

Article

Beyond the Canopy: In Situ Evidence of Urban Green Spaces' Cooling Potential Across Three Chilean Cities

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Abstract

Vegetation in urban green spaces plays a critical role in mitigating surface heat, yet the magnitude of this effect remains uncertain across scales and measurement methods. This study assesses the cooling performance during the summer of 94 green spaces in three Chilean cities—classified in three types according to their size—combining satellite-derived land surface temperature (LST) data with high-resolution in situ thermal imaging. We performed comparisons of the cooling effects of green spaces and their components (vegetation, impermeable and semi-permeable surfaces). Spearman's correlation analysis, the Mann-Whitney U test and Kruskal-Wallis and Dunn post hoc were used to evaluate associations and differences. Results demonstrate that vegetation quantity and composition—particularly tree and shrub cover—are key determinants of cooling performance. In situ measurements reveal that green spaces are on average 9.3 °C cooler than their urban surroundings, substantially exceeding differences captured by LST. Additionally, shaded surfaces within green spaces exhibit temperature reductions of 12 °C to 17 °C compared to sun-exposed areas, underscoring the role of vegetation in mitigating surface heat extremes. These findings challenge the sole reliance on remote sensing for urban heat assessments and highlight the value of integrating ground-based observations. This study advances understanding of vegetation's localized cooling potential in Latin American cities and provides actionable insights for urban climate resilience planning.

Keywords: urban heat mitigation; land surface temperature; thermal imaging; Latin America; urban climate resilience



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1. Introduction

The urban heat island effect (UHI) is a pressing global issue resulting from the urbanization process, which involves the conversion of natural vegetated soils into impermeable surfaces and complex urban geometries [1]. Urban materials, characterized by high heat absorption, storage, and emissivity, significantly alter the energy balance of urban ar-

eas, leading to elevated air and land surface temperatures compared to the surrounding regions [2,3].

This phenomenon has detrimental environmental impacts, increasing energy consumption for cooling purposes and negatively affecting human well-being in summer, increasing exposure to high temperatures and thermal discomfort in urban spaces [4]. Urban warming also increases the morbidity and mortality linked to heat stress-related illnesses such as cardiovascular, pulmonary, renal, and cerebrovascular diseases and mental health problems [5–9]. Global climate change contributes to extreme meteorological phenomena, such as heat waves, and increases the frequency of high-temperature episodes; therefore, there is an urgent demand to identify and implement effective mitigation strategies to address these impacts [2,5].

The inclusion of extensive vegetation within urban green spaces is widely recognized as a highly effective strategy for mitigating the impacts of the UHI by regulating the urban microclimate [2,10,11]. Unlike urban materials, which function as heat sources [12], green spaces serve as heat sinks, thanks to the cooling effect or cool island effect generated by vegetation [3,13,14]. However, the limited availability of green spaces in highly urbanized cities exacerbates the influence of urban areas on the microclimate, highlighting the need for research focused on assessing the role of vegetation as a strategy to improve urban thermal conditions at the street level [11].

Through evapotranspiration and shade, primarily provided by trees, vegetation plays a crucial role in temperature regulation [14]. Evapotranspiration, the process of water vapor release into the atmosphere [15], actively cools both leaves and the surrounding air temperature [14–16]. Many studies have empirically assessed the cooling effect of urban parks on daytime [3] and nighttime [17] urban air temperatures, showing their potential to mitigate the UHI intensity throughout the day. During the daytime, vegetation also plays a crucial role in reducing thermal heat stress by providing shade. Tree shade allows for reducing solar radiation flux on the human body and surrounding surfaces, significantly reducing mean radiant temperature and thermal sensation [18]. However, the spatial distribution of mean radiant temperature at the street level is highly variable, as it depends on the relative position with respect to the trees and the sun [19]. For this reason, high-resolution street-level data are essential to understand the actual potential of urban vegetation to mitigate heat stress.

Monitoring and evaluation of the cooling effect of vegetation have been conducted using various methodological techniques, including the use of remotely sensed data and in situ measurements [1,20–23]. Satellite imagery (e.g., Landsat and MODIS) provides valuable land surface temperature (LST) information by measuring the temperature of material structures, like buildings, pavement, or vegetation, and covering a wide spatial extension in long time scales, with high or medium resolutions [1,24,25]. However, these imageries are limited by the frequency and time of day at which the data are acquired, which can influence the accuracy of thermal representation, as satellites typically capture LST during specific periods without reflecting continuous thermal variations [25,26]. Moreover, satellite images do not accurately capture temperatures at the street level (SLT) or in the lower layers of the atmosphere, where people experience heat directly [24]. Conversely, the use of thermal images obtained through in situ measurements can offer higher spatial and temporal resolution, providing detailed information on surface temperatures of various components and facilitating the assessment of the thermal conditions experienced by pedestrians [22,26]. However, although in situ measurements provide great detail, they are limited in terms of spatial coverage and have high costs, which restricts their ability to assess large areas [22]. Therefore, many recent studies recommend combining both techniques to achieve a more comprehensive and accurate analysis of the urban thermal

environment and a better understanding of the cooling effect of vegetation, and especially of the different urban elements that can integrate differently, a rich gradient, and diverse forms of vegetation, ranging from different built elements to urban trees or grass types [20,23,26].

Urban climate studies have also investigated the cooling potential of urban vegetation using different types of numerical models [27]: atmospheric models (i.e., WRF), CFD models (ENVI-met, PALM4), or energy balance models (i.e., SOLWEIG or VCWG). The advantage of the modeling approach is the possibility to generate high-resolution microclimate data to assess the multi-scale benefits of urban vegetation. However, this comes at a high computational cost and requires detailed input data for the simulations, limiting its application to specific case studies [18]. In opposite to that, satellite land surface temperature (LST) data are available for all cities worldwide and can be used to perform extensive spatial analysis to assess the variability of the cooling effect of urban green spaces with different characteristics. Studies of this kind reported that key influencing factors of the cooling effect of urban vegetation are size, land use, park perimeter, and internal green area [28,29]. Remote sensing data can also be combined with air temperature from local fixed weather station networks and digital elevation models to derive higher resolution near-surface air temperature data [30]. However, this is still limited to outdoor thermal comfort analysis, which is highly variable at the microscale depending on solar access and radiation fluxes. For this reason, street-level measurements are crucial to understand the range of variability of the thermal environment and corresponding thermal sensation, which cannot be detected by remote sensing images.

Research efforts on this topic have primarily focused on countries in the northern hemisphere and temperate climate regions, with limited attention given to understanding the thermal benefits of vegetation in southern hemisphere countries and regions [26]. As a result, Latin American cities show a reduced cooling capacity of urban green infrastructure compared to cities of the global north, which can be explained by the lower quantity and quality of urban green spaces [31]. For these reasons, it is particularly critical to understand how to improve urban green spaces and their cooling potential in typical urban areas of Latin America, characterized by high population density and substantial exposure to the impacts of the urban heat island phenomenon [21]. To this aim, the present study aims to assess the cooling effect of vegetation in green spaces across three cities in Chile, combining remote sensing data and in situ measurements for a more detailed assessment of the street-scale thermal environment influencing thermal sensation. Specifically, this research aims to analyze the average surface temperature differences between green spaces and their surrounding environments, considering different elements within the green spaces in both shaded and sunny conditions. This allows us to identify the range of variation in thermal conditions of urban green spaces, enhancing our understanding of the actual cooling effect of vegetation experienced by pedestrians in the context of the studied cities.

2. Materials and Methods

This study assesses the cooling effect of vegetation in 94 green spaces (GS) of diverse typologies based on their quantity of vegetation and their surroundings by analyzing diurnal surface temperatures in different components (i.e., types of vegetation, impermeable, and permeable surfaces; Figure 1). It employs and compares two distinct methodological approaches: remote sensing based on Sentinel-2 and Landsat 8 imagery and in situ measurements using a thermal camera (FLIR C2) and fieldwork to characterize soil components and coverage (Figure 1). Remote sensing is used to analyze spectral indices to determine vegetation quantity/characteristics using the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST).

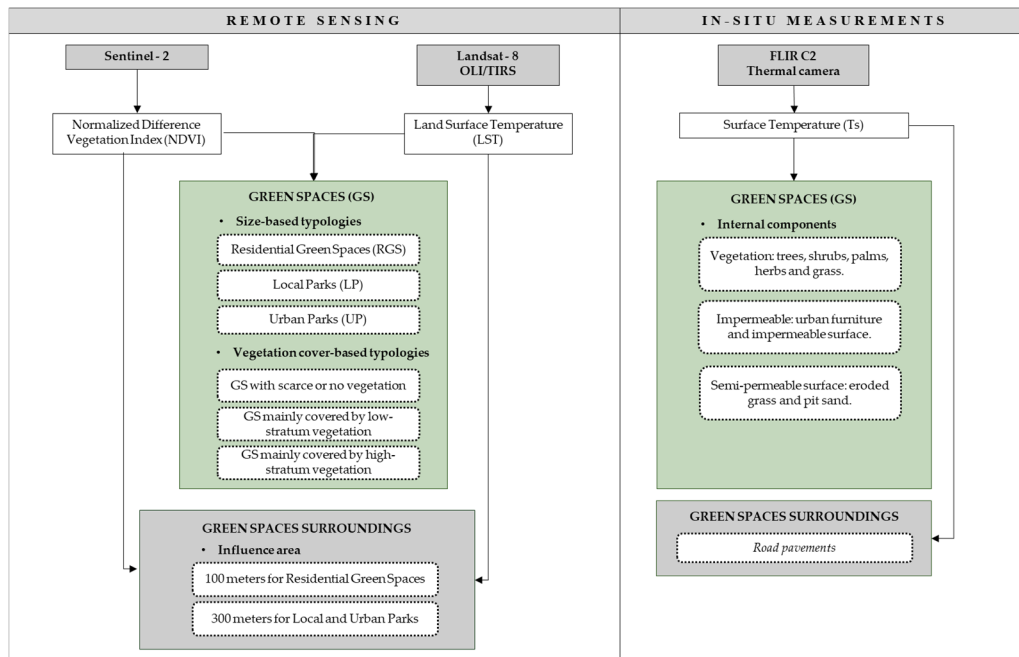


Figure 1. Schematic diagram of the methodology.

2.1. Study Areas

Three cities were analyzed, based on their representation of a latitudinal gradient across Chile, encompassing cities that are representative of different climatic conditions, covering Mediterranean conditions ranging from semi-arid to temperate transitions. They are cities that constitute metropolitan areas, each comprising two or more municipalities with populations exceeding 250,000 inhabitants and sharing common urban services. The three cities are La Serena–Coquimbo (29.90° S; hereafter LSC), Metropolitan Santiago (33.43° S; hereafter MS), and Metropolitan Concepción (36.82° S; hereafter MC), with coordinates referring to latitude (Figure 2). The latter two cities encompass 37 and 11 communes, respectively, while LSC is a conurbation of two communes. Together, these cities have a combined population of over 7.5 million inhabitants, accounting for 43% of the national population. MS is the most populous, with over 6 million inhabitants, followed by MC with nearly 1 million inhabitants and LSC with over 400,000 inhabitants [32]. The climate in LSC is characterized as cold semi-arid, with a dry summer and oceanic influence, while MS and MC have a Mediterranean climate with hot, dry summers, and MC also experiences coastal influence [33].

2.1.1. Selection of Green Spaces Sample

We studied a selected sample of green spaces (GS) from three cities in Chile. Due to the large diversity of GS, we focused on those ranging in size from 0.2 to 10 ha, used for recreation, and containing vegetation. We applied a clustering-based selection to ensure a representative sample across the spectrum of soil/surface coverage (e.g., vegetation). Following Sánchez [34], clusters were defined to maximize within-cluster homogeneity and between-cluster differentiation without imposing topological contiguity (i.e., membership was not constrained by adjacency). We used K-means (with the number of clusters specified a priori) and performed a collinearity analysis prior to variable selection to remove highly correlated predictors that contributed little additional information.

Clustering was based on the soil-cover characterization derived from an object-based classification of Sentinel 2 images, encompassing all public GS included in the database of the Chilean System of Indicators and Standards for Urban Development (SIEDU) (INE,

n.d.). Six soil-cover variables were used consistently: tree and shrub cover, grass cover, spontaneous vegetation, scarce vegetation, impermeable surfaces, and water bodies.

The procedure produced 41, 30, and 23 homogeneous groups for LSC, MS, and MC, respectively. From each cluster, one representative GS was randomly selected, using a systematic rotation among three candidates to reduce selection bias. Thus, we studied 94 GS (Figure 2).

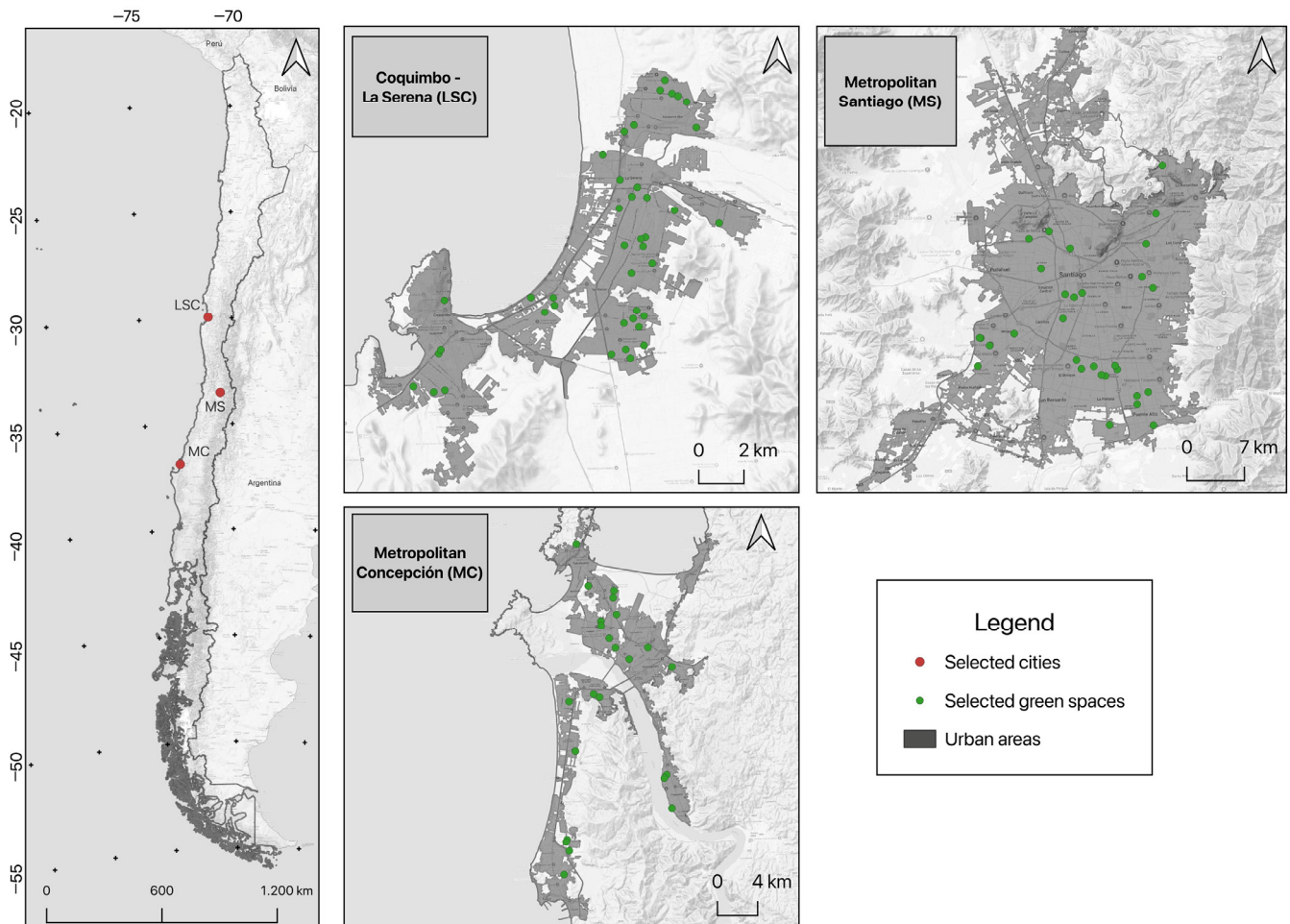


Figure 2. Location of the three cities analyzed and the 94 urban green spaces under study. Two communes in La Serena-Coquimbo (LSC), 18 communes in Metropolitan Santiago (MS) and 6 communes in Metropolitan Concepción (MC) were visited.

This approach yielded a sample that captures the full gradient of vegetation composition and surface conditions observed in the GS population, while ensuring statistical diversity and comparability across cities.

2.1.2. Typology of Urban Green Spaces

Building on the clustering-based selection described above, we then classified the selected GS into typologies to streamline subsequent analyses. Three size-based typologies were used: Residential Green Spaces (RGS; 0.05–0.5 ha), Local Parks (LP; 0.5–2.0 ha), and Urban Parks (UP; 2.0–10.0 ha, Figure 3). Within each size class, GS were further differentiated by tree (high-stratum) cover to capture structural variability: (1) GS with scarce or no vegetation and a prevalence of impermeable surfaces (approximately less than 8% of tree and shrub cover); (2) GS predominantly covered by low-stratum vegetation and at least 13–26% of tree and shrub cover; and (3) GS mainly covered by high-stratum (mainly tree) vegetation.



Figure 3. Examples of green space typologies: (a) represents a green space with low vegetation cover located in La Serena-Coquimbo; (b) shows a green space of Metropolitan Concepcion with medium vegetation cover, and (c) represents a green space in Metropolitan Santiago with high vegetation (tree) cover.

2.2. General Explanation of Processing of Satellite Imagery

We used satellite imagery to calculate two indices, which were then compared to the following in-situ measurements: the Normalized Difference Vegetation Index (NDVI), calculated from Sentinel 2 imagery (10 m resolution), and the Land Surface Temperature (LST), calculated from Landsat 8 OLI/TIRS images (30 m resolution). Both Sentinel and Landsat datasets were obtained from the Google Earth Engine Code Editor platform.

The Landsat 8 OLI/TIRS images were Level-2 processed, i.e., they are atmospherically corrected to surface reflectance. For the thermal bands (B10 and B11), atmospheric correction was applied using the split-window method. The selected scenes correspond to 9 April 2021, for LSC; 1 March 2021, for MS; and 21 December 2021, for MC.

The Sentinel-2 multispectral images were part of the Harmonized Sentinel-2 MSI Surface Reflectance collection (COPERNICUS/S2_SR_HARMONIZED), which includes atmospheric correction. For LSC, a single scene was used (8 April 2021), whereas for MS and MC, mosaics composed of multiple scenes were generated to match the dates associated with surface temperature data (MS = 1–10 March 2021; four images; MC = 20–25 December 2021; four images). Cloud cover was filtered for each scene, averaging 4% across all processed images. Regarding acquisition geometry, the mean solar zenith angle was below 50°, and the incidence angles of the individual images used in the mosaics were not cross-checked, as differences were minimal. Scene selection prioritized temporal alignment with the Landsat 8 product.

The workflow consisted of (1) selecting the image collection and filtering scenes based on the parameters described; (2) selecting scenes and creating mosaics in the two specific cases; (3) applying the NDVI to the scenes; (4) exporting the resulting products; and (5) performing zonal statistics by GS based on their areas of influence using QGIS v3.40.12 Lima.

2.3. Calculation of Vegetation

To evaluate the vegetation extent in GS and their surroundings, we used two indicators: (1) NDVI with values ranging from -1 to 1 , where higher values indicate greater vegetation vitality; NDVI was extracted for all pixels within each GS and its surrounding buffer; and (2) vegetation coverage (VC), computed as the percentage of the GS area covered by vegetation, as a total and by vegetation type. To characterize GS surroundings, we

delineated an influence area around each GS: 100 m for Residential Green Spaces (RGS) and 300 m for Local Parks (LP) and Urban Parks (UP).

The NDVI was calculated using Landsat bands B8 (Near-Infrared, NIR: 0.78–0.90 μm) and B4 (Red, RED, 0.65–0.68 μm), following Equation (1):

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (1)$$

VC was estimated in the field based on the proportion of each GS area covered by vegetation (trees and grass) relative to the total GS area.

2.4. Calculation of Temperatures from Remote Sensing

The daytime Land Surface Temperature (LST) was derived from three Landsat 8 OLI/TIRS images (30 m resolution) acquired on April 9th for LSC, March 1st for MS, and December 21st for MC, all from the year 2021. All the images were taken by the satellite at 14:30 approx. Surface radiance values ($B_\lambda(T)$) were calculated using the radiative transfer equation (RTE), with emissivity derived from the NDVI. Surface radiances were then converted to surface temperature using Planck's law, following Equation (2):

$$LST = \frac{c2}{\lambda \ln \left\{ \frac{c1}{\lambda^5 * [B_\lambda(T)]} + 1 \right\}} \quad (2)$$

where the constant (c) values are: $c1 = 1.19104 \times 10^8 \text{ W m}^4 \text{ m}^{-3} \text{ sr}^{-1}$, and $c2 = 14,387.7 \text{ } \mu\text{m k}$. $B_\lambda(T_s)$ is the result of Equation (3):

$$B_\lambda(T_s) = \frac{\left[(L_\lambda^{sen} - L_\lambda^\uparrow) - (1 - \epsilon_\lambda) * L_\lambda^\downarrow * \tau \right]}{\tau * \epsilon_\lambda} \quad (3)$$

where L_λ^{sen} is the radiance measured by the sensor; $L_\lambda^\uparrow$ is atmospheric upward radiance, $L_\lambda^\downarrow$ is atmospheric downward radiance; ϵ_λ is the emissivity of Earth's surface; and τ is atmospheric transmittance.

The values of $L_\lambda^\downarrow$, $L_\lambda^\uparrow$, y τ are taken from <https://atmcorr.gsfc.nasa.gov/> (accessed on 10 December 2022), while ϵ_λ is calculated from the NDVI of each image.

The surface temperature values were atmospherically corrected using the Split Windows equation. Temperatures were retrieved for the interior of the green space and its surrounding area from the pixels within their respective spatial domains and influence areas (100 m for RGS, 300 m for LP and UP). Subsequently, the temperature difference (Delta LST) between the green space and its surroundings was calculated using the following Equation (4):

$$\Delta LST = LST_{green\ space} - LST_{surroundings} \quad (4)$$

where negative values indicate the cooling effect of the GS, while positive values indicate that the surroundings have less temperature than the GS.

The same buffer zones as those used in the vegetation calculation were employed to determine the urban surroundings.

2.5. In-Situ Temperature Measurements

The in situ measurements involved using a FLIR C2 thermal camera (FLIR Systems, Wilsonville, OR, USA) to capture thermal images. This camera detects and captures the infrared radiation emitted by objects, converting it into a radiometric image with a resolution of 320×240 pixels, providing up to 76,800 surface temperature measurement

points. It has a temperature detection range of $-10\text{ }^{\circ}\text{C}$ to $+50\text{ }^{\circ}\text{C}$, with an accuracy of $\pm 2\text{ }^{\circ}\text{C}$ or 2% [35].

To compensate for variations in emissivity among different surfaces, the camera's emissivity setting was adjusted to a matte configuration ($\epsilon = 0.95$). This adjustment accounts for the emissivity values of vegetation (0.9–0.98), pit sand (decomposed granite) (0.6–0.9), and concrete-asphalt (0.92–0.97) [35–39]. This assumption is based on the premise that these components exhibit similar infrared emissivity characteristics. Therefore, the analysis of apparent surface temperatures provides an approximation of the actual temperatures [40].

The image capture took place on hot summer days between 11 am and 4 pm. The procedure involved walking along the perimeter of the green space and capturing images of both the inside and the surroundings of GS at each cardinal point (Figure 4). To prevent the capture of sky portions that could affect temperature readings, the camera was slightly tilted toward the ground. For interior images, the distance was determined using an identifying object to ensure precise measurements and facilitate image processing. If the initial captures from each cardinal point did not cover all internal components of the GS, a second round of captures was conducted at a closer distance to the center. Similarly, if the initial captures did not adequately represent the urban surroundings of the green space due to its size or shape, additional captures were taken, as necessary.

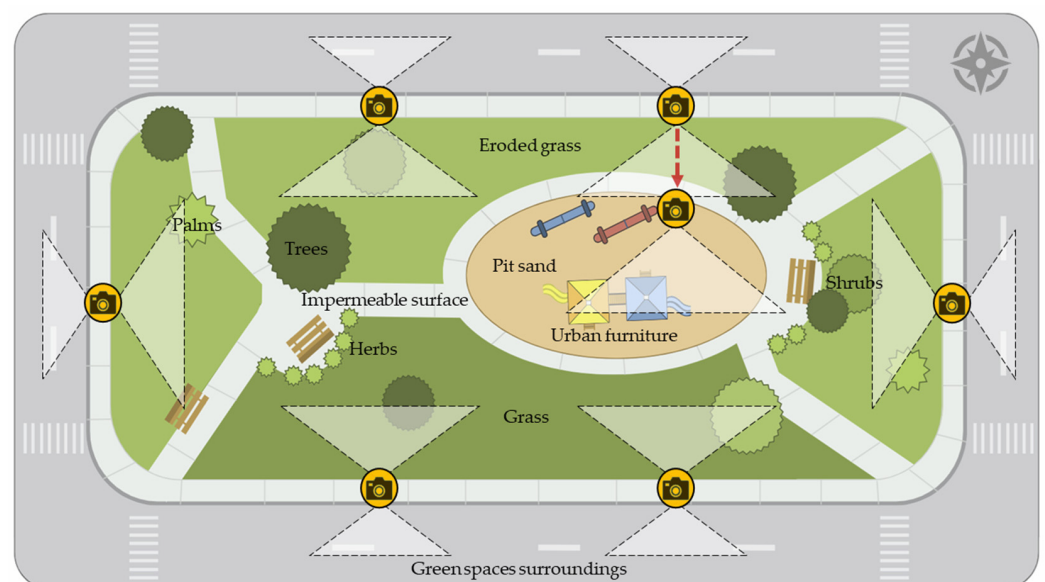


Figure 4. Schematic diagram illustrating the procedure for capturing in situ images using a pocket thermal camera in an illustrative example of a residential green space (RGS). The diagram highlights various components within the green space, including trees, shrubs, grass, urban furniture, and pit sand.

2.5.1. Measurement of the Temperature of Internal Components in Green Spaces

The thermal behavior of the following internal components within the green spaces was characterized (Figure 5):

- Vegetation: including trees, shrubs, palm trees, herbaceous plants, and grass (healthy grass or lawn).
- Urban furniture: encompassing all components present in GS that aim to provide specific services to citizens, such as benches, playground equipment, and sports facilities.
- Impermeable surface: referring to the hard and compact surface, made of materials such as concrete and asphalt, which have low porosity and limit water infiltration.
- Semipermeable surface: characterized by a softer surface, typically composed of materials like sand, gravel, and pit sand, with higher porosity allowing for better

water infiltration [41]. This category also includes eroded grass components, which are areas where the presence of grass cover has been eroded or deteriorated, resulting in an exposed vegetation-free surface.



Figure 5. Examples of internal components in green spaces. (a) Tree canopy (high-stratum vegetation); (b) healthy grass (lawn); (c) impermeable surface; (d) semipermeable surface (sand).

To extract temperature data, manual selection was performed using the point measurement tool in FLIR Tools 6.1 [35]. The procedure involved placing two measurement points on each identified component within each image. One measurement point was placed on the component exposed to direct sunlight, while the other was placed on the component shaded primarily by the vegetation within the green space. Through this process, a total of 1685 and 1079 surface temperature measurements were extracted under sunny and shaded conditions, respectively, from a dataset of 590 thermal images corresponding to the 94 green spaces (see Figure A1 for examples, in Appendix A).

2.5.2. Comparing Temperature of Green Spaces and Their Surroundings

To assess ground-temperature differences between the GS and its immediate surroundings, we adapted the method proposed by Baró et al. [42]. The cooling effect was quantified using a canopy coverage indicator (VC; see Section 2.2) together with empirical temperature data from satellite imagery (Section 2.3) and in situ measurements (Section 2.4), collected under both shaded and sunny conditions, inside and outside the GS.

To calculate the internal temperature of each green space (T_s^{GS}), a weighting approach was employed using temperature data from trees, grass, impermeable surfaces, and pit sand (semi-permeable) exposed to sunlight. Additionally, the proportion of each component relative to the total area of the green space was estimated at ground level, except for the tree canopy. Thus, the surface temperature of the urban green space was calculated using the following Equation (5):

$$T_s^{GS} = \frac{1}{p} \sum_{i=1}^n P_i x T_i \quad (5)$$

where i indexes the component types, n is the total number of components within the urban green space, P_i is the planimetric (horizontal) proportion of component i (in the same units as p ; percentage or fraction), T_i is the average surface temperature of component i , and p is the sum of all component percentages in the space. Because vegetation strata can overlap (e.g., tree canopy over grass), p may exceed 100% when using percentages.

The surrounding temperature T_s^{SUR} was derived from satellite and thermal captures of components outside the GS boundary—road pavements, buildings and vegetation (e.g., urban trees). We then computed the temperature difference (Delta Ts) following Equation (6):

$$\Delta T_s = T_s^{GS} - T_s^{SUR} \quad (6)$$

where negative values indicate the cooling effect of the GS (i.e., the GS is cooler than its surroundings), and positive values indicate the opposite.

2.6. Data Analysis

To examine significant associations and differences between the interior and exterior of the urban green space (GS), temperature and vegetation variables captured through remote sensing and in-situ measurements were subjected to Spearman's correlation analysis and the Mann-Whitney U test. The Kruskal-Wallis test was employed to compare the thermal behavior of internal components within the green spaces. Likewise, this test was applied to compare temperature variables and vegetation indices obtained from both remote and in situ measurements across the three analyzed cities. If significant differences were found, the Dunn post hoc test was applied. Furthermore, the Mann-Whitney U test was utilized to determine significant temperature differences between components under sunny and shaded conditions. Statistical significance was defined as p -values below 0.05. Data analysis and tabulation were carried out using XLSTAT (version 2023).

3. Results

3.1. Vegetation in Green Spaces and Surroundings

Remote sensing and in situ measurements indicate that vegetation cover is higher within green spaces (GS) than in their surroundings. The Normalized Difference Vegetation Index (NDVI), which ranges from -1 to $+1$ (with $+1$ representing maximum vegetation presence), showed that the average NDVI within GS was $0.29 (\pm 0.15)$, significantly higher than the average NDVI in the surrounding urban areas (0.17 ± 0.09 ; Table 1). Notably, almost four-fifths of the 94 GS assessed (79%) exhibited NDVI values above their respective surroundings, highlighting that GS act as reservoirs of vegetation. When comparing all GS with their surroundings, the mean NDVI was significantly higher inside GS. Moreover, NDVI values inside and outside GS were positively correlated ($r = 0.63$, $p < 0.05$; Table 2), indicating that greener parks tend to be embedded within greener urban contexts.

Table 1. Descriptive statistics of temperature and vegetation variables derived from remote sensing data and in situ measurements of the 94 GS.

Statistics	Vegetation				Temperature			
	NDVI Green Spaces	NDVI Surroundings	VC Trees (%)	VC Grass (%)	LST Green Spaces (°C)	LST Surroundings (°C)	Ts Green Spaces (°C)	Ts Surroundings (°C)
Media ($\pm$ SD)	0.29 (± 0.15)	0.17 (± 0.09)	16.8 (± 19.7)	38.8 (± 20.9)	30.3 (± 3.8)	30.7 (± 3.8)	36.4 (± 7.1)	45.7 (± 9.2)
Range (min–max)	0.08–0.76	0.05–0.50	0–84.0	0–80.0	24.1–40.7	24.3–40.6	18.4–55.0	25.6–65.5

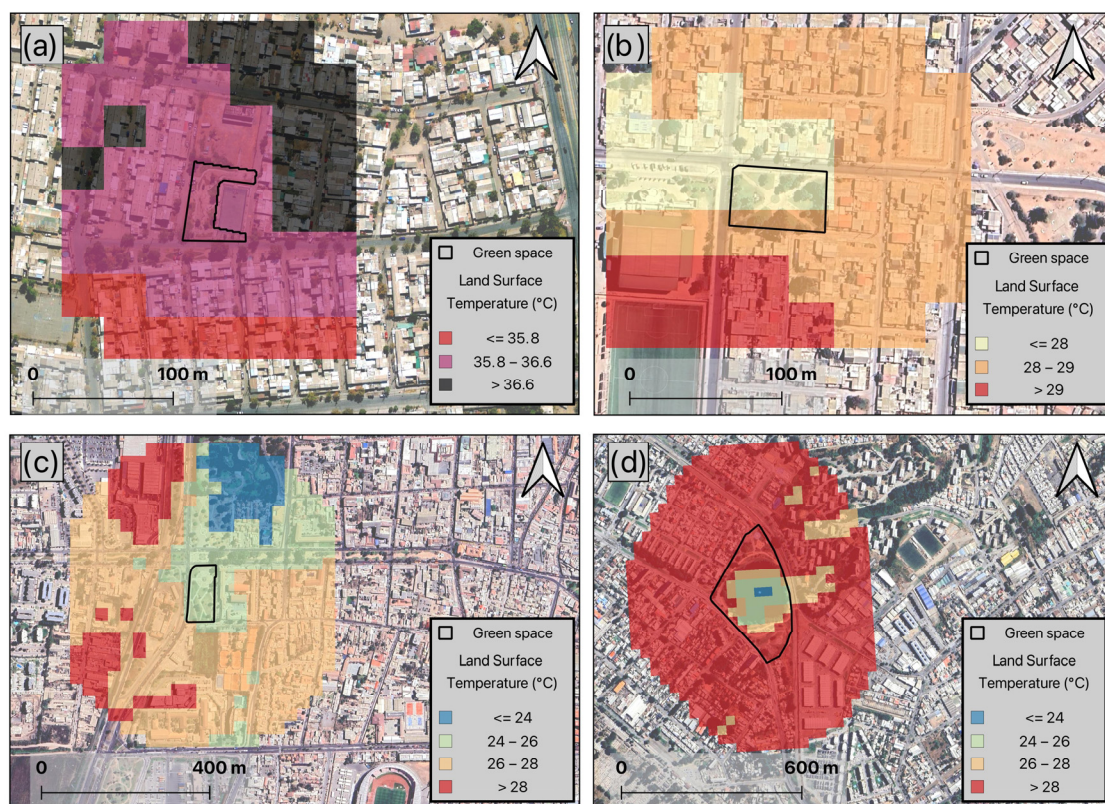
In situ estimations of vegetation cover show that the average tree proportion (VC trees) within GS was 16.8% (± 19.7). In contrast, the grass proportion (VC grass) averaged 38.8% (± 20.9) and was significantly correlated with NDVI ($r = 0.44$). No significant association was observed between NDVI and tree proportion ($r = 0.14$; Table 2).

Table 2. Correlation coefficients of temperature and vegetation variables between the GS and its urban surroundings, and between remote sensing data and in situ measurements. * p -value < 0.05.

Variables	Remote Sensing Data				In Situ Measurements			
	LST Green Spaces	LST Surroundings	NDVI Green Spaces	NDVI Surroundings	Ts Green Spaces	Ts Surroundings	Vc Trees	VC Grass
Remote sensing data								
LST green spaces	1	0.97 *	0.23 *	−0.02				
LST surroundings		1	0.30 *	−0.03				
NDVI green spaces			1	0.63 *				
NDVI surroundings				1				
In situ measurements								
Ts green spaces	0.39 *	0.36 *	−0.21 *	−0.19	1	0.53 *	−0.37 *	−0.48 *
Ts surroundings	0.66 *	0.68 *	0.28 *	0.07		1	−0.02	−0.03
VC trees	−0.18	−0.15	0.14	−0.08			1	0.22 *
VC grass	−0.05	<0.01	0.44 *	0.24 *				1

3.2. Temperature in Green Spaces and Surroundings

Table 1 summarizes descriptive statistics for vegetation (NDVI, VC) and temperature variables (LST and in situ surface temperature, Ts) inside GS and in their surroundings. The mean LST inside the 94 GS was 30.3 °C (± 3.8), only 0.4 °C cooler than the surroundings, with similar minima and maxima. As shown in Figure 6, this small difference likely reflects the 30 m pixel size—which does not conform to GS boundaries and often mixes edge pixels with adjacent paved surfaces—and the acquisition time (~14:30), when shade is limited; both factors tend to overestimate within-GS LST. Accordingly, LST inside and outside GS were highly correlated ($r = 0.97$, $p < 0.05$; Table 2), consistent with minimal contrasts at this spatial/temporal resolution.

**Figure 6.** Spatial distribution of land surface temperature in the surroundings of four green spaces. Parts (a–c) are residential green spaces from Santiago, and La Serena-Coquimbo (b,c), and part (d) is an urban park with a lagoon inside in Concepcion.

By contrast, in situ Ts averaged 36.4 °C (± 7.1) inside GS and 45.7 °C (± 9.2) in the surroundings, yielding $\Delta T_s = -9.3$ °C and a wider temperature range (Table 1). Microclimate was locally variable: Ts showed substantially greater dispersion than LST (SDs: 7.1 vs. 3.8 °C inside GS; 9.2 vs. 3.8 °C in surroundings), consistent with fine-scale heterogeneity detectable only in situ. Because the two methods sense different quantities and scales, in situ Ts values were significantly higher than satellite-derived LST both inside and outside GS (Table 2).

3.3. Relationship Between Remote Sensing and In Situ Temperature Measurements

As shown in Table 2, inside–outside coupling differs by method: LST is strongly correlated ($r = 0.97$), whereas Ts shows a moderate association ($r = 0.53$), indicating lower sensitivity to park-scale microclimate at the satellite scale. Cross-method relationships were weaker inside GS than in the surroundings: LST–Ts correlated at $r = 0.39$ inside GS and $r = 0.68$ in the surrounding buffers. Additionally, LST within GS correlated with surrounding Ts ($r = 0.66$; Table 2), further suggesting that satellite LST primarily reflects the broader thermal background, while in situ Ts captures fine-scale heterogeneity within parks. These patterns are consistent with the mixed nature of 30 m pixels and the distinct quantities sensed by each method.

3.4. Relationship Between Vegetation and Green Space Temperature

Within GS, Ts decreased with greater vegetation: Ts correlated negatively with grass coverage (VC-grass; $r = -0.48^*$, $p < 0.05$) and tree coverage (VC-trees; $r = -0.37^*$, $p < 0.05$), and only weakly with NDVI ($r = -0.21^*$, $p < 0.05$) (Table 3). Consistently, the cooling contrast relative to the surroundings (ΔT_s) was strongly associated with NDVI ($r = -0.52^*$, Table 3), indicating that greener parks exhibit larger cooling; ΔT_s also related negatively to VC-grass and VC-trees.

Table 3. Correlation coefficients between vegetation and temperature variables derived from remote sensing and in situ measurements within the GS. * p -value < 0.05 .

Variables	Vegetation			GS Typology
	NDVI Green Spaces	VC Trees	VC Grass	
Remote Sensing Data				
LST green spaces	0.23 *	−0.18	−0.05	−0.34 *
Delta LST	−0.30 *	−0.22 *	−0.23 *	−0.20 *
In Situ Measurements				
Ts green spaces	−0.21 *	−0.37 *	−0.48 *	−0.39 *
Delta Ts	−0.52 *	−0.30 *	−0.40 *	−0.22 *

By comparison, satellite-derived LST was largely insensitive to within-GS structure: correlations between LST (inside GS) and VC-trees/VC-grass were negligible ($r = -0.18$ and -0.05), while LST showed a small positive association with NDVI ($r \approx 0.23$). ΔLST correlated negatively with NDVI (-0.30^*), VC-trees (-0.22^*), and VC-grass (-0.23) (Table 3), reflecting the limited within-park sensitivity of 30 m pixels.

Typology comparisons reinforced the canopy effect (Table 4). GS with scarce tree cover were hotter ($T_s 39.4$ °C ± 6.7) than those with medium (36.9 °C ± 5.5) or high tree cover (32.8 °C ± 6.8) and showed smaller cooling relative to surroundings ($\Delta T_s = -6.9$ °C, -10.8 °C, and -11.1 °C, respectively). Differences in T_s and ΔT_s between scarce and high tree-cover classes were significant. No relevant differences were found for the three sizes of GS.

Table 4. Descriptive statistics of temperature variables derived from in situ measurements for the green space typology.

Statistics	GS with Scarce Tree Cover (<i>n</i> = 39)		GS with Medium Tree Cover (<i>n</i> = 20)		GS with High Tree Cover (<i>n</i> = 35)	
	Ts Green Spaces (°C)	Delta Ts (°C)	Ts Green Spaces (°C)	Delta Ts (°C)	Ts Green Spaces (°C)	Delta Ts (°C)
Media (±SD)	39.4 (±6.7)	−6.9 (±7.8)	36.9 (±5.5)	−10.8 (±6.5)	32.8 (±6.8)	−11.1 (±7.9)
Range (Min–Max)	27.9–55.0	−23.9–7.0	26.0–46.4	−20.8–0.2	18.4–46.4	−31.2–1.4

In terms of differences between cities (Table 5), remote sensing indicates that Santiago (MS) and Concepción (MC) had significantly higher temperatures than La Serena–Coquimbo (LSC) for both LST inside GS and LST in their surroundings (groups a vs. b). NDVI inside GS was likewise higher in MS and MC than in LSC (groups a vs. b). NDVI in the surroundings was highest in MC (group a) and lower in MS and LSC (group b). As expected, Δ LST did not differ among cities (all group a).

Table 5. Descriptive statistics of results for each city evaluated.

Variables		LSC		MS		MC	
		Media (±SD)	Group	Media (±SD)	Group	Media (±SD)	Group
Remote sensing data	LST green spaces (°C)	26.7 (±1.3)	b	33.8 (±2.1)	a	32.3 (±2.8)	a
	LST surroundings (°C)	27.1 (±1.3)	b	34.3 (±1.7)	a	32.4 (±3.0)	a
	Delta LST (°C)	−0.4 (±0.6)	a	−0.5 (±0.9)	a	−0.1 (±1.2)	a
	NDVI green spaces	0.23 (±0.12)	b	0.35 (±0.14)	a	0.34 (±0.16)	a
	NDVI surroundings	0.14 (±0.05)	b	0.16 (±0.09)	b	0.23 (±0.11)	a
In situ measurements	Ts green spaces (°C)	33.8 (±6.7)	b	40.5 (±6.0)	a	35.8 (±6.8)	b
	Ts surroundings (°C)	38.8 (±6.7)	c	55.3 (±5.2)	a	45.6 (±5.4)	b
	Delta Ts (°C)	−5.0 (±5.7)	c	−14.8 (±7.6)	a	−9.8 (±6.7)	b

In situ measurements showed a clearer separation: MS recorded the highest Ts inside GS, Ts in the surroundings, and the most negative Δ Ts (largest cooling), followed by MC and then LSC (groups a > b > c). MC also had higher Ts in the surroundings and a more negative Δ Ts than LSC (group b vs. c), consistent with its greener surrounding context (higher NDVI surroundings).

These differences may partly reflect image-acquisition timing and meteorological conditions, and they align with regional climate: MS is generally hotter than the other two cities, whereas MC is the coolest, consistent with its higher latitude and cooler maritime influence. In addition, MS is the only inland city (the others are coastal), typically exhibiting greater thermal variability and lower humidity—factors that influence heat accumulation and dissipation.

3.5. Analysis of Internal Components of the Green Spaces

Under sunlit conditions, component behavior follows its categorical grouping (Figure 7). Vegetation showed significantly lower surface temperatures than other components; trees and shrubs had the narrowest ranges and the lowest means (23.7 °C and 24.4 °C, respectively), whereas grass was the warmest vegetated element (29.0 °C). In contrast, semi-permeable pit sandpit sand recorded the highest temperatures (44.8 °C), followed by eroded grass and impermeable surfaces (both near 40 °C). The span between the coolest and warmest elements (trees vs. pit sand) was 21 °C.

Under shaded conditions, vegetation again exhibited the lowest temperatures and the tightest dispersion (Figure 7). Trees, shrubs, and grass clustered around 22 °C, whereas impermeable surfaces, pit sand, and urban furniture were warmer (28 °C) and showed wider ranges. The extreme shaded contrast (shrubs vs. pit sandpit sand) was 6 °C. Where

shaded observations were insufficient for a component (e.g., specific graminoids), those cases were omitted from shaded-only comparisons.

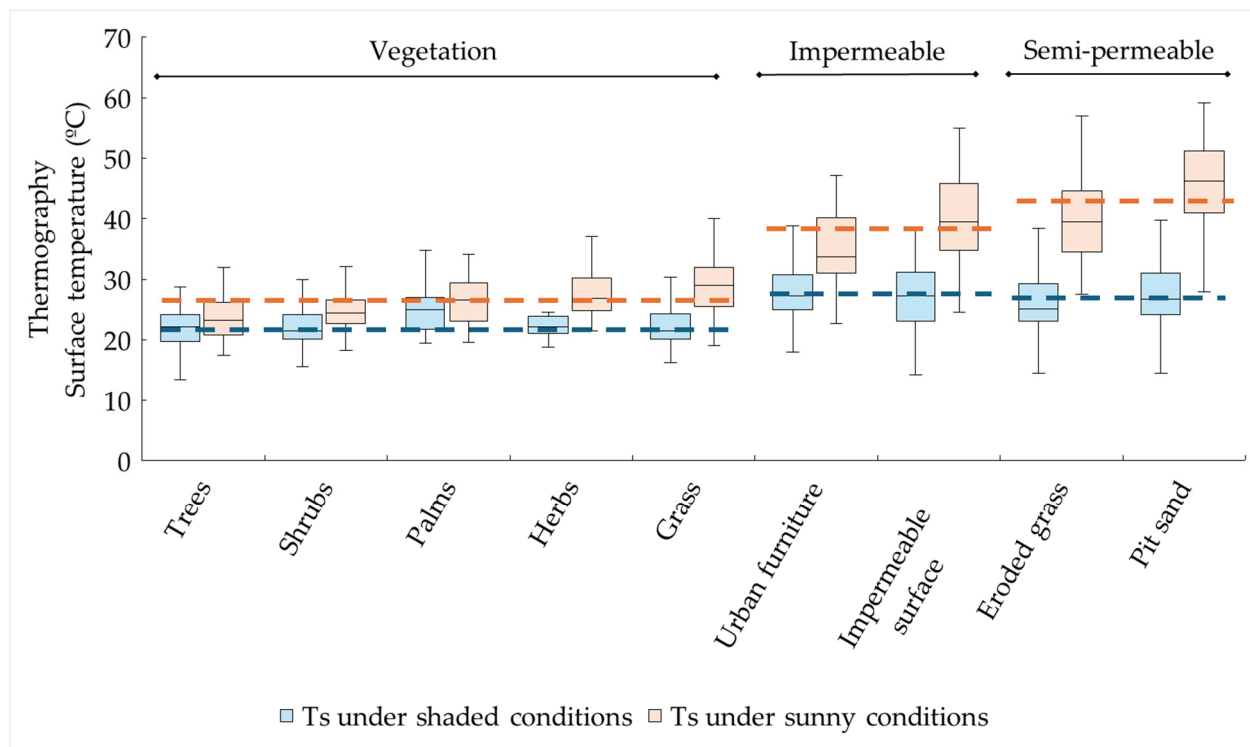


Figure 7. Box plot illustrating the surface temperatures of the internal components under sunny and shaded conditions in the 94 green spaces. Dotted lines indicate the mean temperature by component type in the shade (light blue) and in the sun (orange).

Across all components, shade significantly reduced Ts ($p < 0.05$). The largest sunshade drops occurred on pit sand (17 °C cooler in shade), eroded grass (14 °C), and impermeable surfaces (12 °C). Within vegetation, grass showed the greatest shade-related reduction (7 °C), while trees and shrubs remained coolest in absolute terms.

These patterns are consistent with differences in albedo, thermal inertia, moisture content, and evapotranspiration: dry, granular substrates (e.g., pit sand) and heat-retentive materials (impermeable surfaces) warm most under the sun and therefore benefit most from shade, whereas vegetated elements—especially tree canopies—buffer surface heating through shading and latent heat fluxes. Temperature dispersion increased under sunlit conditions, particularly for semi-/impermeable materials, indicating fine-scale heterogeneity in material properties, moisture, and micro-shading. From a design standpoint, prioritizing tree canopy and targeted shading over heat-retentive or granular substrates yields the largest component-level temperature reductions; pairing canopy with the replacement or treatment of spit sand/eroded surfaces is likely to provide especially high returns (see Supplementary Materials for data of each green space).

4. Discussion

4.1. Comparing the Results Obtained from Remote Sensing Data and In Situ Measurements

Although the results reveal a correlation between land surface temperature obtained from satellite imagery and in situ measurements, remote sensing encounters challenges in discerning temperature variations between the interior and exterior of green spaces. The significant disparities in temperature values obtained through both methods, along with the underestimation caused by the coarser instrument, can be attributed to differences

in scale and resolution between the two approaches [43,44], as well as limitations in the resolution of satellite images used for temperature calculations [26,44]. Remote sensing simplifies the surface structure by treating the temperature of various components as an aggregate [33], while in situ thermal cameras provide higher spatial resolution in both vertical and horizontal dimensions, enabling the distinction of individual component temperatures [26,45,46]. In addition, the time of measurement can influence the detection of temperature differences, as both satellite and camera imagery were acquired at midday, while the most pronounced heat island effects typically occur at night [47].

The extensive spatial coverage and the ease of data collection offered by remote sensing have led to its widespread and growing usage in urban environments [1,11,26]. However, there is a need to validate surface temperature derived from satellite images using high-resolution spatial and temporal measurements to enhance measurement accuracy and reduce uncertainties in remote estimation [1,43]. This validation would facilitate data extrapolation to large urban areas and encourage research focused on evaluating cooling effects [1,48].

To perform the atmospheric correction for the LST calculation, this study used the platform <https://atmcorr.gsfc.nasa.gov/> to obtain the transmittance, upwelling radiance, and downwelling radiance values for the specific scenes. Since the platform is no longer accessible, an option for future studies may be to use the MODTRAN web platform (http://modtran.spectral.com/modtran_home accessed on 10 December 2022) to obtain the required atmospheric parameters and thus continue with the Split-Window methodology workflow.

Regarding vegetation variables, the results demonstrate a significant correlation between satellite-derived vegetation indices (e.g., NDVI) and the actual vegetation coverage within green spaces. In this case, the higher spatial resolution of Sentinel 2 images, which were used to obtain NDVI, allows for clear differentiation of vegetation coverage between the green space and its surrounding environment, thereby enabling the determination of the amount of vegetation present in these areas.

The integration of high-resolution thermal imaging exposes spatial temperature variations that are often overlooked by remote sensing alone. To advance toward a corrective factor that enables more precise use of satellite-derived temperature data, additional ground-based measurements and, ideally, higher-resolution satellite imagery are required. Although the datasets did not exhibit a strong correlation, we derived a simple linear calibration model for temperature inside GS ($LST = 13.873 + 0.744 \times T_S$; $R^2 = 0.16$, RMSE = 6.44 °C), which yielded a mean cross-validated error of 6.67 ± 0.86 °C. Including vegetation cover (VC trees + VC grass) results in a new model ($LST = 22.479 + 0.669T_S - 0.110VC$; $R^2 = 0.43$, RMSE = 5.43 °C); that nearly reduces the cross-validated RMSE by 1 °C and doubles the explained variance, confirming that vegetation exerts a clear cooling influence measurable in ground thermal data. The negative coefficient for vegetation (−0.11 °C per % of vegetation cover) indicates that, within green spaces, every 10% increase in vegetation cover is associated with roughly 1.1 °C lower surface temperature, after controlling for satellite-measured LST. Further refinements could incorporate surface characteristics, emissivity, or canopy composition to enhance predictive performance and reduce residual uncertainty.

4.2. Contribution of Green Spaces Vegetation to Urban Temperature

The findings indicate a strong relationship between vegetation coverage and surface temperature, while the vegetation index derived from satellite images shows a weaker relationship. From these results, it can be inferred that the effect of vegetation is more clearly observed through in situ measurements, as remote data tends to underestimate the

cooling effect, at least by half. This underestimation can be caused by using the average of all pixels, as well as by their size, which hides larger temperature differences in very small areas. Despite that, this finding is novel considering the numerous studies that only support the effect of vegetation in reducing temperatures through remote sensing [3,21].

All vegetation variables correlate with the surface temperature of green spaces. This means that green spaces with higher or denser vegetation coverage, particularly those covered mainly by trees, have lower temperatures than those with less vegetation. The results highlight the effect of vegetation in reducing surface temperature. The strong association between vegetation variables and the temperature difference between green spaces and their surroundings corroborates this.

These results reinforce the significant role played by vegetation and green spaces in temperature regulation and their effectiveness as mitigation strategies, as extensively documented in other regions [1–3,21,49,50]. The cooling capacity of vegetation is attributed to factors such as shading and the process of evapotranspiration [2,3,51], highlighting the contribution of tree cover.

A higher extent of vegetation coverage within green spaces, particularly dense vegetation, results in enhanced shading capabilities, thereby reducing the direct solar radiation exposure to the components and surfaces of the green space. Vegetation intercepts radiation through its foliage, and lower heat absorption capacity decreases the amount of heat absorbed by the components, thus reducing surface temperature [2,3,39,52]. Through the process of evapotranspiration, vegetation contributes to increased relative humidity in the atmosphere and converts sensible heat into latent heat [2,51]. This leads to the cooling of foliage and the surrounding air, as well as the dissipation of radiation absorbed by the components, thereby reducing surface temperature [3,16,50].

Regarding the comparative performance of the three GS typologies based on size, the absence of findings confirming GS size as a key variable for the cooling effect may be due to the limited number of large GS assessed (2 UP) compared with smaller ones (8 LP and 84 RGS). Future research should include more measurements in larger GS and aim for a more balanced sample to enable meaningful comparisons for this variable.

Based on the results of green space typology (Table 4), it can be inferred that spaces with scarce or little tree coverage, which in addition have large extensions covered by impermeable surfaces, are associated with higher surface temperatures, while those with predominantly high-strata vegetation are associated with lower temperatures. These findings are consistent with the negative impact of impermeable surfaces and artificial materials on urban temperatures, contributing to the Urban Heat Island effect [3,37]. Urban materials with low permeability, low solar reflection, and low moisture retention capacity exhibit high heat absorption and storage during the day [2,3,12]. The cooling capacity of grass and herbaceous vegetation has been well documented [49], and our results confirm this effect. However, the findings also highlight that the trees and shrubs are particularly notable for their greater temperature regulation capabilities, especially during daytime, consistent with previous research [1,2,53]. Therefore, the properties and effects of vegetation described earlier are verified with this research, supporting its potential as a mitigation strategy against heat hazards.

4.3. Thermal Trends of Green Spaces Components

The results from Section 3.4 reveal the unequal behavior exhibited by the different components identified within green spaces. As expected, vegetation exhibits the lowest surface temperatures. The significant temperature differences observed between the grass component and the tree and shrub components can be attributed to the inherent greater exposure of grass surfaces to direct solar radiation, resulting in higher surface tempera-

tures [54]. On the other hand, due to the structure of trees and shrubs, they create shaded conditions, leading to lower surface temperatures, which may also be influenced by their higher evapotranspiration rates, according to some studies [49].

Materials characterized by low or no moisture content and high capacity for absorbing radiation influence the temperatures of non-vegetation components. Consequently, these components are unable to dissipate heat, resulting in the highest surface temperatures [2,12,55]. Temperature differences among these components can be associated with their heat absorption capacity, albedo, materiality, texture, and even their color [15,55,56]. The pit sand component has a lower average albedo (between 20 and 25%) compared to the impermeable component (between 15 and 37%) [57]. It also has higher roughness and heat absorption capacity, which explains its higher surface temperature values [15,55,56]. As for the eroded grass or bare soil component, with an albedo close to 30% [58], it exhibits intermediate surface temperature values between the impermeable and pit sand components.

Based on the results comparing exposure conditions to solar radiation, it is evident that shade significantly affects the surface temperatures of the components. As expected, all components show lower temperatures when shaded. It is noteworthy that impermeable and semi-permeable surfaces, which exhibit the highest surface temperatures, also present the largest thermal differentials between shaded and unshaded conditions, with average temperatures reduced by 12 °C to 17 °C under shading. This emphasizes the importance of analyzing the configuration and design of these spaces to optimize the shading effect provided by vegetation, thereby maximizing temperature regulation [1,54,59].

5. Conclusions

By combining satellite-derived LST with in situ thermal measurements across 94 green spaces, we show that method and scale strongly condition the estimated cooling effect. At 30 m resolution, LST detected only a minor inside–outside contrast, whereas in situ measurements captured a much larger cooling ($\Delta T_s \approx -9.3$ °C) and greater microclimatic variability. Thus, satellite LST alone can understate vegetation's cooling at GS scales, cautioning against sole reliance on remote sensing for urban heat assessments.

Within green spaces, surface temperature (T_s) decreased with higher vegetation coverage—most strongly with grass (VC-grass) and also with trees (VC-trees). Greener GS according to NDVI, and canopy-based typologies confirmed that high-tree-cover GS were cooler and exhibited greater cooling than GS with scarce canopy.

Shade significantly reduced T_s across all materials, with the largest sun–shade drops on pit sand (~ 17 °C), eroded grass (~ 14 °C), and impermeable surfaces (~ 12 °C). Vegetated elements—especially tree and shrub canopy—maintained the lowest absolute T_s , and grass experienced the greatest shade-related reduction within the vegetation group (~ 7 °C). These patterns are consistent with differences in albedo, thermal inertia, moisture, and evapotranspiration.

To address extreme meteorological phenomena such as heat waves and the increasing frequency of high-temperature episodes due to climate change, having and visiting green spaces (GS) can help alleviate the negative effects on human health. To mitigate extreme heat events, it is necessary to promote GS with abundant vegetation, which is sometimes opposed due to concerns about water consumption, especially where water is scarce or needed for other purposes. Therefore, progress is needed in selecting plant species with lower water requirements, reusing greywater for irrigation, and developing complementary materials that provide additional shading and support tree cooling effects. More specifically, GS should (i) prioritize tree canopies, (ii) provide shading over heat-retentive or granular substrates, (iii) replace pit sand with alternative substrates, and (iv) restore eroded grass areas. These GS can serve as climate refugia during hours or days of extreme heat, but to do

so, they must be designed to efficiently reduce temperatures relative to their surroundings, thereby increasing the resilience of urban inhabitants.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/urbansci9110485/s1>.

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Appendix A

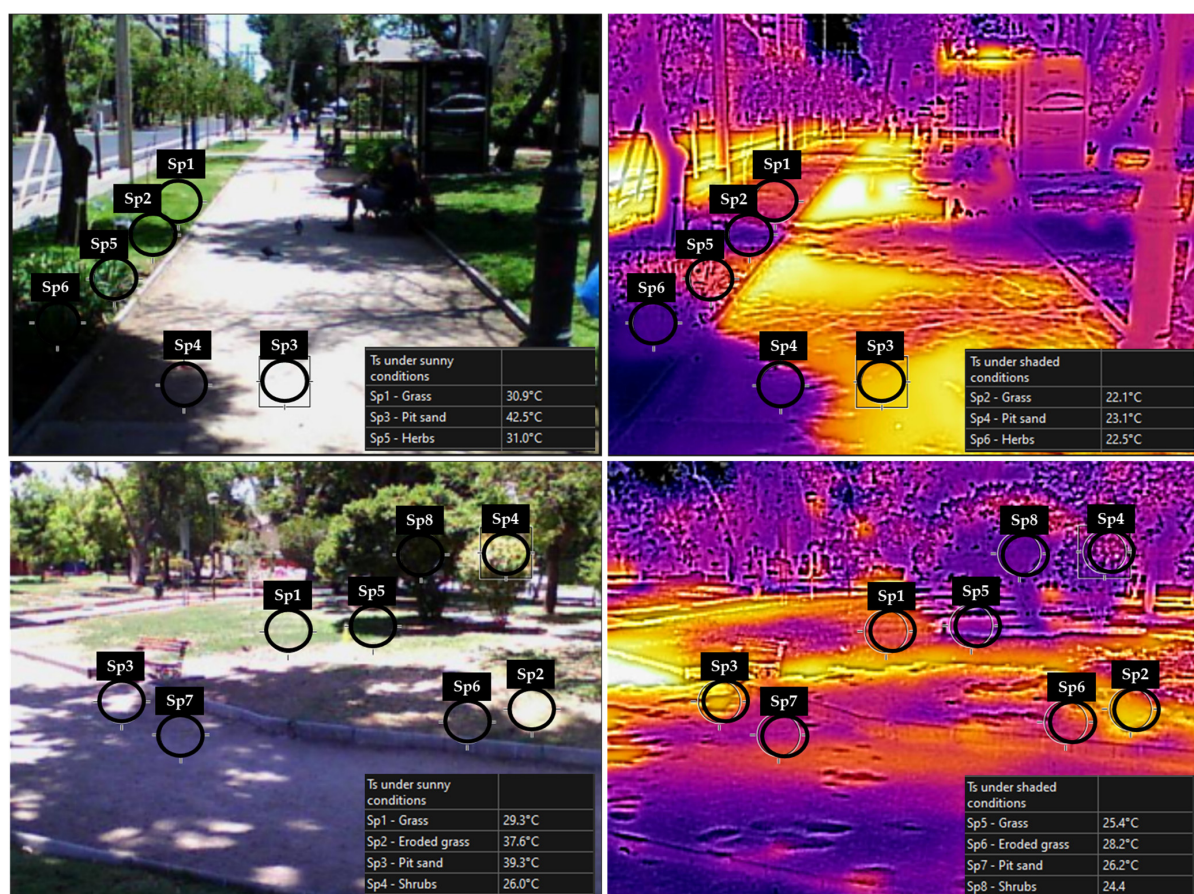


Figure A1. Example of two thermal images compared with a digital image of the same GS. The points marked in FLIR TOOLS[®] 6.1 software used to collect temperature data are shown.

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