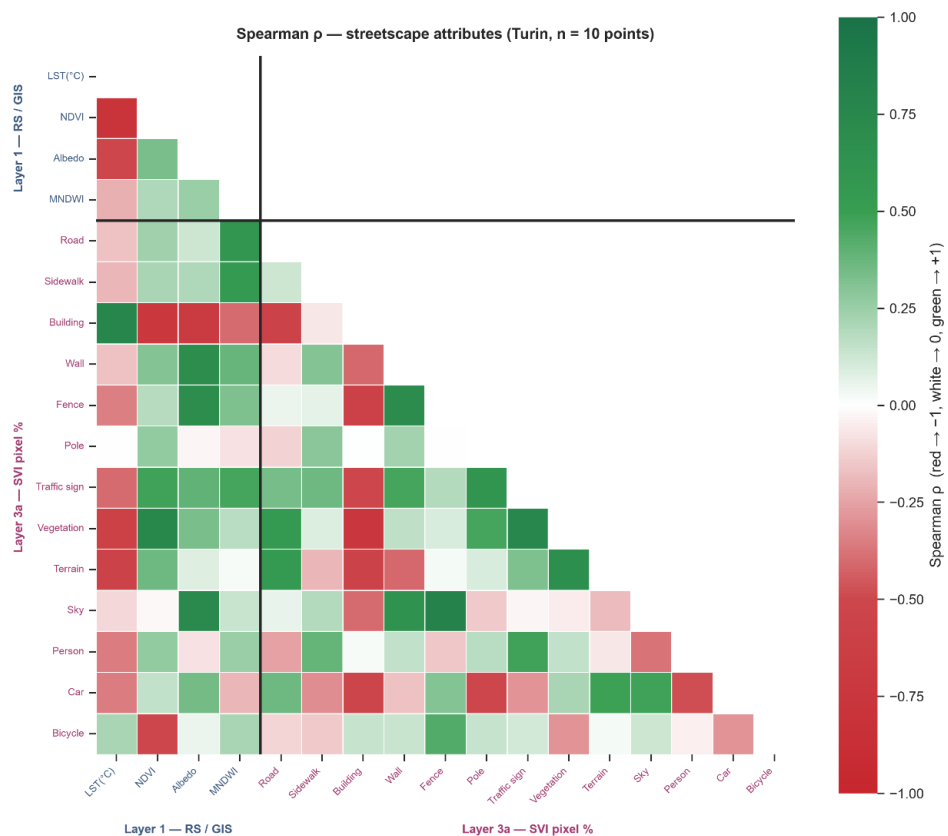


Figure 31. the heatmaps of Spearman correlation matrices for Turin. (produced by Author)

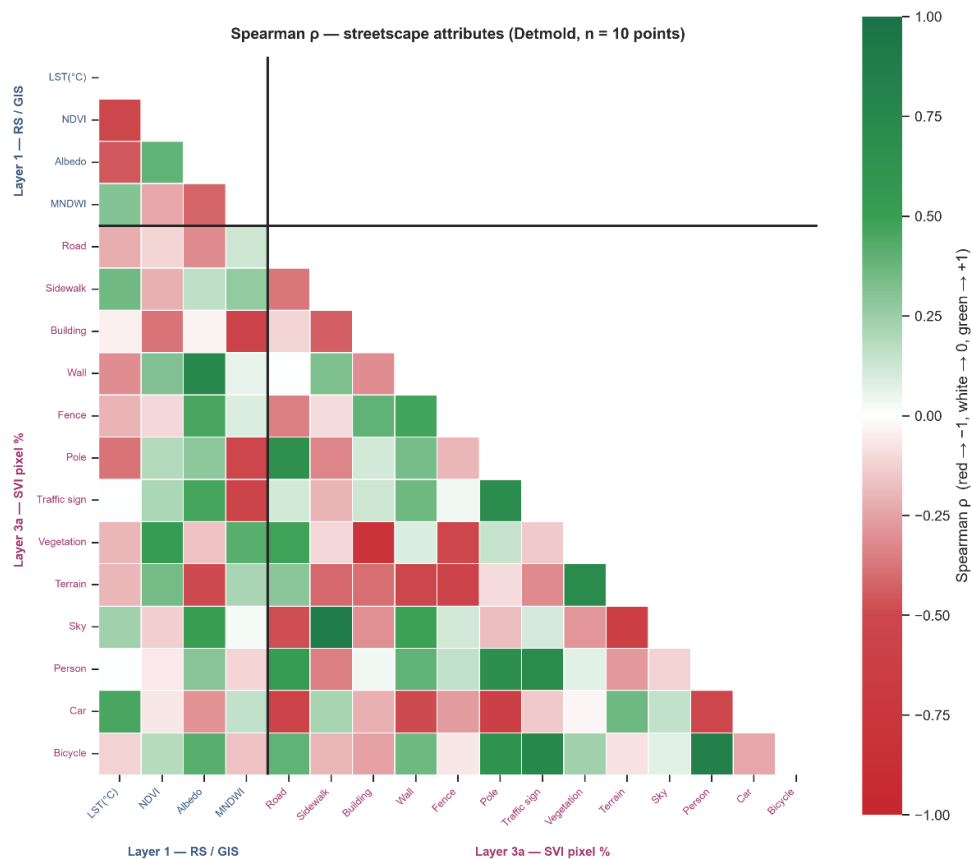


Figure 32. the heatmaps of Spearman correlation matrices for Detmold. (produced by Author)

Turin; iterative review

The nine flagged pairs identified in Turin are listed in Table 30.

Attribute	Partner attribute
Fence (%)	Sky (%)
LST(°C)	NDVI
Building (%)	LST(°C)
Traffic sign (%)	Vegetation (%)
Building (%)	Vegetation (%)
Vegetation (%)	NDVI
Building (%)	NDVI
Sky (%)	Albedo
Fence (%)	Wall (%)

Table 31. the initial flagged pairs of iterative review of Turin. produced by author.

Round 1: NDVI and Building (%) were removed. NDVI duplicates the greenness signal already carried by Vegetation (%); Building (%) appeared in three flagged pairs, entangled with LST, Vegetation (%), and NDVI simultaneously. Four flagged pairs remained:

Attribute	Partner attribute
Fence (%)	Sky (%)
Traffic sign (%)	Vegetation (%)
Sky (%)	Albedo
Fence (%)	Wall (%)

Table 32. round 1 of data cleaning to identify the flagged pairs of iterative review of Turin. produced by author.

Round 2: Fence (%) was removed, as it was strongly linked to both sky and wall openness. Retaining Wall (%) and Sky (%) preserves enclosure and openness as separate interpretable dimensions. Two flagged pairs remained:

Attribute	Partner attribute
Traffic sign (%)	Vegetation (%)
Sky (%)	Albedo

Table 33. round 2 of data cleaning to identify the flagged pairs of iterative review of Turin. produced by author

Round 3: Traffic sign (%) and Albedo were removed. Traffic sign (%) overlaps the vegetation and Vegetation (%) was retained as the more interpretable descriptor of street-level greenness. Albedo duplicates the openness signal carried by Sky %)(H. Yang & Zeng, 2025). No flagged pairs remained among Turin survivors.

Detmold; iterative review

The eight flagged pairs identified in Detmold are listed in Table 33.

Attribute	Partner attribute
Sidewalk (%)	Sky (%)
Bicycle (%)	Person (%)
Building (%)	Vegetation (%)
Bicycle (%)	Traffic sign (%)
Wall (%)	Albedo
Terrain (%)	Vegetation (%)

Person (%)	Traffic sign (%)
Pole (%)	Traffic sign (%)

Table 34. the initial flagged pairs of iterative review of Detmold. produced by author

Round 1: NDVI was removed for cross-city consistency, as it was identified as the primary redundancy hub in Turin and would produce an asymmetric predictor set if retained only in Detmold. The eight flagged pairs within Detmold remained unchanged by this removal, as NDVI did not appear among them.

Round 2: Building (%) and Fence (%) were removed. Building (%) clears the building–vegetation flagged pair; Fence (%) is excluded for cross-city consistency with Turin, where it was dropped in Round 2. Two flagged pairs remained:

Attribute	Partner attribute
Traffic sign (%)	Vegetation (%)
Sky (%)	Albedo

Table 35. round 2 of data cleaning to identify the flagged pairs of iterative review of Detmold. produced by author

Round 3: Traffic sign (%) and Albedo were removed on the same substantive grounds as Turin, retaining Vegetation (%) and Sky (%) as the interpretable streetscape descriptors for greenness and openness respectively. No flagged pairs remained among Detmold survivors.

Shared modelling set: Five attributes of NDVI, Building (%), Fence (%), Traffic sign (%), and Albedo were excluded following the iterative review in both cities.

It should be noted that this screening procedure removes the most problematic correlations, those exceeding $|\rho| > 0.7$, but does not guarantee that all surviving predictors are fully independent of one another. Moderate correlations below the threshold may still exist among retained attributes, and the procedure is therefore understood as a practical filter rather than a claim of complete statistical independence (Dormann et al., 2013).

Results of survey collinearity screening

Among the 105 unique pairs across the 15 surviving fields in each city, no pair exceeded $|\rho| = 0.8$ in either Turin or Detmold. The strongest associations observed were age and education in Detmold ($\rho \approx 0.75$), age and occupation in Detmold ($\rho \approx -0.65$), and heat adaptation and summer description in Turin ($\rho \approx -0.44$). No questionnaire field was removed following the collinearity review, and all fifteen fields in each city were carried forward to the subsequent analysis.

12. Final Analysis

This section addresses RQ1 and RQ2 of the present research, which aim to investigate how people visually assess street-level thermal comfort potential in Turin and Detmold, and to identify the streetscape attributes and demographic characteristics most strongly associated with these assessments. Following data collection and pre-processing, the analysis is structured in two parts. The first part assesses the perceived thermal comfort potential at each study point in each city, based on respondents' visual ratings. The second part investigates which streetscape attributes and demographic characteristics are most strongly associated with how comfortable a streetscape is perceived to be. The following sections present these two analyses in detail.

12.1 The analysis of RQ1; Visual Assessment of Thermal Comfort Across Cities and Social Groups

This research question asks how thermal comfort is perceived at the city scale, and whether that perception differs systematically across respondent profiles. The analysis draws on the survey data prepared during pre-processing (Section 10.8). Only questionnaire fields that passed the city-specific variation screening and collinearity review are included in the respondent-profile analyses below.

The analysis proceeds are inter-rater agreement in, (A) city-level perception profiles, and (B) city-level comfort ratings across respondent profiles, for Detmold and Turin.

City-level Comfort Rating Summary

Based on the section 10.3 of the Methodology, these results were obtained:

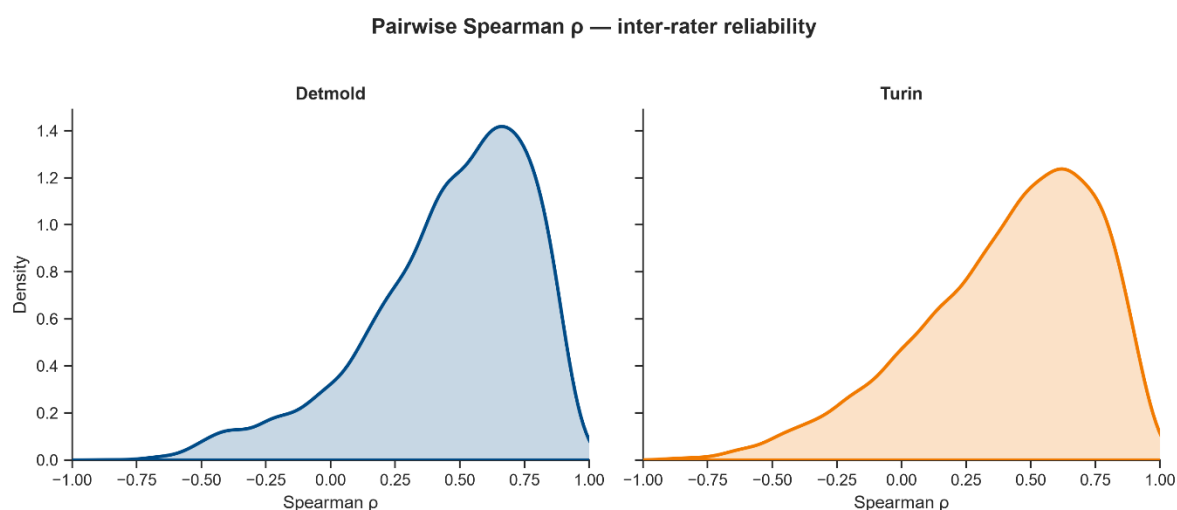


Figure 33. Results of Pairwise Spearman ρ for inter-rater reliability analysis in Turin and Detmold. Produced by Author

city	n_pairs	mean	std	min	p25	median	p75	max
Detmold	6441	0.46	0.316	-0.859	0.285	0.52	0.702	1
Turin	6903	0.409	0.345	-0.906	0.194	0.471	0.675	1

Table 36. Summary statistics of pairwise Spearman ρ for city-level inter-rater agreement. Produced by author.

The abbreviations used in this table:

- n_pairs: number of respondent pairs included in the analysis (6,441 in Detmold, 6,903 in Turin)
- mean: the average pairwise Spearman ρ across all respondent pairs
- std: standard deviation, showing how spread out the ρ values are around the mean
- min: the lowest (most negative) pairwise ρ observed
- p25: the 25th percentile (first quartile, Q1) of the ρ distribution (25% of pairs have a ρ below this value)
- median: the 50th percentile (Q2), the middle value of the ρ distribution
- p75: the 75th percentile (Q3) (75% of pairs have a ρ below this value)
- max: the highest pairwise ρ observed (capped at 1.0, perfect agreement)

city	image	n_rate rs	n_pai rs	mea n	std	mi n	p2 5	medi an	p7 5	ma x	mean_rati ng	std_rati ng
Detmo ld	point_ 1	116	6670	0.75 1	0.22 3	0	0.7 5	0.75	1	1	2.267	0.945
Detmo ld	point_ 2	116	6670	0.76 4	0.20 2	0	0.7 5	0.75	1	1	3.362	0.879
Detmo ld	point_ 3	116	6670	0.73 8	0.22 7	0	0.5	0.75	1	1	2.043	0.982
Detmo ld	point_ 4	116	6670	0.80 2	0.18 3	0.2 5	0.7 5	0.75	1	1	4.026	0.763
Detmo ld	point_ 5	116	6670	0.77 3	0.20 9	0	0.7 5	0.75	1	1	2.931	0.872
Detmo ld	point_ 6	116	6670	0.77 1	0.2	0	0.7 5	0.75	1	1	2.759	0.861
Detmo ld	point_ 7	116	6670	0.72 9	0.22 2	0	0.5	0.75	1	1	2.974	0.991
Detmo ld	point_ 8	116	6670	0.74 9	0.22 3	0	0.5	0.75	1	1	2.397	0.95
Detmo ld	point_ 9	116	6670	0.81 2	0.2	0	0.7 5	0.75	1	1	3.759	0.776
Detmo ld	point_ 10	116	6670	0.77	0.19 8	0	0.7 5	0.75	1	1	3.483	0.86
Turin	point_ 1	119	7021	0.73 5	0.21 3	0	0.5	0.75	1	1	2.706	0.96
Turin	point_ 2	119	7021	0.73 2	0.21 5	0	0.5	0.75	1	1	2.891	0.972
Turin	point_ 3	119	7021	0.81 6	0.18 5	0	0.7 5	0.75	1	1	1.622	0.736
Turin	point_ 4	119	7021	0.74 5	0.21 4	0	0.5	0.75	1	1	2.168	0.942
Turin	point_ 5	119	7021	0.75 3	0.20 9	0	0.7 5	0.75	1	1	2.588	0.915
Turin	point_ 6	119	7021	0.82 9	0.19 6	0	0.7 5	0.75	1	1	1.496	0.735
Turin	point_ 7	119	7021	0.79 9	0.20 5	0	0.7 5	0.75	1	1	1.681	0.812
Turin	point_ 8	119	7021	0.74 2	0.20 8	0.2 5	0.5	0.75	1	1	2.487	0.938
Turin	point_ 9	119	7021	0.71 1	0.22 9	0.2 5	0.5	0.75	1	1	2.185	1.041

Turin	point_ 10	119	7021	0.78 9	0.19 3	0	0.7 5	0.75	1	1	3.303	0.808
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Table 37. Image-level inter-rater agreement and comfort ratings, by city and point. Produced by author.

The image-level pair counts (6,670 in Detmold; 7,021 in Turin) exceed the city-level figures (6,441 and 6,903 respectively) because the two checks operate on different units: city-level agreement requires each respondent to have completed all ten image ratings in order to compute a full profile-level correlation. whereas image-level agreement is computed per image independently, so respondents who rated only some images contribute to the image-level counts but are excluded from the city-level pairwise ρ .

Respondent pairs in which one member assigned identical ratings across all ten images were excluded prior to computing pairwise ρ , as zero within-person variance cannot yield a meaningful correlation.

In Detmold, across 6,441 respondent pairs, the median pairwise Spearman ρ was 0.52 (mean 0.46; interquartile range 0.29–0.70). In Turin, among 6,903 pairs, the median was 0.47 (mean 0.41; interquartile range 0.19–0.68). In both cities, the central mass of the distribution lies clearly above zero, indicating that most respondents ordered the same streetscapes similarly on the comfort scale, although perfect agreement was neither expected nor observed for a perceptual outcome of this kind.

These positive medians are inconsistent with arbitrary use of the rating scale, and instead suggest that respondents were responding to shared visual cues within the images, a precondition for pooling ratings into city-level comfort profiles (Urban et al., 2022). Some negative pairwise correlations remain at the tails of the distribution (minimum $\rho \approx -0.86$ in Detmold, -0.91 in Turin), reflecting individual disagreement on specific scenes; these outliers do not outweigh the broader pattern of within-city consensus observed across the majority of respondent pairs.

On this basis, comfort ratings were treated as comparable within each city and aggregated for the descriptive and group-based analyses presented in the following sections. This agreement check does not establish universal consensus among respondents, but it does support the interpretability of city-scale comfort summaries derived from pooled subjective responses.

Inter-rater agreement, city-level comfort ratings

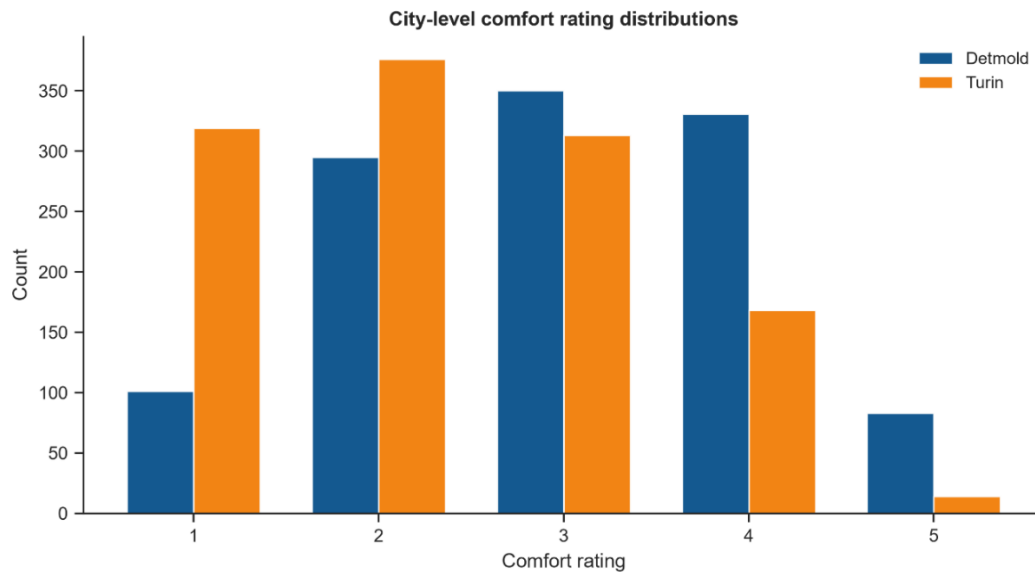


Figure 34. city-level comfort ratings across respondent profiles. Produced by author.

city	mean	std	n_ratings	n_respondents
Detmold	3	1.084	1160	116
Turin	2.313	1.051	1190	119

Table 38. City-level comfort rating summary across all street-view images. Produced by author

Across all image ratings, mean comfort was higher in Detmold (mean = 3.00, SD = 1.08, n = 1,160 ratings from 116 respondents) than in Turin (mean = 2.31, SD = 1.05, n = 1,190 ratings from 119 respondents). The Detmold distribution is shifted toward the upper half of the five-point scale, whereas Turin responses concentrate more on lower categories, indicating that the Turin sample rated the same set of streetscape images as less thermally comfortable overall.

This city-level gap is descriptive rather than inferential: it summarizes how the two respondent pools used the ordinal scale when judging an identical image set, rather than testing whether the difference is statistically significant. The pattern is consistent with cross-city photo-based perception research, where background climate, lived experience, and expectations can shift reported comfort even when visual stimuli are held constant (Nikolopoulou & Steemers, 2003; Urban et al., 2022). These city-level profiles serve as the reference point against which respondent-group differences are examined in the following sections.

Comfort ratings comparison across respondent profiles

Each of the respondents’ profiles consists of different socio-demographic variables, and the following figure explain what is the Mean comfort rating of each of these variables. For example, the first bar chart shows the mean comfort ratings of male and female respondents in each city. On the five-point scale, higher bars indicate that a respondent group perceives the streetscape images as more thermally comfortable; lower bars indicate less comfortable expectations.

Each of these socio-economic variables are explained in the following sections.

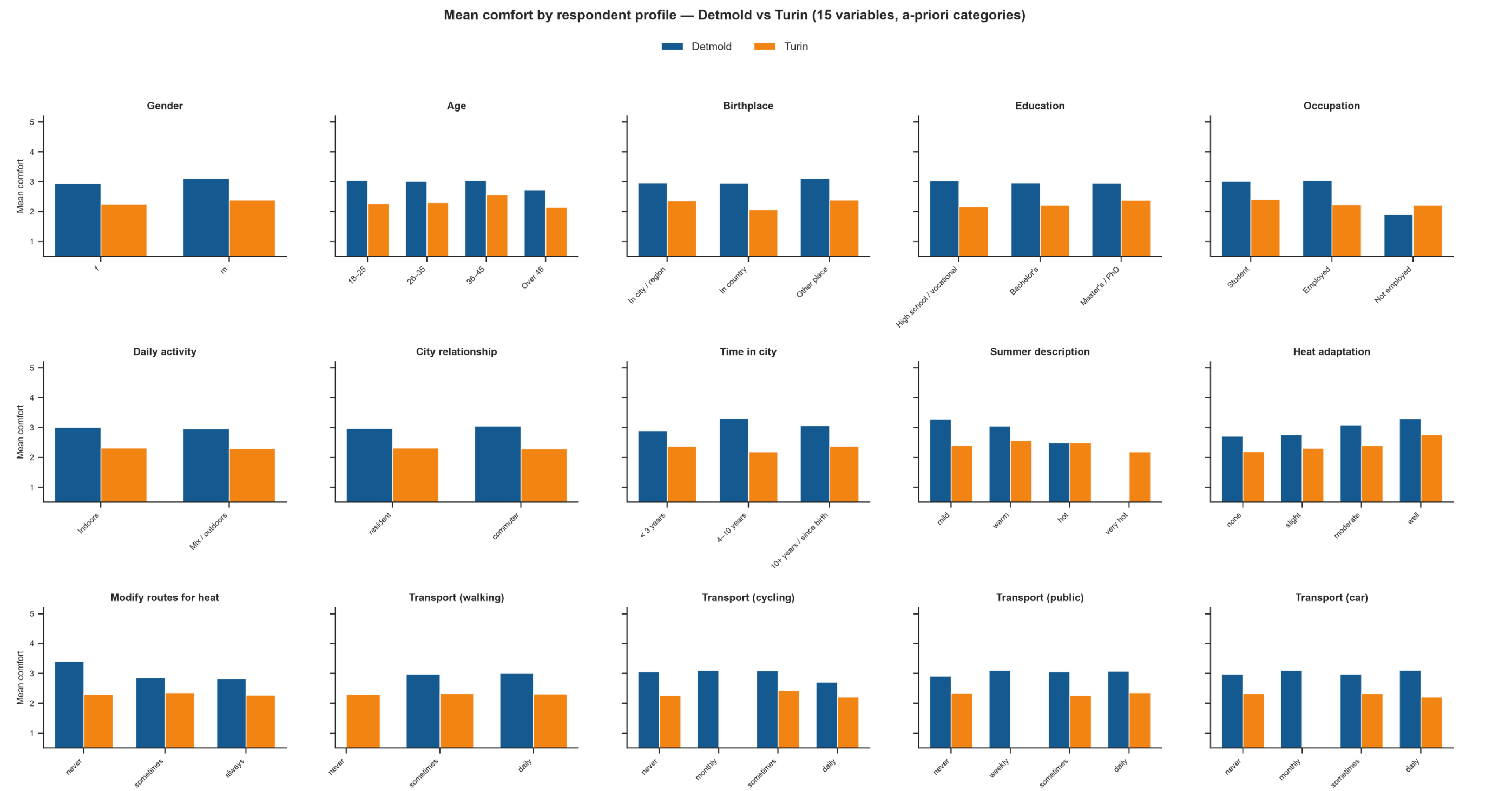


Figure 35. Mean comfort rating by respondent profile, Detmold vs Turin. Produced by Author.

Based on the rating-scale rationale, on the five-point comfort scale, higher mean ratings indicate that respondents perceive the streetscape images as thermally more comfortable; lower ratings indicate less comfortable expectations. The following section indicates each of the socio-demographic variables and their mean ratings and difference from average ratings in detail:

- **Gender**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	f	77	2.949	-0.053
Detmold	m	38	3.111	0.108
Turin	f	64	2.248	-0.064
Turin	m	55	2.387	0.075

Table 39. Mean comfort rating by gender, Detmold and Turin. Produced by author.

A consistent gender gap appears in both cities: male respondents rate the streetscapes 0.16 points higher than female respondents in Detmold, and 0.14 points higher in Turin. Both gaps clear the modest threshold (≥ 0.10) but stay well short of a full scale point. Gender therefore appears to carry a small, directionally stable effect on visually assessed thermal comfort across both cities, rather than producing a sharp profile split.

- **Age**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	18–25	61	3.049	0.047
Detmold	26–35	33	3.015	0.013
Detmold	36–45	8	3.038	0.035
Detmold	Over 46	13	2.731	-0.272
Turin	18–25	23	2.265	-0.047
Turin	26–35	70	2.303	-0.01
Turin	36–45	15	2.56	0.247
Turin	Over 46	11	2.136	-0.176

Table 40. Mean comfort rating by age, Detmold and Turin. In Detmold, 1 respondent has been dropped in the previous stage because the non-binary category was dropped. Produced by author.

In Detmold, younger age bands (18–25, 26–35, 36–45) differ from one another by at most 0.03 points (so it is negligible) and report similarly higher comfort. Over 46 respondents' rate 0.28–0.32 points that is lower than each younger band (pronounced). This means that Over 46 respondents perceive the images as substantially less thermally comfortable.

In Turin, 36–45 age group of respondents' rate 0.42 points higher than Over 46 (pronounced) and 0.26 points higher than 26–35 age group (pronounced). Younger bands remain closely aligned (≤ 0.04). The age–comfort association differs across cities: Detmold shows markedly lower comfort among older respondents, whereas Turin shows stronger separation between middle and older bands.

- **Birth place**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	In city / region	54	2.969	-0.034

Detmold	In country	32	2.956	-0.046
Detmold	Other place	29	3.117	0.115
Turin	In city / region	26	2.362	0.049
Turin	In country	26	2.065	-0.247
Turin	Other place	67	2.39	0.077

Table 41 Mean comfort rating by birth place, Detmold and Turin. Produced by author.

Birthplace contrasts in Detmold stay small throughout (0.01–0.16 points); the largest gap, Other place rating 0.16 points above In country, is only modest. Birthplace does not meaningfully differentiate comfort perception in this city.

Turin tells a different story. Both the In city/region and Other place groups rate the streetscapes notably higher than the In country group (by 0.30 and 0.33 points respectively, both pronounced) while the two higher-rating groups differ from each other by just 0.03 points. Place of birth, in other words, structures perceived comfort clearly in Turin but not in Detmold.

- **Education**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	High school / vocational	65	3.032	0.03
Detmold	Bachelor's	27	2.967	-0.036
Detmold	Master's / PhD	23	2.961	-0.042
Turin	High school / vocational	9	2.156	-0.157
Turin	Bachelor's	34	2.215	-0.098
Turin	Master's / PhD	76	2.375	0.062

Table 42 Mean comfort rating by education, Detmold and Turin. Produced by author.

Education level makes almost no difference in Detmold, where the widest gap between categories is just 0.07 points that is negligible by any reading. Turin shows somewhat more structure: respondents with a Master's or PhD rate comfort 0.22 points above the High school/vocational group and 0.16 points above Bachelor's holders, both modest contrasts. The vocational group reports the lowest comfort overall, though that cell holds only nine respondents, so no contrast here reaches the pronounced band and the finding should be read cautiously.

- **Occupation**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	Student	85	3.016	0.014
Detmold	Employed/Self-employed	28	3.039	0.037
Detmold	Not employed	2	1.9	-1.103
Turin	Student	57	2.404	0.091
Turin	Employed/Self-employed	52	2.233	-0.08
Turin	Not employed	10	2.21	-0.103

Table 43 Mean comfort rating by occupation, Detmold and Turin. Produced by author.

Students and Employed/Self-employed respondents in Detmold differ by only 0.02 points, that means effectively no difference. The Not employed category sits 1.12–1.14 points below the other two groups, which on its own looks dramatic, but with only two respondents in that cell, the contrast cannot be treated as a reliable finding rather than noise.

Turin shows a milder pattern: students rate comfort 0.17–0.19 points higher than both the Employed/Self-employed and Not employed groups (modest), while those latter two groups are nearly identical to each other (0.02 points apart, negligible).

- **Main Daily Activity**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	Indoors	91	3.013	0.011
Detmold	Mix / outdoors	24	2.962	-0.04
Turin	Indoors	87	2.32	0.007
Turin	Mix / outdoors	32	2.294	-0.019

Table 44 Mean comfort rating by main daily activity, Detmold and Turin. Produced by author.

Once mixed and outdoor activity patterns are merged, the gap between Indoors and Mix/outdoors respondents comes to 0.05 points in Detmold and 0.03 in Turin that means negligible in both cases. Daily activity pattern does not appear to be a meaningful driver of perceived thermal comfort in either city.

- **Relationship to the city**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	resident	71	2.97	-0.032
Detmold	commuter	44	3.055	0.052
Turin	resident	109	2.315	0.002
Turin	commuter	10	2.29	-0.023

Table 45 Mean comfort rating by relationship to the city, Detmold and Turin. Produced by author.

Residents and commuters rate the streetscapes almost identically , a 0.09-point gap in Detmold and just 0.03 in Turin, both negligible. Commuters do trend slightly lower than residents in Detmold, but the difference is too small to interpret as substantively meaningful in either city.

- **The duration of their relationship with the city**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	< 3 years	74	2.897	-0.105
Detmold	4–10 years	21	3.314	0.312
Detmold	10+ years / since birth	20	3.065	0.062
Turin	< 3 years	61	2.37	0.058
Turin	4–10 years	38	2.189	-0.123
Turin	10+ years / since birth	20	2.37	0.057

Table 46 Mean comfort rating by the duration of the relationship to the city, Detmold and Turin. Produced by author.

In Detmold, respondents with 4–10 years in the city rate 0.42 points higher than those with < 3 years (pronounced) and 0.25 points higher than 10+ years / since birth (pronounced), i.e. mid-tenure residents report the most comfortable expectations.

In Turin, < 3 years and 10+ years / since birth groups share the same mean (contrast 0.00), while 4–10 years respondents rate 0.18 points lower than the < 3 years group (modest) that is a weaker and differently ordered pattern than in Detmold.

- **Summer climate description**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	mild	18	3.283	0.281
Detmold	warm	79	3.056	0.053
Detmold	hot	18	2.489	-0.514
Turin	mild	1	2.4	0.087
Turin	warm	13	2.569	0.257
Turin	hot	32	2.484	0.172
Turin	very_hot	73	2.19	-0.122

Table 47 Mean comfort rating by the summer climate description, Detmold and Turin. Produced by author.

How respondents describe their local summer climate tracks closely with how comfortable they find the streetscapes. In Detmold, those who describe summers as mild rate the images 0.79 points higher than those describing summers as hot, and warm-summer respondents rate 0.57 points higher than the hot group, both pronounced gaps. Unsurprisingly, respondents who experience hot summers perceive the least comfort.

Turin shows the same underlying logic, if somewhat less extreme: warm-summer respondents rate 0.38 points higher than the very-hot group, and hot-summer respondents rate 0.29 points higher than very-hot, both pronounced (the mild category rests on a single respondent and can't be read meaningfully). Overall, the link between subjective summer climate and visual comfort assessment is sharper in Detmold than in Turin.

- **Heat adaptation**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	none	6	2.717	-0.286
Detmold	slight	37	2.762	-0.24
Detmold	moderate	51	3.084	0.082
Detmold	well	21	3.31	0.307
Turin	none	39	2.197	-0.115
Turin	slight	47	2.311	-0.002
Turin	moderate	28	2.396	0.084
Turin	well	5	2.76	0.447

Table 48 Mean comfort rating by the heat adaptation, Detmold and Turin. Produced by author.

In Detmold, well adapted respondents rate 0.55–0.59 points higher than slight or not adapted groups (pronounced), and moderate adaptation sits 0.32 points above slight adaptation (pronounced). Greater self-reported heat adaptation co-occurs with more comfortable streetscape ratings.

Turin shows a similar direction but a noisier picture. Contrasts involving the well-adapted group reach 0.36–0.56 points (pronounced), but that cell holds only five respondents, limiting how much weight the finding can bear. Among the larger groups, separation tops out at modest. The adaptation-comfort relationship, in short, is more reliably established in Detmold than in Turin.

- **Route modification to avoid heat**

City	Category	Count	Mean Rating	Difference from Average Rating
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Detmold	never	32	3.406	0.404
Detmold	sometimes	69	2.852	-0.15
Detmold	always	14	2.821	-0.181
Turin	never	5	2.3	-0.013
Turin	sometimes	59	2.354	0.042
Turin	always	55	2.269	-0.044

Table 49 Mean comfort rating by the route modification to avoid heat, Detmold and Turin. Produced by author.

Detmold respondents who never alter their routes because of heat rate the streetscapes 0.55–0.59 points higher than those who sometimes or always do (pronounced) , that means they evidently perceive the same scenes as substantially more comfortable. The sometimes and always groups differ from each other by only 0.03 points, a negligible gap.

In Turin, all pairwise contrasts are negligible (maximum 0.09). based on this analysis, route-modification behavior separates perceived thermal comfort strongly in Detmold but not in Turin.

- **Transport mode, walking**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	sometimes	46	2.976	-0.027
Detmold	daily	69	3.02	0.018
Turin	never	8	2.3	-0.013
Turin	sometimes	53	2.323	0.01
Turin	daily	58	2.305	-0.007

Table 50 Mean comfort rating by the walking mode of transportation, Detmold and Turin. Produced by author.

All between-category contrasts are negligible (maximum 0.04 in Detmold; 0.02 in Turin). Walking frequency does not differentiate how comfortable respondents judge the streetscape images.

- **Transport mode, cycling**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	never	51	3.049	0.046
Detmold	monthly	1	3.1	0.097
Detmold	sometimes	42	3.093	0.09
Detmold	daily	21	2.705	-0.298
Turin	never	65	2.265	-0.048
Turin	sometimes	40	2.427	0.115
Turin	daily	14	2.207	-0.105

Table 51 Mean comfort rating by the cycling mode of transportation, Detmold and Turin. Produced by author.

In Detmold, daily cyclists rate 0.34–0.39 points lower than never or sometimes cyclists (pronounced), this means that they perceive the images as less comfortable. Non-daily frequency categories differ by at most 0.05 (negligible).

In Turin, sometimes cyclists rate 0.22 points higher than daily cyclists (modest), indicating somewhat greater perceived comfort among occasional cyclists. The association is weaker than in Detmold.

- **Transport mode, public transportation**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	never	42	2.907	-0.095
Detmold	weekly	1	3.1	0.097
Detmold	sometimes	57	3.053	0.05
Detmold	daily	15	3.073	0.071
Turin	never	11	2.345	0.033
Turin	sometimes	53	2.258	-0.054
Turin	daily	55	2.358	0.046

Table 52 Mean comfort rating by the public mode of transportation, Detmold and Turin. Produced by author.

In Detmold, between-category contrasts are generally small (0.02–0.19); the largest is never versus weekly (0.19, modest), with weekly based on one respondent.

In Turin, the maximum gap is 0.10 (sometimes versus daily, modest). Public-transport frequency does not strongly separate more versus less comfortable judgements in either city.

- **Transport mode, private car**

City	Category	Count	Mean Rating	Difference from Average Rating
Detmold	never	40	2.98	-0.023
Detmold	monthly	1	3.1	0.097
Detmold	sometimes	56	2.982	-0.02
Detmold	daily	18	3.111	0.109
Turin	never	81	2.33	0.017
Turin	sometimes	22	2.327	0.015
Turin	daily	16	2.206	-0.106

Table 53 Mean comfort rating by the private car mode of transportation, Detmold and Turin. Produced by author.

In Detmold, daily car users rate 0.13 points higher than never or sometime users (modest), a slightly more comfortable profile.

In Turin, daily car users rate 0.12 points lower than never or sometimes users (modest), the opposite direction to Detmold. Overall, car-use frequency shows at most modest separation in how comfortable the streetscapes are judged.

12.2 Results of the comfort rating comparison

Based on the above analysis, most fields exhibit limited between-category separation, yet several dimensions show clearer structure in one or both cities. Among them are age, summer climate description, heat adaptation, route modification, and cycling frequency in Detmold. Male respondents consistently rate 0.14–0.16 points higher than female respondents (modest), i.e. they perceive somewhat greater thermal comfort. Pronounced pairwise gaps (≥ 0.25) appear where some categories judge the scenes substantially more or less comfortable than others. notably in summer description, heat adaptation, route modification, and time in city (Detmold), while many other dimensions remain negligible (often 0.01–0.05).

These patterns indicate that the influence of respondent profile on visually assessed thermal comfort varies depending on which characteristic is examined and which city is considered, rather than following a uniform pattern across Detmold and Turin.

12.3 The Analysis of RQ2: Streetscape and Respondent-Profile Predictors of Thermal Comfort

This section addresses RQ2 by reporting the outcomes of the predictive modelling and SHAP analysis described in Section 10.5. Results are presented in two parts: first, the model comparison and selection, identifying the best-performing learner for each city; second, the variable influence analysis, distinguishing the relative contribution of streetscape attributes from respondent-profile characteristics and identifying which specific predictors drive comfort assessments most strongly in Detmold and Turin.

Model Comparison and Selection

Model	MAE	MSE	RMSE	Adjusted R2
Decision tree	0.8632	1.3088	1.144	-0.7991
Support vector regression	0.722	0.8295	0.9108	-0.1402
KNN regression	0.6994	0.8019	0.8955	-0.1023
Extreme gradient boosting	0.6914	0.8112	0.9007	-0.115
LightGBM	0.6607	0.7292	0.8539	-0.0023
OLS / linear regression	0.636	0.6432	0.802	0.1159
ENRM (Lasso + Ridge)	0.6349	0.6411	0.8007	0.1188
CatBoost	0.6227	0.6682	0.8174	0.0815
Random forest	0.5969	0.5965	0.7724	0.18

Table 54. Model performance on the held-out test set, Detmold. Models ranked by ascending MAE. Produced by author.

Model	MAE	MSE	RMSE	Adjusted R2
Decision tree	0.9111	1.332	1.1541	-0.6347
KNN regression	0.8617	1.1098	1.0535	-0.362
Extreme gradient boosting	0.8315	1.1039	1.0506	-0.3547
LightGBM	0.8246	1.0989	1.0483	-0.3486
Support vector regression	0.8059	0.9229	0.9607	-0.1326
OLS / linear regression	0.775	0.848	0.9209	-0.0407
ENRM (Lasso + Ridge)	0.7747	0.8456	0.9195	-0.0377
CatBoost	0.7685	0.8705	0.933	-0.0683
Random forest	0.7306	0.7704	0.8777	0.0546

Table 55. Model performance on the held-out test set, Turin. Models ranked by ascending MAE. Produced by author.

City	Model	Split	MAE	MSE	RMSE	R ²	Adjusted R ²	n
Detmold	random_forest	test	0.5969	0.5965	0.7724	0.3446	0.18	290
Turin	random_forest	test	0.7306	0.7704	0.8777	0.2348	0.0546	300

Table 56. Summary of retained model performance on the held-out test set, Detmold and Turin. Produced by author.

Test-set performance for all nine models is summarized in Tables 53 and 54. Random forest achieves the lowest test MAE in both cities (0.5969 in Detmold; 0.7306 in Turin) and is the only model carried forward to the SHAP analysis. CatBoost and ENRM perform competitively in both cities, ranking second and third respectively by MAE, while tree-based ensemble methods generally outperform simpler learners such as KNN regression and decision tree across both settings.

Adjusted R^2 values are negative for the majority of learners, indicating that those models fail to outperform a naïve mean baseline on the held-out test set. Random forest is the sole exception in both cities, returning a positive adjusted R^2 of 0.18 in Detmold and 0.05 in Turin. The modest R^2 in Turin relative to Detmold suggests that comfort ratings in Turin are harder to predict from the available predictors alone, which is consistent with the greater respondent heterogeneity observed in the RQ1 profile analysis. On the basis of lowest test MAE and positive adjusted R^2 in both cities, random forest is retained as the sole model for SHAP.

- **Global Variable Importance (Mean |SHAP|)**

Table 56 reports mean |SHAP| values for all twenty-seven predictors retained after pre-processing, ranked within each macro-group.

Macro Group	Attribute	Turin Mean SHAP	Detmold Mean SHAP
Questionnaire	Age	0.013342	0.011247
Questionnaire	Birthplace	0.033396	0.025583
Questionnaire	City relationship	0.005679	0.008317
Questionnaire	Daily activity	0.009243	0.007826
Questionnaire	Education	0.022785	0.008655
Questionnaire	Gender	0.030157	0.014585
Questionnaire	Occupation	0.013914	0.011532
Questionnaire	Time in city	0.014897	0.0369
Questionnaire	Heat adaptation	0.012053	0.033524
Questionnaire	Modify routes for heat	0.026509	0.056489
Questionnaire	Summer description	0.017004	0.039579
Questionnaire	Transport (car)	0.009711	0.006949
Questionnaire	Transport (cycling)	0.023892	0.009288
Questionnaire	Transport (public)	0.016706	0.01578
Questionnaire	Transport (walking)	0.011334	0.014163
Streetscape attribute	LST(°C)	0.01514	0.019238
Streetscape attribute	MNDWI	0.011182	0.019775
Streetscape attribute	Bicycle (%)	0.002541	0.015251
Streetscape attribute	Car (%)	0.035153	0.007981
Streetscape attribute	Person (%)	0.004568	0.016069
Streetscape attribute	Pole (%)	0.01104	0.021056
Streetscape attribute	Road (%)	0.01066	0.009086
Streetscape attribute	Sidewalk (%)	0.042629	0.390045
Streetscape attribute	Sky (%)	0.321753	0.021182
Streetscape attribute	Terrain (%)	0.023409	0.006641
Streetscape attribute	Vegetation (%)	0.033828	0.208039
Streetscape attribute	Wall (%)	0.068518	0.006759

Table 57. Global mean |SHAP| values for all streetscape attributes and questionnaire fields, Detmold and Turin. Produced by author.

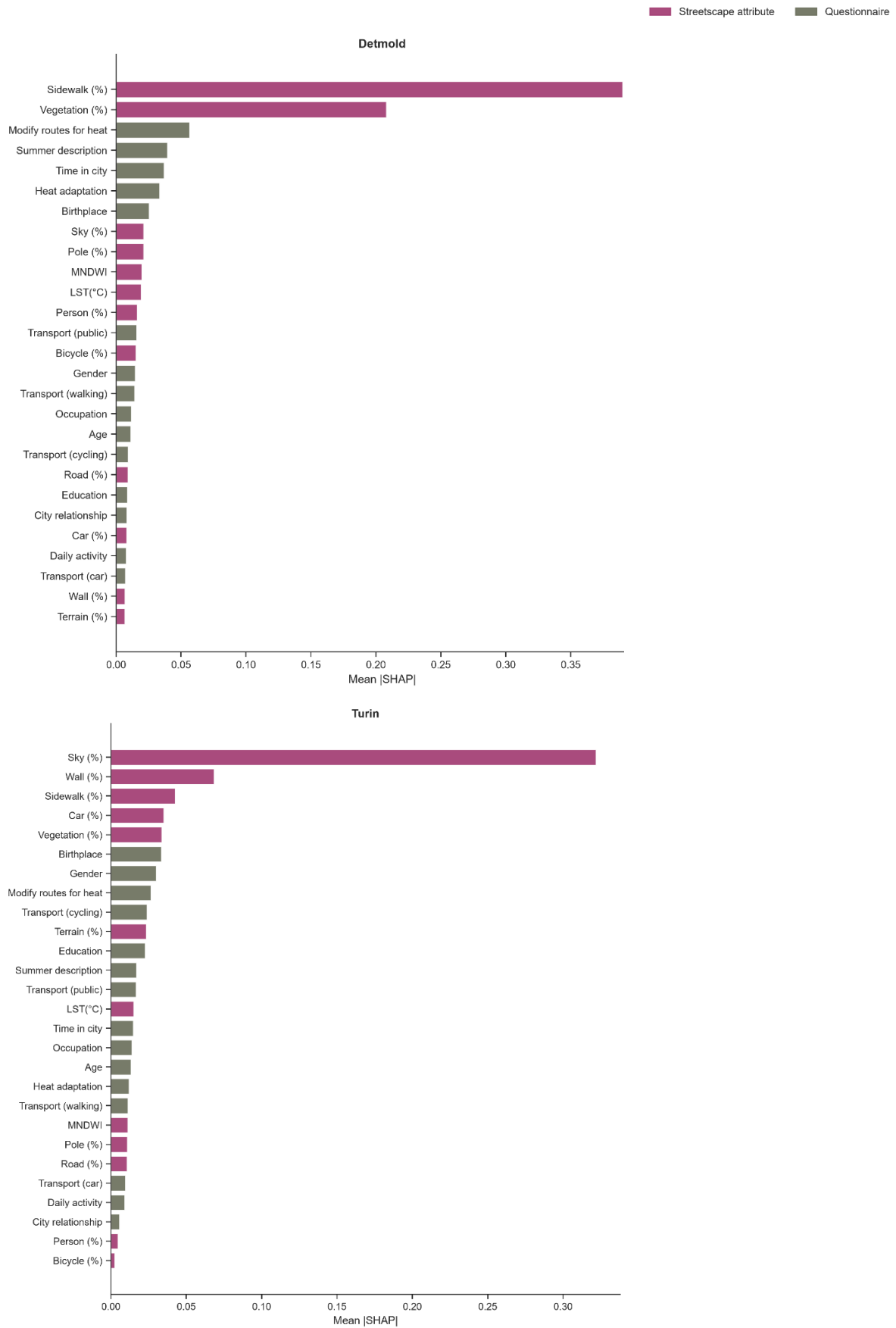


Figure 36. Global attribute importance expressed as mean $|SHAP|$ values for all streetscape attributes and questionnaire fields, Detmold (top) and Turin (bottom). Pink bars indicate streetscape attributes; olive bars indicate questionnaire variables. Produced by author.

City	Group	Mean SHAP
Detmold	Streetscape attribute	0.06176
Detmold	Questionnaire	0.020028
Turin	Streetscape attribute	0.048368
Turin	Questionnaire	0.017375

Table 58. Block-level mean |SHAP| summary contrasting streetscape attributes and questionnaire fields, Detmold and Turin. Produced by author.

The block-level summary and variable-level rankings reported above address whether the random forest weights scene composition more heavily than respondent profile when both are considered jointly.

In both cities, streetscape attributes return a higher block-level mean |SHAP| than questionnaire fields (Table 56), and individual streetscape predictors dominate the upper ranks in both settings. In Detmold, sidewalk share and vegetation share account for the majority of model-attributed influence, while in Turin, sky share and wall share lead by a comparable margin. Among questionnaire variables, heat adaptation, route modification behavior, and time in city register the largest values in Detmold, while birthplace and gender lead in Turin. All of these, remain modest relative to the dominant streetscape predictors.

Taken together, these patterns indicate that visually assessed comfort in both cities is reproduced by the random forest primarily through streetscape cues, with questionnaire fields playing a secondary role once scene and profile predictors are modelled jointly (L. Chen et al., 2022). This finding does not imply that personal characteristics are unimportant to thermal experience overall, but rather that the visual content of the streetscape carries greater weight than respondent profile when predicting image-level comfort ratings from the available predictors.

- **Directional Influence of Streetscape Attributes (Signed Mean SHAP)**

Group	Attribute	Turin Mean SHAP	Detmold Mean SHAP
RS / GIS	LST(°C)	0.002768	-0.00253
RS / GIS	MNDWI	0.001989	0.000859
Streetscape	Road (%)	-0.00279	0.002364
Streetscape	Sidewalk (%)	-0.00071	-0.02873
Streetscape	Wall (%)	0.001344	0.001281
Streetscape	Pole (%)	0.002539	0.004537
Streetscape	Vegetation (%)	0.001042	0.01936
Streetscape	Terrain (%)	-0.00387	-0.00045
Streetscape	Sky (%)	0.000638	0.006664
Streetscape	Person (%)	0.000325	-0.0027
Streetscape	Car (%)	-8.6E-05	-0.00034
Streetscape	Bicycle (%)	0.000114	-0.00234

Table 59. Signed mean SHAP values for retained streetscape attributes, Detmold and Turin. Positive values indicate association with higher predicted comfort; negative values indicate association with lower predicted comfort. Produced by author.

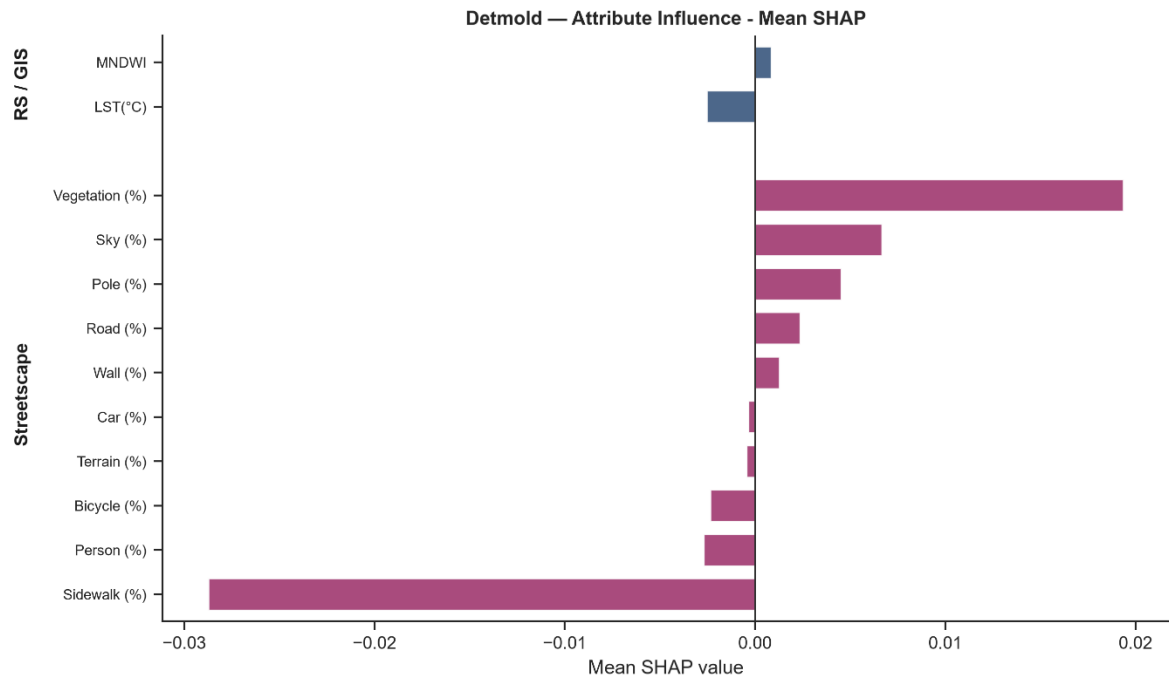


Figure 37. Signed mean SHAP values for retained streetscape attributes, Detmold. Positive values indicate association with higher predicted comfort; negative values indicate association with lower comfort. Pink bars indicate pixel-fraction attributes; blue bars indicate RS/GIS-derived attributes. Produced by author.

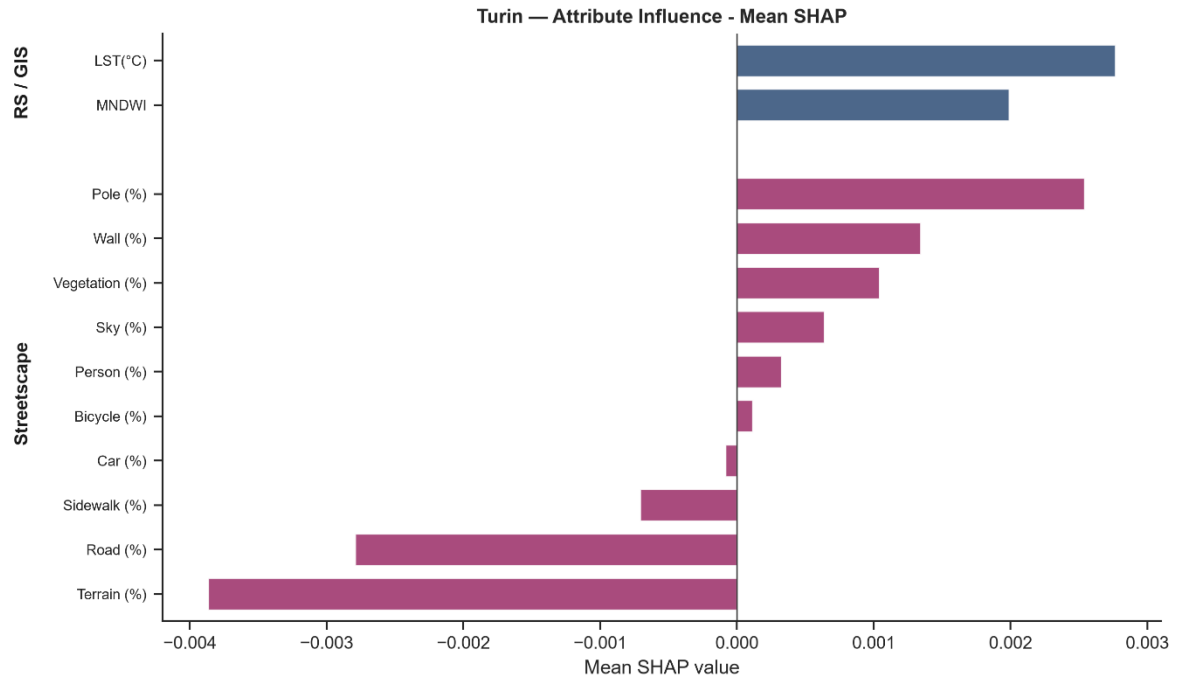


Figure 38. Signed mean SHAP values for retained streetscape attributes, Turin. Positive values indicate association with higher predicted comfort; negative values indicate association with lower comfort. Pink bars indicate pixel-fraction attributes; blue bars indicate RS/GIS-derived attributes. Produced by author.

Table 58 and Figures 36 and 37 report signed mean SHAP values for the twelve retained streetscape attributes in Detmold and Turin. Several predictors show the same direction of association in both cities, indicating that the random forest consistently links them to either higher or lower predicted comfort regardless of city context, even when magnitudes differ.

Five attributes are positively signed in both cities, indicating association with higher predicted comfort. MNDWI (+0.002 Turin; +0.001 Detmold), wall share (+0.001; +0.001), pole share (+0.003; +0.005), vegetation share (+0.001; +0.019), and sky share (+0.001; +0.007) all push predictions toward greater comfort in both models. The association is most pronounced for vegetation share and sky share in Detmold, where magnitudes are considerably larger than their Turin counterparts, but the directional consistency across cities is notable.

Three attributes are negatively signed in both cities, indicating association with lower predicted comfort. Sidewalk share (−0.001 Turin; −0.029 Detmold), terrain share (−0.004; −0.000), and car share (−0.000; −0.000) are associated with reduced comfort in both settings. The effect is most pronounced for sidewalk share in Detmold, where the mean SHAP magnitude is an order of magnitude larger than in Turin, while terrain share and car share contribute only marginally in either city.

The remaining four attributes that are LST, road share, person share, and bicycle share, do not share the same directional sign across cities. LST, for instance, is positively signed in Turin (+0.003) but negatively signed in Detmold (−0.003), and road share is negative in Turin (−0.003) but positive in Detmold (+0.002). These reversals suggest that the comfort associations of certain physical attributes are context-dependent, varying with the broader urban morphology and climate conditions of each city. Taken together, the signed SHAP analysis refines the importance rankings from Step 1: the attributes that dominate mean |SHAP| also show the most stable directional associations, while lower-ranked predictors contribute inconsistently across cities (Urban et al., 2022; S. Yang et al., 2025; Zhu et al., 2026).

12.4 Synthesis

Taken together, the two-step SHAP analysis shows that streetscape attributes carry greater mean |SHAP| than questionnaire variables when respondent-profile fields are summarized at variable level, and documents consistent directional associations for the morphological and RS/GIS predictors to which the forest assigns the most weight. This structure aligns the modelling evidence with the separation of scene and profile established in RQ1, while shifting the analytical outcome from descriptive rating differences to model attribution on held-out respondent–image pairs. The findings describe random-forest behavior under the available predictor set and should not be interpreted as verified causal effects on human thermal perception (Lenzholzer & de Vries, 2020).

The implications of these city-specific patterns for urban design and thermal comfort planning are discussed in Chapter 6.

Chapter six: Conclusion

13. Conclusion

This thesis investigated how people visually assess the thermal comfort potential of street-level environments in Turin (Italy) and Detmold (Germany) and which streetscape attributes and respondent socio-demographic characteristics most strongly shape those assessments. Structured around two research questions, the study combined a multi-layer attribute data collection framework, containing remote sensing indices, semantic segmentation of street-view imagery, and LCZ-based point selection, with an image-rating questionnaire distributed to residents of both cities. The analysis proceeded from inter-rater validation through descriptive profile comparisons to machine learning modelling and SHAP-based variable influence analysis. The findings are summarized below in relation to each research question.

RQ1: How do people visually assess the thermal comfort potential of street sections across cities with different climatic backgrounds?

Inter-rater agreement analysis confirmed that respondents in both cities ordered the same streetscapes similarly on the comfort scale, with median pairwise Spearman ρ of 0.52 in Detmold and 0.47 in Turin. This result establishes that pooling ratings into city-level profiles was methodologically justified.

At the city level, mean visual comfort rating was notably higher in Detmold (mean = 3.00, SD = 1.08) than in Turin (mean = 2.31, SD = 1.05), despite both respondent pools judging an identical set of street images. This difference is consistent with the psychological adaptation literature, which demonstrates that climatic background, lived experience, and thermal expectations shift comfort assessments (Nikolopoulou & Steemers, 2003; Urban et al., 2022). Respondents from Turin applied more demanding comfort expectations to the same image settings than respondents from the milder oceanic climate of Detmold.

Across the fifteen respondent-profile variables examined in each city, the influence of socio-demographic and behavioral characteristics on visually assessed comfort varied considerably depending on which characteristic was examined and in which city. Several dimensions produced differences in at least one city. In Detmold, summer climate description, heat adaptation, and route modification behavior showed the strongest profile-level separation. respondents who described their summers as mild, rated the images up to 0.79 points higher than those who described them as hot, and well-adapted respondents rated 0.55–0.59 points higher than non-adapted groups. In Turin, the same dimensions showed a similar but weaker pattern, with the exception of birthplace, where respondents born outside Italy rated the images notably higher than those born within Italy. A small but consistent gender gap appeared in both cities, with male respondents rating approximately 0.14–0.16 points higher than female respondents. Many other variables, including daily activity pattern, city relationship, and transport modes, showed negligible between-category differences in both settings.

Taken together, the RQ1 findings indicate that visual thermal comfort potential is shaped by a combination of what is visually present in the streetscape and who is doing the judging. The

city-level difference and the stronger profile effects observed in Detmold for heat-related variables show climatic background as a meaningful moderator of how people use the visual comfort rating scale.

RQ2: Which streetscape attributes and personal demographic characteristics influence how people visually assess thermal comfort from street images?

When streetscape attributes and questionnaire variables were modelled jointly using a random forest, scene composition consistently outweighed respondent profile as the dominant source of predicted comfort. At the block level, streetscape attributes returned mean |SHAP| values of 0.062 in Detmold and 0.048 in Turin, compared to 0.020 and 0.017 respectively for questionnaire variables, confirming that the visual content of the street carries greater weight than demographic or behavioral characteristics when predicting image-level comfort ratings.

The specific attributes that mattered most, however, differed between cities. In Detmold, sidewalk share dominated by a wide margin (mean |SHAP| = 0.390), followed by vegetation share (0.208), pointing to surface cover and greenery as the primary visual drivers of perceived comfort. In Turin, sky share dominated (mean |SHAP| = 0.322), followed by wall share (0.069) and sidewalk share (0.043), pointing to spatial openness and enclosure geometry as the principal reasons. Among questionnaire variables, heat adaptation, route modification, and time in city registered the largest influence in Detmold, while birthplace and gender led in Turin, but all remained below the dominant streetscape predictors.

The signed SHAP analysis revealed that five attributes pushed predicted visual comfort upward in both cities: vegetation share, sky share, pole share, wall share, and MNDWI. Three attributes were consistently associated with lower comfort in both cities: sidewalk share, terrain share, and car share. The magnitude of these effects was larger in Detmold for vegetation and sidewalk, while four attributes of LST, road share, person share, and bicycle share, reversed direction between cities, suggesting that their comfort associations are context-dependent rather than universal.

These findings are consistent with the thermal affordance framework established by Yang et al. (2025) and the broader streetscape perception literature, while extending it to a cross-city comparative design with matched LCZ typologies. The dominance of scene-level visual cues over respondent profile in joint modelling aligns with Chen et al. (2022) and Zhu et al. (2026). However, the city-specificity of which attributes dominate underscores that no single set of streetscape features drives comfort universally across climatic contexts.

13.1 Contribution of the Study

This thesis makes several contributions to the literature on visual thermal comfort assessment. First, it applies the LCZ classification framework as an organizing basis for selecting comparable street-level study points across two European cities, providing a replicable template for cross-city visual comfort research. Second, it combines two complementary attribute layers of remote sensing indices and SVI semantic segmentation pixel fractions, with a structured image-rating questionnaire. Therefore, enabling the relative contribution of streetscape attributes and respondent profile to be evaluated jointly rather

than separately. Third, the application of SHAP-based explainability to a joint streetscape-and-questionnaire predictor set extends the analytical approach of Hu and Zeng (2025) and Yang et al. (2025) to a multi-city comparative design, revealing that the attributes that matter most differ between cities even when the attribute set is held constant. Fourth, the study provides empirical evidence that climatic background systematically shifts how urban residents use the visual comfort rating scale, supporting the theoretical position of Nikolopoulou and Steemers (2003).

13.2 Implications for Urban Design and Policy

The finding that vegetation share and sky share are consistently associated with higher predicted comfort across both cities, alongside the negative association of large sidewalk fractions and car presence, has direct implications for street design. Design interventions that the modelling evidence identifies as likely to improve perceived thermal comfort across both compact (LCZ 2) and open (LCZ 5) urban typologies:

- Increasing canopy cover and preserving sky exposure through building setbacks or height regulation,
- reducing the visual dominance of impervious surfaces and vehicle infrastructure.

The city-specific divergence in which attributes dominate (surface cover in Detmold, spatial openness in Turin) suggests that thermal comfort design strategies should be calibrated to local climatic context rather than applying universal prescriptions. In hotter, more compact urban environments such as Turin, interventions that reduce enclosure and increase sky exposure may produce greater perceptual benefit. The stronger influence of heat adaptation and climate description on comfort ratings in Detmold further suggests that thermal experience and behavioral acclimatization moderate the impact of streetscape interventions on perceived comfort.

14. Limitations

Several limitations of the present study should be acknowledged when interpreting the findings.

Sample size and study points: The analysis is based on ten survey points per city yielding twenty study points in total. This number is sufficient to establish within-city patterns and cross-city contrasts, but limits the generalizability of the streetscape attribute findings. Expanding the number of study points in the future research, or extending it to more LCZ classes, would strengthen the robustness of the findings.

Respondent samples: The survey collected 116 valid responses in Detmold and 119 in Turin. While this is comparable to similar studies in the literature, the data variety is limited. The over-46 age group in particular is sparsely represented (13 respondents in Detmold, 11 in Turin), limiting the reliability of age-related findings in that band. The Turin sample also contains a high proportion of international respondents (56.3%), which may reflect the composition of a large university city rather than the general population.

Remote sensing data and spatial resolution: LST and albedo were derived from Landsat at 30 m spatial resolution, and MNDWI from Sentinel-2 at 20 m. At this resolution, the RS values extracted at each survey point capture the broader thermal environment rather than the precise microclimate of the street section depicted. This mismatch between the spatial scale of the RS data and the visual scale of the survey images is a structural limitation of the research.

Visual comfort potential only: The study measures visual thermal comfort potential, how thermally comfortable a street appears from a photograph, rather than experienced thermal comfort during actual outdoor exposure. this approach is validated in the literature and captures a meaningful and policy-relevant dimension of thermal perception. However, combining it with in-situ thermal experience, which is also shaped by air temperature, wind speed, solar radiation, humidity, and physical activity level may enrich the research.

15. Bibliography

- Abedrabbah, O., Alfarra, M. R., Al-Ansari, T., & Fountoukis, C. (2025). Enhancing human thermal comfort in hot arid cities: A systematic review of urban heat island observations and mitigation strategies. *Building and Environment*, 283, 113398.
- Abi Deivanayagam, T., English, S., Hickel, J., Bonifacio, J., Guinto, R. R., Hill, K. X., Huq, M., Issa, R., Mulindwa, H., & Nagginda, H. P. (2023). Envisioning environmental equity: climate change, health, and racial justice. *The Lancet*, 402(10395), 64–78.
- Abunnasr, Y., & Mhawej, M. (2022). Towards a combined Landsat-8 and Sentinel-2 for 10-m land surface temperature products: The Google Earth Engine monthly Ten-ST-GEE system. *Environmental Modelling & Software*, 155, 105456.
- Aslam, A., & Rana, I. A. (2022). The use of local climate zones in the urban environment: A systematic review of data sources, methods, and themes. *Urban Climate*, 42, 101120.
- Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., & Wood, E. F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data*, 5(1), 180214.
- Ben Ratmia, F. Z., Ahriz, A., Santi, G., Bouzaher, S., Mahar, W. A., Ben Ratmia, M. A. E., & Matallah, M. E. (2024). Street design strategies based on spatial configurations and building external envelopes in relation to outdoor thermal comfort in arid climates. *Sustainability*, 16(1), 221.
- Biljecki, F., & Ito, K. (2021). Street view imagery in urban analytics and GIS: A review. *Landscape and Urban Planning*, 215, 104217.
<https://doi.org/https://doi.org/10.1016/j.landurbplan.2021.104217>
- Britannica. (2026). *Detmold*. Britannica. <https://www.britannica.com/place/Detmold-Germany>
- Chen, J., Tang, L., Liu, S., Zuo, X., & Cao, J. (2026). View factors estimation from street view imagery and its correlation with intra-urban thermal variation. *Geography and Sustainability*, 100453.
- Chen, L., Kántor, N., & Nikolopoulou, M. (2022). Meta-analysis of outdoor thermal comfort surveys in different European cities using the RUROS database: The role of background climate and gender. *Energy and Buildings*, 256, 111757.
- Chen, L., Mak, C. M., Hang, J., & Dai, Y. (2024). Influence of elevated walkways on outdoor thermal comfort in hot-humid climates based on on-site measurement and CFD modeling. *Sustainable Cities and Society*, 100, 105048.
- Chen, Q., Liu, R., Cheng, Q., Chen, Y., Cao, S., Du, M., & Li, K. (2023). Evaluating the impact of sky view factor and building shadow ratio on air temperature in different residential and commercial building scenarios: A case study of Beijing,

- China. *Urban Climate*, 49, 101509.
- Chen, X. P., Han, M., He, J. Y., Ma, H., Han, M. L., Liu, Y. H., & Wu, X. G. (2024). Integrated effect of aspect ratio and tree spacing on pedestrian thermal comfort of street canyon. *INTERNATIONAL JOURNAL OF BIOMETEOROLOGY*, 68(10), 2115–2131. <https://doi.org/10.1007/s00484-024-02735-0>
- Chiang, Y.-C., Liu, H.-H., Li, D., & Ho, L.-C. (2023). Quantification through deep learning of sky view factor and greenery on urban streets during hot and cool seasons. *Landscape and Urban Planning*, 232, 104679.
- Cicchino, J. B., McCarthy, M. L., Newgard, C. D., Wall, S. P., DiMaggio, C. J., Kulie, P. E., Arnold, B. N., & Zubby, D. S. (2020). Not all protected bike lanes are the same: Infrastructure and risk of cyclist collisions and falls leading to emergency department visits in three U.S. cities. *Accident Analysis & Prevention*, 141, 105490. <https://doi.org/https://doi.org/10.1016/j.aap.2020.105490>
- Climate Data. (2026). *Climate Data*. Climate-Data.Org. <https://en.climate-data.org/europe/>
- Cook, M. J. (2014). *Atmospheric compensation for a landsat land surface temperature product*. Rochester Institute of Technology.
- Cordts, M., Omran, M., Ramos, S., Rehfeld, T., Enzweiler, M., Benenson, R., Franke, U., Roth, S., & Schiele, B. (2016). The cityscapes dataset for semantic urban scene understanding. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 3213–3223.
- Cortês, J., Brandão Alves, F., & Raaphorst, K. (2020). Photographic comparison: a method for qualitative outdoor thermal perception surveys. *International Journal of Biometeorology*, 64(2), 173–185.
- Costa, I. T., Wollmann, C. A., Writzl, L., Iense, A. C., da Silva, A. N., Baumhardt, O. D., Gobo, J. P. A., Shooshtarian, S., & Matzarakis, A. (2024). A Systematic Review on Human Thermal Comfort and Methodologies for Evaluating Urban Morphology in Outdoor Spaces. *CLIMATE*, 12(3). <https://doi.org/10.3390/cli12030030> WE - Emerging Sources Citation Index (ESCI)
- Das, M., Das, A., & Mandal, S. (2020). Outdoor thermal comfort in different settings of a tropical planning region: A study on Sriniketan-Santiniketan Planning Area (SSPA), Eastern India. *Sustainable Cities and Society*, 63, 102433.
- de Quadros, B. M., & Mizgier, M. G. O. (2023). Urban green infrastructures to improve pedestrian thermal comfort: A systematic review. *Urban Forestry & Urban Greening*, 88, 128091.
- Del Serrone, G., Peluso, P., & Moretti, L. (2022). Evaluation of microclimate benefits due to cool pavements and green infrastructures on urban heat islands. *Atmosphere*, 13(10), 1586.

- Demuzere, M., Kittner, J., & Bechtel, B. (2021). LCZ Generator: a web application to create Local Climate Zone maps. *Frontiers in Environmental Science*, 9, 637455.
- Dialesandro, J., Brazil, N., Wheeler, S., & Abunnasr, Y. (2021). Dimensions of thermal inequity: neighborhood social demographics and urban heat in the Southwestern US. *International Journal of Environmental Research and Public Health*, 18(3), 941.
- Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J. R. G., Gruber, B., Lafourcade, B., & Leitão, P. J. (2013). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, 36(1), 27–46.
- Dwivedi, A., & Soni, R. (2024). Impacts of urban heat island effect on critical urban infrastructure: a review of studies published between 2012 and 2022. *Environmental Reviews*, 32(4), 457–469.
- EROS Center. (2020). *Landsat 8-9 Operational Land Imager / Thermal Infrared Sensor Level-2, Collection 2 [dataset]*. U.S. Geological Survey. <https://doi.org/10.5066/P9OGBGM6>
- Esposito, A., Pappaccogli, G., Donateo, A., Salizzoni, P., Maffei, G., Semeraro, T., Santiago, J. L., & Buccolieri, R. (2024). Urban morphology and surface urban heat island relationship during heat waves: A study of Milan and Lecce (Italy). *Remote Sensing*, 16(23), 4496.
- Evgenia, T., Mela, A., & Tseliou, A. (2024). Thermal stress in outdoor spaces during Mediterranean heatwaves: a PET and UTCI analysis of different demographics. *Urban Science*, 8(4), 193.
- Favero, M., Luparelli, A., & Carlucci, S. (2023). Analysis of subjective thermal comfort data: A statistical point of view. *Energy and Buildings*, 281, 112755.
- Gong, F.-Y., Zeng, Z.-C., Zhang, F., Li, X., Ng, E., & Norford, L. K. (2018). Mapping sky, tree, and building view factors of street canyons in a high-density urban environment. *Building and Environment*, 134, 155–167.
- Grokipedia. (2026). *Detmold*. Grokipedia. <https://grokipedia.com/page/Detmold>
- Guo, R., Yang, B., Guo, Y., Li, H., Li, Z., Zhou, B., Hong, B., & Wang, F. (2024). Machine learning-based prediction of outdoor thermal comfort: Combining Bayesian optimization and the SHAP model. *Building and Environment*, 254, 111301.
- Hadibasyir, H. Z., & Firdaus, N. S. (2022). Effect of Vegetation and Building Densities to Urban Thermal Comfort (Case Study of Denpasar City). *Jurnal Purifikasi*, 21(1), 11–19.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis*.

- Hosseini, M., Miranda, F., Lin, J., & Silva, C. T. (2022). CitySurfaces: City-scale semantic segmentation of sidewalk materials. *Sustainable Cities and Society*, 79, 103630.
- Hou, Y., & Biljecki, F. (2022). A comprehensive framework for evaluating the quality of street view imagery. *International Journal of Applied Earth Observation and Geoinformation*, 115, 103094.
- Hu, C.-B., Zhang, F., Gong, F.-Y., Ratti, C., & Li, X. (2020). Classification and mapping of urban canyon geometry using Google Street View images and deep multitask learning. *Building and Environment*, 167, 106424.
<https://doi.org/https://doi.org/10.1016/j.buildenv.2019.106424>
- Hu, C., & Zeng, H. (2025). Decoding spatial patterns of urban thermal comfort: Explainable machine learning reveals drivers of thermal perception. *Environmental Impact Assessment Review*, 114, 107895.
- Hu, L., Wu, X., Huang, J., Peng, Y., & Liu, W. (2020). Investigation of clusters and injuries in pedestrian crashes using GIS in Changsha, China. *Safety Science*, 127, 104710.
- Hu, Y., Qian, F., Yan, H., Middel, A., Wu, R., Zhu, M., Han, Q., Zhao, K., Wang, H., & Shao, F. (2024). Which street is hotter? Street morphology may hold clues-thermal environment mapping based on street view imagery. *Building and Environment*, 262, 111838.
- Huang, F., Jiang, S., Zhan, W., Bechtel, B., Liu, Z., Demuzere, M., Huang, Y., Xu, Y., Ma, L., & Xia, W. (2023). Mapping local climate zones for cities: A large review. *Remote Sensing of Environment*, 292, 113573.
- Iqbal, N., Ravan, M., Mitarka, Z., Birkmann, J., Grimmond, S., Hertwig, D., Chrysoulakis, N., Somarakis, G., Wendnagel-Beck, A., & Panagiotakis, E. (2025). How does perceived heat stress differ between urban forms and human vulnerability profiles? Case study Berlin. *NATURAL HAZARDS AND EARTH SYSTEM SCIENCES*, 25(7), 2481–2502. <https://doi.org/10.5194/nhess-25-2481-2025> WE - Science Citation Index Expanded (SCI-EXPANDED)
- Jabbar, H. K., Hamoodi, M. N., & Al-Hameedawi, A. N. (2023). Urban heat islands: a review of contributing factors, effects and data. *IOP Conference Series: Earth and Environmental Science*, 1129(1), 12038.
- Jamei, E., & Rajagopalan, P. (2019). Effect of street design on pedestrian thermal comfort. *Architectural Science Review*, 62(2), 92–111.
- Jia, S., Wang, Y., Wong, N. H., Chen, W., & Ding, X. (2022). Influences of the thermal environment on pedestrians' thermal perception and travel behavior in hot weather. *Building and Environment*, 226, 109687.
- Johnson, B. A., & Jozdani, S. E. (2019). Local climate zone (LCZ) map accuracy

- assessments should account for land cover physical characteristics that affect the local thermal environment. *Remote Sensing*, 11(20), 2420.
- Ki, D., Chen, Z., Lee, S., & Lieu, S. (2023). A novel walkability index using google street view and deep learning. *Sustainable Cities and Society*, 99, 104896.
<https://doi.org/https://doi.org/10.1016/j.scs.2023.104896>
- Kraff, N. J., Wurm, M., & Taubenböck, H. (2020). The dynamics of poor urban areas - analyzing morphologic transformations across the globe using Earth observation data. *Cities*, 107, 102905.
<https://doi.org/https://doi.org/10.1016/j.cities.2020.102905>
- Kumar, P., Debele, S. E., Khalili, S., Halios, C. H., Sahani, J., Aghamohammadi, N., de Fatima Andrade, M., Athanassiadou, M., Bhui, K., & Calvillo, N. (2024). Urban heat mitigation by green and blue infrastructure: Drivers, effectiveness, and future needs. *The Innovation*, 5(2).
- Kursah, M. B. (2023). Satellite image analysis of thermal comfort for a sustainable urban ecology of Winneba, Ghana. *Urban Climate*, 52, 101685.
- Labib, S. M., Huck, J. J., & Lindley, S. (2021). Modelling and mapping eye-level greenness visibility exposure using multi-source data at high spatial resolutions. *Science of The Total Environment*, 755, 143050.
<https://doi.org/https://doi.org/10.1016/j.scitotenv.2020.143050>
- Lai, B., Fu, J.-M., Guo, C.-K., Zhang, D.-Y., & Wu, Z.-G. (2025). Street geometry factors influencing outdoor pedestrian thermal comfort in a historic district. *Buildings*, 15(4), 613.
- Lam, C. K. C., & Lau, K. K.-L. (2018). Effect of long-term acclimatization on summer thermal comfort in outdoor spaces: a comparative study between Melbourne and Hong Kong. *International Journal of Biometeorology*, 62(7), 1311–1324.
- Lam, C. K. C., Shooshtarian, S., & Kenawy, I. (2023). Assessment of urban physical features on summer thermal perceptions using the local climate zone classification. *Building and Environment*, 236, 110265.
- Larkin, A., Gu, X., Chen, L., & Hystad, P. (2021). Predicting perceptions of the built environment using GIS, satellite and street view image approaches. *Landscape and Urban Planning*, 216, 104257.
- Lau, K. K.-L., Chung, S. C., & Ren, C. (2019). Outdoor thermal comfort in different urban settings of sub-tropical high-density cities: An approach of adopting local climate zone (LCZ) classification. *Building and Environment*, 154, 227–238.
- Lau, K. K.-L., Shi, Y., & Ng, E. Y.-Y. (2019). Dynamic response of pedestrian thermal comfort under outdoor transient conditions. *International Journal of Biometeorology*, 63(7), 979–989.

- Leap, S. R., Soled, D. R., Sampath, V., & Nadeau, K. C. (2024). Effects of extreme weather on health in underserved communities. *Annals of Allergy, Asthma & Immunology*, 133(1), 20–27.
- Lee, Y., Kim, M., & Seo, E. (2025). Explaining Street-Level Thermal Variability Through Semantic Segmentation and Explainable AI: Toward Climate-Responsive Building and Urban Design. *Atmosphere*, 16(12), 1413.
- Lefebvre, A., Sannier, C., & Corpetti, T. (2016). Monitoring urban areas with Sentinel-2A data: Application to the update of the Copernicus high resolution layer imperviousness degree. *Remote Sensing*, 8(7), 606.
- Lenzholzer, S., & de Vries, S. (2020). Exploring outdoor thermal perception—a revised model. *International Journal of Biometeorology*, 64(2), 293–300.
- Li, J., & Roy, D. P. (2017). A global analysis of Sentinel-2A, Sentinel-2B and Landsat-8 data revisit intervals and implications for terrestrial monitoring. *Remote Sensing*, 9(9), 902.
- Li, J. Y., Sun, R. H., & Chen, L. D. (2023). A review of thermal perception and adaptation strategies across global climate zones. *URBAN CLIMATE*, 49. <https://doi.org/10.1016/j.uclim.2023.101559>
- Li, Y., Fei, W., Yang, M., Wang, Y., Du, Y., & Wang, Y. (2025). How to realize large-scale outdoor thermal comfort studies? A systematic review based on OTC characterization, methods and research trends. *Frontiers in Sustainable Cities*, 7, 1552994.
- Li, Y., Li, L., Wang, W., Kong, H., Chen, L., & Yang, L. (2024). How to enhance thermal comfort in greenway walking? An exploration of the physical environment, walking status, and emotional perspectives. *Urban Climate*, 56, 102053.
- Liang, S. (2001). Narrowband to broadband conversions of land surface albedo I: Algorithms. *Remote Sensing of Environment*, 76(2), 213–238.
- Ličina, V. F., Cheung, T., Zhang, H., De Dear, R., Parkinson, T., Arens, E., Chun, C., Schiavon, S., Luo, M., & Brager, G. (2018). Development of the ASHRAE global thermal comfort database II. *Building and Environment*, 142, 502–512.
- Liu, R., Chen, Q., Du, M., Wang, R., Yixiao, H., Li, L., Cheng, Q., Han, H., Dong, X., & Wang, X.-C. (2026). Assessing the influence of sky view factor and building shadow ratio on thermal comfort in different local climate zones: Evidence from Beijing, China. *Journal of Urban Management*.
- Liu, Z., Yuan, H., & Luo, J. (2025). Exploring the effects of street canyon morphology on LST within different street types using causal inference and machine learning. *Sustainable Cities and Society*, 106814.
- López-Lambas, M. E., Sánchez, J. M., & Alonso, A. (2021). The walking health: A route

- choice model to analyze the street factors enhancing active mobility. *Journal of Transport & Health*, 22, 101133.
- Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30.
- Ma, X., Fukuda, H., Zhou, D., & Wang, M. (2019). A study of the pedestrianized zone for tourists: Urban design effects on humans' thermal comfort in Fo Shan City, Southern China. *Sustainability*, 11(10), 2774.
- McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17(7), 1425–1432.
- Melis, G., Di Gangi, E., Ellena, M., Zengarini, N., Ricciardi, G., Mercogliano, P., & Costa, G. (2023). Urban Heat Island effect and social vulnerability in Turin: Prioritizing climate change mitigation action with an equity perspective. *Science Talks*, 8, 100258.
- Milelli, M., Bassani, F., Garbero, V., Poggi, D., von Hardenberg, J., & Ridolfi, L. (2023). Characterization of the Urban Heat and Dry Island effects in the Turin metropolitan area. *Urban Climate*, 47, 101397.
- Min, W., Mei, S., Liu, L., Wang, Y., & Jiang, S. (2019). Multi-task deep relative attribute learning for visual urban perception. *IEEE Transactions on Image Processing*, 29, 657–669.
- Nice, K. A., Wijnands, J. S., Middel, A., Wang, J., Qiu, Y., Zhao, N., Thompson, J., Aschwanden, G. D. P. A., Zhao, H., & Stevenson, M. (2020). Sky pixel detection in outdoor imagery using an adaptive algorithm and machine learning. *Urban Climate*, 31, 100572.
<https://doi.org/https://doi.org/10.1016/j.uclim.2019.100572>
- Nikolopoulou, M., & Steemers, K. (2003). Thermal comfort and psychological adaptation as a guide for designing urban spaces. *Energy and Buildings*, 35(1), 95–101.
- Nishikawa-Pacher, A. (2022). Research questions with PICO: a universal mnemonic. *Publications*, 10(3), 21.
- Novack, T., Vorbeck, L., Lorei, H., & Zipf, A. (2020). Towards Detecting Building Facades with Graffiti Artwork Based on Street View Images. In *ISPRS International Journal of Geo-Information* (Vol. 9, Issue 2, p. 98).
<https://doi.org/10.3390/ijgi9020098>
- Nurfaizah, D. A., Dahliani, E., & Widyaputri, M. A. (2025). Analysis of the Impact of Radiation and Albedo on Variations in Earth's Surface Temperature. *Jurnal Penelitian Fisika Dan Terapannya (Jupiter)*, 7, 1.

- Ojha, S. K., & Mukherjee, M. (2025). Influence of elevated and regular corridor on pedestrian thermal comfort employing on-site measurements and CFD simulation. *Urban Climate*, 64, 102658.
- Oke, T. R., Mills, G., Christen, A., & Voogt, J. A. (2017). *Urban climates*. Cambridge university press.
- Pani, M. M., Urbinati, S., Mastellari, C., Mariani, L., & Tucci, F. (2026). Climate Change in Built Environment: Remote Sensing for Thermal Assessment Measurement Paradigms. *Applied Sciences*, 16(8), 3992.
- Pappalardo, S. E., Zanetti, C., & Todeschi, V. (2023). Mapping urban heat islands and heat-related risk during heat waves from a climate justice perspective: A case study in the municipality of Padua (Italy) for inclusive adaptation policies. *Landscape and Urban Planning*, 238, 104831.
- Park, K., Baik, J.-J., & Jin, H.-G. (2025). Investigation into the causes of surface urban heat islands using an urban canopy model: comparison between bulk and facet approaches. *Theoretical and Applied Climatology*, 156(8), 442.
- Peng, Y., Feng, T., & Timmermans, H. (2019). A path analysis of outdoor comfort in urban public spaces. *Building and Environment*, 148, 459–467.
- Pizzolato, N. (2013). The “American Model” in Turin. In *Challenging Global Capitalism: Labor Migration, Radical Struggle, and Urban Change in Detroit and Turin* (pp. 47–57). Springer.
- Potchter, O., Cohen, P., Lin, T.-P., & Matzarakis, A. (2022). A systematic review advocating a framework and benchmarks for assessing outdoor human thermal perception. *Science of the Total Environment*, 833, 155128.
- Rahmani, N., & Sharifi, A. (2025). Urban heat dynamics in Local Climate Zones (LCZs): A systematic review. *Building and Environment*, 267, 112225.
- Rana, D. P., Tripathi, A., Siddiqui, S. S., Sabahat, S., Chattopadhyaya, R., & Munshi, S. (2025). Exploring the Interplay Between Urban Morphology and Microclimate in Urban Heat Island Formation. *Int. Res. J. Adv. Eng. Manag*, 3, 194–202.
- Richardson, W. S., Wilson, M. C., Nishikawa, J., & Hayward, R. S. (1995). The well-built clinical question: a key to evidence-based decisions. *ACP Journal Club*, 123(3), A12-3.
- Rouse Jr, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1973). *Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation*.
- Sajjad, H. W., Raheem, A., Laraib, M., Khalid, O., Arshed, A. B., & Mustafa, K. (2025). Spatiotemporal Analysis of Hydrological and Land Cover Transformations in the Upper Indus Basin Insights from MNDWI. *Evidence in Earth Science*, 1(02), 125–

144.

- Schiavenato, M., & Chu, F. (2021). PICO: What it is and what it is not. *Nurse Education in Practice*, 56, 103194.
- Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, 27(3), 379–423.
- Sharma, R., Pradhan, L., Kumari, M., & Bhattacharya, P. (2021). Assessing urban heat islands and thermal comfort in Noida City using geospatial technology. *Urban Climate*, 35, 100751.
- Shoghi, F., Hosseini, S. M., Heidari, S., Wang, J., Mahdavinejad, M., & Attia, S. (2025). Human Interaction with Urban Morphology under the Influence of Urban Heat Island: A Systematic Review. *JOURNAL OF DAYLIGHTING*, 12(2), 468–490. <https://doi.org/10.15627/jd.2025.28> WE - Emerging Sources Citation Index (ESCI)
- Shooshtarian, S. (2015). *Socio-economic factors for the perception of outdoor thermal environments: towards climate-sensitive urban design*.
- Shooshtarian, S., Lam, C. K. C., & Kenawy, I. (2020). Outdoor thermal comfort assessment: A review on thermal comfort research in Australia. *Building and Environment*, 177, 106917.
- Shooshtarian, S., & Ridley, I. (2016). The effect of individual and social environments on the users thermal perceptions of educational urban precincts. *Sustainable Cities and Society*, 26, 119–133.
- Siqi, J., Yuhong, W., & Hien, W. N. (2023). The effect of urban greening on pedestrian's thermal comfort and walking behaviour. *E3S Web of Conferences*, 396, 5013.
- Spearman, C. (1987). The proof and measurement of association between two things. *The American Journal of Psychology*, 100(3/4), 441–471.
- Stewart, I. D., & Oke, T. R. (2012). Local climate zones for urban temperature studies. *Bulletin of the American Meteorological Society*, 93(12), 1879–1900.
- Suo, W., & Zhao, J. (2025). Exploring the Streetscape Perceptions from the Perspective of Salient Landscape Element Combination: An Interpretable Machine Learning Approach for Optimizing Visual Quality of Streetscapes. *Land*, 14(7), 1408.
- Talhi, A., Barlet, A., Bouzoudja, R., & Leconte, F. (2026). Microclimate walk for Outdoor Thermal Comfort assessment of four Old and New Urban Configurations in a Mediterranean Climate. *Urban Transitions*, 100028.
- Todeschi, V., Pappalardo, S. E., Zanetti, C., Peroni, F., & Marchi, M. De. (2022). Climate justice in the city: mapping heat-related risk for climate change

- mitigation of the urban and peri-urban area of padua (Italy). *ISPRS International Journal of Geo-Information*, 11(9), 490.
- Tong, S., Prior, J., McGregor, G., Shi, X., & Kinney, P. (2021). Urban heat: an increasing threat to global health. *Bmj*, 375.
- Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, 8(2), 127–150.
- Tyagi, G., & Danish, M. (2025). Reflective Building Façades: The Effect of Albedo on Outdoor Thermal Comfort—A Case Study of Low-Rise Apartments. *Nature Environment and Pollution Technology*, 24(2), 1–13.
- Urban, J., Pikl, M., Zemek, F., & Novotný, J. (2022). Using Google Street View photographs to assess long-term outdoor thermal perception and thermal comfort in the urban environment during heatwaves. *Frontiers in Environmental Science*, 10, 878341.
- Vasconcelos, L., Langemeyer, J., Cole, H. V. S., & Baró, F. (2024). Nature-based climate shelters? Exploring urban green spaces as cooling solutions for older adults in a warming city. *URBAN FORESTRY & URBAN GREENING*, 98. <https://doi.org/10.1016/j.ufug.2024.128408>
- Villadiego, K., & Velay-Dabat, M. A. (2014). Outdoor thermal comfort in a hot and humid climate of Colombia: A field study in Barranquilla. *Building and Environment*, 75, 142–152.
- Wikipedia. (2024). *Wikipedia*. <https://en.wikipedia.org/wiki/Turin>
- Wikipedia. (2026). *Detmold*. Wikipedia. <https://de.wikipedia.org/wiki/Detmold>
- worldweatheronline. (2026a). *Detmold Annual Weather Averages*. World Weather Online.Com. <https://www.worldweatheronline.com/detmold-weather-averages/nordrhein-westfalen/de.aspx>
- worldweatheronline. (2026b). *Turin Annual Weather Averages*. World Weather Online.Com. <https://www.worldweatheronline.com/turin-weather-averages/piemonte/it.aspx>
- Wu, C., Peng, N., Ma, X., Li, S., & Rao, J. (2020). Assessing multiscale visual appearance characteristics of neighbourhoods using geographically weighted principal component analysis in Shenzhen, China. *Computers, Environment and Urban Systems*, 84, 101547.
- Wu, Z., Xu, K., Li, Y., Zhao, X., & Qian, Y. (2024). Application of an integrated model for analyzing street greenery through image semantic segmentation and accessibility: A case study of Nanjing City. *Forests*, 15(3), 561.
- Xu, G., Zhao, H., Li, J., Shi, Y., Feng, X., & Zhang, Y. (2023). Multivariate thermal environment data extraction and evaluation: A neighborhood scale case in

- Guangzhou, China. *Building and Environment*, 234, 110190.
- Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*, 27(14), 3025–3033.
- Xu, H., Ren, M., & Lin, M. (2024). Cross-comparison of Landsat-8 and Landsat-9 data: A three-level approach based on underfly images. *GIScience & Remote Sensing*, 61(1), 2318071.
- Yang, H., & Zeng, H. (2025). Impact of Changes in Blue and Green Spaces on the Spatiotemporal Evolution of the Urban Heat Island Effect in Ningbo and Its Implications for Sustainable Development. *Sustainability*, 17(9), 4156.
- Yang, M., Ma, C.-P., Zhao, S.-X., Zhao, F.-Y., & Guo, J.-H. (2025). Aiding and opposing cooling the street canyon through trees and water bodies: Conflicting effects from temperature reduction and ambient humidification. *Building and Environment*, 270, 112513.
- Yang, S., Chong, A., Liu, P., & Biljecki, F. (2025). Thermal comfort in sight: Thermal affordance and its visual assessment for sustainable streetscape design. *Building and Environment*, 271, 112569.
<https://doi.org/https://doi.org/10.1016/j.buildenv.2025.112569>
- Ye, Y., & Li, T. (2026). Large-scale winter streetscape perception assessments via integrating street view images with generative AI technique. *Building and Environment*, 114335.
- Yin, S., Wang, F., Xiao, Y., & Xue, S. (2022). Comparing cooling efficiency of shading strategies for pedestrian thermal comfort in street canyons of traditional shophouse neighbourhoods in Guangzhou, China. *Urban Climate*, 43, 101165.
- Yoo, W., Mayberry, R., Bae, S., Singh, K., He, Q. P., & Lillard Jr, J. W. (2014). A study of effects of multicollinearity in the multivariable analysis. *International Journal of Applied Science and Technology*, 4(5), 9.
- Yu, W., Yang, J., Zhou, Y., & Xiao, X. (2026). Global dataset on heat wave exposure due to the urban heat island effect. *Scientific Data*.
- Zhang, H., Wang, Y., Chen, B., Bai, J., Zhao, J., Guo, F., & Zhu, P. (2025). Analyzing spatial disparities in thermal comfort in a coastal city: A multi-parameter comparative study based on local climate zones. *Sustainable Cities and Society*, 107031.
- Zhang, T., Fu, X., Qi, F., Shen, Y., Xu, P., Tao, Y., Liu, T., & Song, Y. (2025). Optimizing pedestrian thermal comfort in urban street canyons for summer and winter: Tree planting or low-albedo pavements? *Sustainable Cities and Society*, 120, 106143.

- Zhang, X., Jiao, Z., Zhao, C., Qu, Y., Liu, Q., Zhang, H., Tong, Y., Wang, C., Li, S., & Guo, J. (2022). Review of land surface albedo: variance characteristics, climate effect and management strategy. *Remote Sensing*, 14(6), 1382.
- Zhang, X., & Ludwig, F. (2025). Shade for pedestrians: A novel approach to calculate the spatio-temporal shade benefits of street trees considering pedestrian flow. *Building and Environment*, 272, 112662.
- Zhang, Y., Feng, S. Y., Liu, J. Y., Mo, Q. Z., Yin, H., & Zhang, J. (2025). Campus microenvironmental factors and their effects on people's outdoor thermal perceptions under different conditions. *SCIENTIFIC REPORTS*, 15(1). <https://doi.org/10.1038/s41598-025-96651-x> WE - Science Citation Index Expanded (SCI-EXPANDED)
- Zhou, L., Ma, L., Johnson, B. A., Yan, Z., Li, F., & Li, M. (2022). Patch-based local climate zones mapping and population distribution pattern in provincial capital cities of China. *ISPRS International Journal of Geo-Information*, 11(8), 420.
- Zhou, Q., & Lin, H. (2019). Investigating the completeness and omission roads of OpenStreetMap data in Hubei, China by comparing with Street Map and Street View. *ArXiv Preprint ArXiv:1909.04323*.
- Zhou, Z., & Xu, Z. (2020). Detecting the Pedestrian Shed and Walking Route Environment of Urban Parks with Open-Source Data: A Case Study in Nanjing, China. In *International Journal of Environmental Research and Public Health* (Vol. 17, Issue 13, p. 4826). <https://doi.org/10.3390/ijerph17134826>
- Zhu, L., Samuelson, H. W., Biljecki, F., Tan, C. L., Wong, N. H., & Ang, Y. Q. (2026). Visual determinants of outdoor thermal comfort: integrating explainable AI and perceptual assessments. *Building and Environment*, 114322.
- Zou, Y., Chen, J., & Yu, Y. (2025). Heat exposure risk assessment of street canyons around urban rail transit station areas: A case study of Shanghai. *International Journal of Disaster Risk Reduction*, 123, 105522.
- Zuur, A. F., Ieno, E. N., & Elphick, C. S. (2010). A protocol for data exploration to avoid common statistical problems. *Methods in Ecology and Evolution*, 1(1), 3–14.

16. Appendix

16.1 Literature review tables

Table 2.1. Summary of representative SVI-based studies reviewed in section: 4.3 Streetscape attributes quantified through Street View Imagery (SVI).

Study	City	Research Aim	Streetscape Attributes	Tools and Methods
(Ito & Biljecki, 2021)	Singapore and Tokyo	Investigate whether SVI + CV techniques can comprehensively assess bikeability within and among cities.	Connectivity: intersections with/without lights. Environment: slope, POIs, land use mix, air quality, pixel ratios of greenery/buildings/water. Infrastructure: road type, pavement, road width, bike lanes, sidewalks. Perception: attractiveness, spaciousness, cleanliness, safety. Vehicle-cyclist interaction: vehicles, parking, traffic lights.	Sampling: 7,142 points via OSMnx. SVI: 12,014 panoramas via GSV API. Semantic Segmentation (ABM), Object Detection (YOLOv3), Scene Classification (ResNet50). Perception: LightGBM trained on Amazon Mechanical Turk ratings. Index: 34 indicators via min-max normalization.
(S. Yang et al., 2025)	Singapore	Develop the Visual Assessment of Thermal Affordance (VATA) framework describing streetscapes' inherent capacity to influence thermal comfort.	Building structures, walls/fences, roads/sidewalks, vegetation (trees, plants), sky, terrain, traffic infrastructure, vehicles, persons. Pixel-level: sharpness, entropy, colorfulness, hue, saturation, contrast. Scene type: commercial, residential, transportation, public spaces, nature.	SVI from GSV. Semantic Segmentation: DeepLabV3+ on Cityscapes (19 elements). ResNet-50 convolutional features. Faster R-CNN (COCO) for object detection. OpenCV pixel features. Survey: 176 respondents, pairwise comparisons, TrueSkill scoring. Model: MTNNL two-stage network.
(Z. Liu et al., 2025)	Hangzhou	Develop a framework for quantifying street canyon morphology via SVI to identify targeted cooling strategies for different street types.	Tree Canopy/Shading (TVF, TCG), street orientation, vegetation (TVF, TCG, NDVI), building morphology (BVF, BCG, ABH, BD), sky morphology (SVF, SCG), wind speed.	SVI acquisition. Semantic Segmentation: DeepLabV3+. Hemispherical image transformation. View factor calculation. Fractal dimension. Spatial grid construction. LST data processing.

Table 2.1. Summary of representative SVI-based studies reviewed in section: 4.3 Streetscape attributes quantified through Street View Imagery (SVI).

Table 2.2. Summary of studies on UH physical drivers and remote sensing indicators reviewed in Section 4.4 Semantic Segmentation, A Standard Method for Quantitative Streetscape Analysis.

Study	Focus / RS Index	Method	Key Finding
(Nurfaizah et al., 2025)	Surface albedo	Experimental radiation analysis	Low-albedo surfaces absorb up to 3× more radiation than high-albedo surfaces.
(Tyagi & Danish, 2025)	Albedo / building facades	ENVI-met simulation, India	Reflective facades raised canyon air temperatures above 43.7°C — paradoxical heating effect.
(X. Zhang & Ludwig, 2025)	Albedo / pavement vs. tree planting	ENVI-met simulation, 120 scenarios, Hangzhou	High-albedo pavements reduce surface temperature but increase pedestrian discomfort in unshaded areas.
(Park et al., 2025)	Sky View Factor (SVF)	Urban canopy modelling	Restricted SVF is the primary cause of nighttime surface urban heat island.
(Esposito et al., 2024)	Building height / SVF	Remote sensing, Milan & Lecce	Mean building height is the main driver of surface urban heat island intensity.
(Wang et al., 2024)	SVF / building height	Empirical study, Xi'an	SVF and building height are significant influencing factors of urban heat in LCZ-defined zones.
(Mansouri & Zarghami, 2025)	Canyon geometry / wind	CFD simulation	Different building arrangements alter wind speeds by up to 0.7 m/s.
(H. Yang & Zeng, 2025)	NDVI / BGI / LST	Decadal satellite analysis, Ningbo (Sentinel-2)	NDVI decline directly linked to rising city temperatures over 10 years.
(W. Ma et al., 2025)	Vegetation / BGI / street heat	Threshold analysis, Shanghai	Dense urban forms reach critical thresholds where heat accumulation begins.
(Del Serrone et al., 2022)	BGI / tree cooling / albedo	ENVI-met simulation, Rome	Reintroducing trees lowers air temperatures by over 3°C.
(M. Yang et al., 2025)	BGI / trees + water / PET	CFD simulation, Changsha	Trees reduce temp 3.2°C; combined tree-water effect reduces perceived stress by 2.2°C.
(Zou et al., 2025)	LST from GEE / walkability	Crichton Risk Triangle, 400 stations, Shanghai	LST from GEE identifies thermally critical street-level zones across a dense network.
(Urban et al., 2022)	LST / 30 m buffer / visual rating	Photographic survey + LST extraction, Czech cities	30 m buffer adequately captures the immediate thermal microenvironment at survey points.
(C. Hu & Zeng, 2025)	LST / NDVI / MNDWI / thermal comfort	Explainable ML, Chinese city	LST, NDVI, and MNDWI are statistically significant predictors of subjective thermal perception scores.
(Z. Liu et al., 2025)	LST / NDVI / SVF / canyon morphology	Causal inference + ML, Hangzhou	Physical morphology and spectral surface properties interact to determine street-level thermal conditions.

(Milelli et al., 2023)	Nocturnal UHI / Turin	Urban climate measurement, Turin	Urban-rural temperature differential in Turin greatest at night; persistent nocturnal heat stress.
(Liang, 2001)	Shortwave broadband albedo formula	Algorithm development for Landsat bands	Liang formula is the validated standard for albedo retrieval from Landsat multispectral bands.
(Estoque et al., 2017)	Albedo / LST / urban heat	Landscape composition analysis, SE Asian megacities	Albedo drives LST as an independent variable in urban surface energy balance studies.

Table 2.3. Summary of quantitative outdoor thermal comfort studies reviewed in section 5.1 Outdoor Thermal Comfort (OTC).

Study	City	Research Aim & Methods	Streetscape Elements / Parameters
(Ojha & Mukherjee, 2025)	Bhopal, India	Investigate effects of asymmetrical street geometry on thermal comfort of the pedestrians. Methods: Multi-seasonal field surveys + ENVI-met 5.0 CFD simulation.	Geometry: Asymmetrical street geometry, Aspect Ratio (AR), Sky View Factor (SVF). Microclimate: Ta, Rh, Ws, MRT, UTCI, WBGT.
(M. Yang et al., 2025)	Changsha, China	Analyze synergistic cooling effects of water bodies and trees in street canyons. CFD simulation (ANSYS Fluent + RayMan Pro).	Street canyons, rectangular trees, central water bodies. Wind speed, air temp, water vapor, PET.
(L. Chen et al., 2024)	Hong Kong, China	Investigate the effect of elevated walkways on outdoor thermal comfort. CFD (LES, ANSYS Fluent) + RayMan Pro.	Elevated walkways, street canyons, sidewalk types. Ta, RH, globe temp, wind velocity, MRT, SVF, PET.
(Yin et al., 2022)	Guangzhou, China	Compare cooling efficiency of four shading strategies. In situ measurements + ENVI-met V4.3 parametric modelling.	Canyon H/W, arcade H/W, tree coverage, street orientation, SVF. Ta, RH, Tg, wind speed, Tmrt.
(T. Zhang et al., 2025)	Hangzhou, China	Optimize street canyon thermal comfort — tree planting vs. pavement albedo. Field measurements + ENVI-met 3D (120 scenarios).	Pavement albedo (0.06-0.36), street orientation, aspect ratio H/W, tree species, canopy diameter.
(X. Zhang & Ludwig, 2025)	Munich, Germany	Develop spatio-temporal tree shade benefit indicator considering pedestrian flow. Rhinoceros 3D + Grasshopper Python scripts.	Street trees (canopy shape, height, diameter), building geometry, pedestrian flow volume.

Table 2.4. Summary of studies on LCZ classification and outdoor thermal comfort reviewed in Section 5.1
Outdoor Thermal Comfort in different LCZs

Study	City / Climate	LCZ Classes Studied	Method	Key Finding
(Stewart & Oke, 2012)	Global (framework paper)	All 17 LCZ types	Conceptual framework development	Established the 17-class LCZ system based on measurable morphological parameters (SVF, building fraction, H/W, roughness height).
(Lau, Chung, et al., 2019)	Hong Kong (sub-tropical, high-density)	Multiple built LCZ types (incl. LCZ 2 and LCZ 5)	In situ microclimate measurement + PET/UTCI calculation	LCZ classes with lower SVF and higher building density produce consistently higher PET and UTCI values.
(Lau, Shi, et al., 2019)	Hong Kong (sub-tropical)	Multiple LCZ types	In situ measurement + questionnaire survey	Pedestrian thermal comfort varies dynamically across transient conditions; LCZ morphology modulates response.
(Das et al., 2020)	Sriniketan, India (tropical)	LCZ classes in a planning region	In situ microclimate + ASHRAE thermal sensation survey	The relationship between LCZ morphological parameters and thermal sensation varies across climatic contexts.
(Lam et al., 2023)	Australia (temperate)	Compact vs. open LCZ classes (incl. LCZ 2 and LCZ 5)	In situ measurement + thermal perception questionnaire	Respondents in compact LCZ zones report systematically lower thermal satisfaction than in open zones under equivalent meteorological conditions.
(H. Zhang et al., 2025)	Coastal city, China	Multiple LCZ types	Multi-parameter field measurement + questionnaire survey	Spatial disparities in thermal comfort correspond to LCZ classification; LCZ type predicts perception patterns.
(Rahmani & Sharifi, 2025)	Global (systematic review)	All LCZ types	Systematic review of 150+ studies	LCZ is the dominant framework for urban heat dynamics research; compact classes consistently

				show higher thermal stress.
(Y. Hu et al., 2024)	Multiple cities	LCZ 2 and LCZ 5 equivalent dense/open zones	SVI semantic segmentation + mobile in situ measurement	Street morphology classification from street view imagery can identify which streets are thermally hottest.
(Aslam & Rana, 2022)	Global (systematic review)	All LCZ types	Systematic review of LCZ methodology papers	LCZ has been widely adopted globally; data sources and methods have diversified considerably since 2012.

Table 2.5. Summary of studies on perceived thermal comfort, psychological adaptation, acclimatization, and visual thermal comfort assessment reviewed in Section 5.2 and 5.3.

Study	Location	Method	Sample / Scale	Key Finding
(Nikolopoulou & Steemers, 2003)	Urban public spaces, Europe	In situ measurement + subjective perception survey	Multiple sites, multiple seasons	Physical parameters explain only ~50% of comfort variation; psychological adaptation (naturalness, expectations, control, stimulation) accounts for the rest.
(Cortesão et al., 2020)	Lisbon, Portugal (Mediterranean, Csa)	Photographic comparison method — visual rating of street photographs	4 outdoor spaces, multiple respondents	Respondents reliably differentiate thermal comfort levels from street photographs; rankings correspond to objective physical properties.
(Urban et al., 2022)	Czech cities (Cfb)	GSV photographs + LST 30 m buffer extraction — thermal comfort perception survey during heatwaves	Multiple survey points, two cities	Respondents predict heat-related discomfort from photographs even without explicit meteorological information shown.
(S. Yang et al., 2025)	Singapore (tropical, Af)	Visual Assessment of Thermal Affordance (VATA) — SegFormer-B5 segmentation + pairwise photographic comparison survey	176 respondents, 500 photographs	Sky fraction, vegetation fraction, and building enclosure are statistically significant predictors of thermal affordance ratings.
(Lam & Lau, 2018)	Melbourne (Cfb) vs. Hong Kong (Cfa)	In situ measurement + thermal	Respondents in both cities, matched	Respondents in warmer cities tolerate conditions

		perception questionnaire — cross-city comparison	thermal conditions	that cooler-city residents' rate as uncomfortable, even when objective thermal indices are identical.
(Shooshtarian & Ridley, 2016)	Educational precincts, Australia (Cfb/Cfa)	In situ microclimate + thermal perception survey	Students and staff in outdoor spaces	Both individual and social thermal environments shape users' thermal perceptions; long-term familiarity with local climate plays a measurable role.
(Shooshtarian et al., 2020)	Australia (multiple climates)	Systematic review of Australian outdoor thermal comfort research	150+ studies reviewed	Cultural and climatic background are among the strongest predictors of individual thermal response.
(Peng et al., 2019)	Urban public spaces, China	In situ measurement + path analysis of subjective comfort	Field surveys across multiple spaces	Physical environment, perceived control, and personal characteristics all contribute to outdoor comfort; psychological factors modulate physical effects.
(Larkin et al., 2021)	56 cities (multiple climates)	GIS + Sentinel-2 satellite data + GSV street view analysis	56 cities globally	NDVI is one of the strongest statistical predictors of perceived built environment quality at street level across different climatic contexts.

16.2 Data availability

All scripts and code developed for this research are documented and publicly available via the following link: https://github.com/Bonin-Mahdavi/thermal_comfort_potential