

Article

Energy Sustainability of Urban Areas by Green Systems: Applied Thermodynamic Entropy and Strategic Modeling Means

Carla Balocco ^{1,*} , Giacomo Pierucci ¹ , Michele Baia ¹, Costanza Borghi ² , Saverio Francini ³ ,
Gherardo Chirici ²  and Stefano Mancuso ² 

¹ Department of Architecture, University of Florence, Via della Mattonaia 8, 50121 Florence, Italy; giacomo.pierucci@unifi.it (G.P.); michele.baia@unifi.it (M.B.)

² Department of Agricultural, Food, Environmental and Forestry Sciences and Technologies, University of Florence, Piazzale delle Cascine 18, 50144 Florence, Italy; costanza.borghi@unifi.it (C.B.); gherardo.chirici@unifi.it (G.C.); stefano.mancuso@unifi.it (S.M.)

³ Department of Agricultural and Food Sciences, University of Bologna, Viale Fanin 50, 40127 Bologna, Italy; saverio.francini@unifi.it

* Correspondence: carla.balocco@unifi.it

Abstract

Global warming, anthropogenic pressure, and urban expansion at the expense of green spaces are leading to an increase in the incidence of urban heat islands, creating discomfort and health issue for citizens. This present research aimed at quantifying the impact of nature-based solutions to support decision-making processes in sustainable energy action plans. A simple method is provided, linking applied thermodynamics to physics-informed modeling of urban built-up and green areas, high-resolution climate models at urban scale, greenery modeling, spatial georeferencing techniques for energy, and entropy exchanges evaluation in urban built-up areas, with and without vegetation. This allows the outdoor climate conditions and thermo-hygrometric well-being to improve, reducing the workload of cooling plant-systems in buildings and entropy flux to the environment. The finalization and post-processing of obtained results allows the definition of entropy footprints. The main findings show a decrease in greenery's contribution for different scenarios, referring to a different climatological dataset, but an increase in entropy that becomes higher for the scenario with higher emissions. The comparison between the entropy footprint values for different urban zones can be a useful support to public administrations, stakeholders, and local governments for planning proactive resilient cities and anthropogenic impact reduction and climate change mitigation.

Keywords: thermodynamics; entropy footprint; climate responsive urban areas; greenery thermodynamic modelling; urban heat islands mitigation; climate change adaptation



Academic Editors: Gianluca Pappaccogli and Ferdinando Salata

Received: 23 July 2025

Revised: 8 August 2025

Accepted: 13 August 2025

Published: 17 August 2025

Citation: Balocco, C.; Pierucci, G.; Baia, M.; Borghi, C.; Francini, S.; Chirici, G.; Mancuso, S. Energy Sustainability of Urban Areas by Green Systems: Applied Thermodynamic Entropy and Strategic Modeling Means. *Atmosphere* **2025**, *16*, 975. <https://doi.org/10.3390/atmos16080975>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Sustainability is a very broad and complex concept in the current climate change and global warming situation [1–8].

In the urban context, the concept of sustainability implies that urban areas should be considered open thermodynamic systems, thus requiring physical definition of entropy, which some of the literature has interpreted based on the connections between entropy and irreversibility [9].

From literature studies comparison, it is deduced that different applications of entropy to urban systems can generate misunderstanding, especially if applied to bioenergetics,

ecology, and evolutionary biology [10–13]. Nevertheless, with the Second Law of Thermodynamics, strong physical approaches can be formulated, at large and small scales, and crucial insights into the sustainability and efficiency of urban processes can be drawn. In detail, statistical entropy, including Shannon’s diversity, and informational entropy have been applied to generally describe diversity, heterogeneity, and spatial patterning of biological systems [14].

While some research studies are oriented towards the study of entropy flows as indicators of urban ecosystems’ integrity [15], others aim to apply thermodynamics entropy to the environment [16], often combining GIS and remote sensing techniques [17]. For instance, there are several literature studies on entropy assessment at large and small scales [18–25], using spatial quantitative–qualitative analyses, implementing GIS, Spearman correlation models, and fractal models. The “low-entropy city” has been explored by considering the role of urban green infrastructure [26–29], also referring to Prigogine and Stengers [30] and, for the Italian context, to [31]. Recent research has used information entropy, highlighting that the higher the value of information entropy, the more diverse the land use functions [32].

Similarly, a recent study has highlighted that urban microclimate models can play an important role for sustainability, management of energy sources, urban design, and urban heat island (UHIs) control [33]. Here, the Shannon entropy coefficient has been used to study spatial and temporal entropy connected to the effective temperature index (ET) [34]. Furthermore, the urban entropy patterns [35] and Entropy Life Cycle Assessment have been applied as a screening tool for ecological footprint [36]. In this context, accurate urban-scale modeling, for energy and entropy analyses, requires high-resolution spatial data (on the order of kilometers) to incorporate orographic effects and reliably represent anthropogenic emission sources [37–39].

Moreover, comparisons of climatic historical data with high-resolution climate models (i.e., the so-called Convection Permitting regional Models, CPMs) to obtain results applicable to future scenarios and quantify impacts across different projections are necessary [40–45] to study entropy dynamics. In fact, CPMs, derived from downscaling regional climate models [37,38], allow more accurate simulations of energy balance, providing detailed information on the statistics and return periods of extreme events.

In this literature background, our method fills the literature’s lack of physics-thermodynamics-informed modeling for the entropy assessment of urban areas. Starting from the physics of the built urban system, through the application of the Laws of Thermodynamics, develops a simple, easy-to-implement method useful for quantifying, via georeferenced modeling, entropy flows at transient conditions and entropic impacts of built-up urban areas, evaluating the effects of greenery to counteract climate change. This approach aligns with the IPCC (2025) [46] issues.

The method is based on a simplified and easy-to-implement model (without the need for large amounts of measured/detected data or obtained from the literature evidence and/or specific data sources). Entropy is the physical quantity that can be used to define the anthropic weight within the evolution of physical phenomena (i.e., heat exchanges at urban scale). The city is one of the contexts in which the environment is most forced by human action from morphology (relationship between built-up and green spaces) and energy use point of view. Therefore, the entropy variation (with and without greenery) can provide a measure of sustainable scenarios, considering the future trends of global warming.

The method provides fundamental indicators, i.e., the entropy footprints, and enables spatial assessment of energy use and entropy fluxes and environmental stress, distinguishing high-impact zones where an increase in greenery and climate adaptation strategies are most urgent. By applying entropy footprints analysis, it is possible to find out effective

solutions for urban design, orienting policies and social action towards resilience and sustainability transitions and energy planning for mitigation of UHIs.

2. Materials and Methods

Energy and entropy analyses of the urban system are implemented by means of the First and Second Law of Thermodynamics application for two conditions, i.e., with and without greenery areas.

The proposed approach integrates simplified model of greenery and a building system to compute leaf surface temperatures, thermal energy exchanges, and entropy balance evaluations of any urban area. We use the by now common term “sustainability” to mean low environmental impact, energy quality, and durability [39,47]. So, the production of entropy is related to energy flows, thermal exchanges, and not to material waste or pollution. Therefore, the entropy “discharged” into the surrounding environment is read as waste heat only. Referring to [39,47], we start from the concept that real sustainability can only be obtained if total irreversible entropy flux, due to anthropogenic weight, is lower than the entropy flux from the Sun.

After an introduction to the general theoretical framework (Section 2.1), Section 2.2 briefly shows and discuss how to organize the climate database and the classification of urban green spaces, which are necessary inputs to identify and estimate all the model parameters, applied at the case study of a Florentine area in Italy (Section 2.3).

The process and method implementation are provided in the flowchart of Figure 1 and cited as a reference.

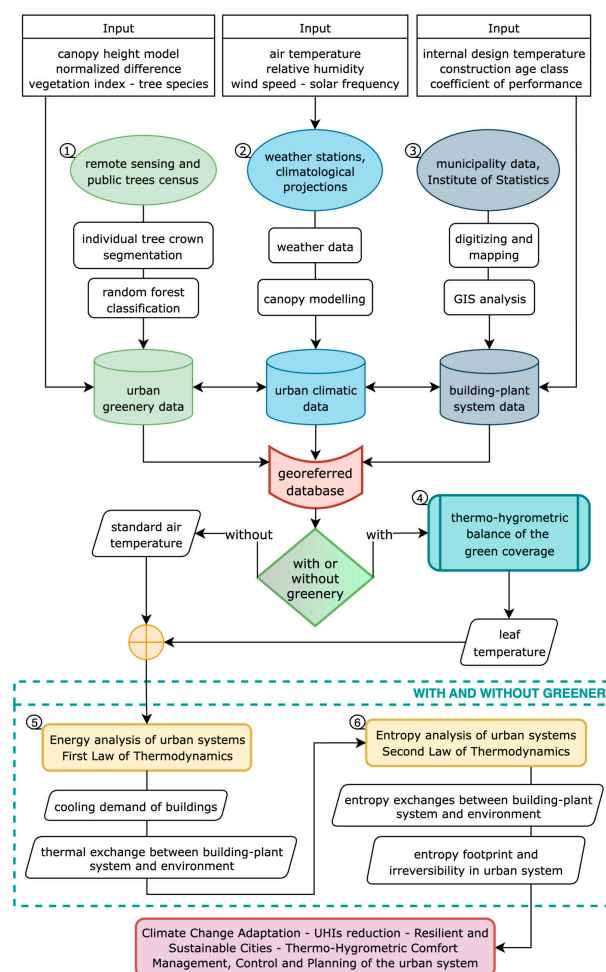


Figure 1. Flowchart of the process and method implementation.

2.1. Theoretical Framework

This study introduces a thermodynamics-informed entropy footprint method to quantify entropy exchanges in urban systems. The urban environment, conceptualized as an open thermodynamic system, is analyzed under two conditions—with and without greenery—through the application of the First and Second Laws of Thermodynamics. The energy balance is applied initially to buildings, and subsequently to the vegetation coverage, treating the leaf surface as continuous, homogeneous, and isotropic. This simplification enables the estimation of the leaf surface temperature and the resulting heat exchange with the environment—via latent and sensible heat—while neglecting physiological and soil interactions, i.e., disregarding the morphology, the physiological and water processes, of plant and leaves, with the soil and the atmosphere (point 4 of the flowchart in Figure 1).

The energy balance at steady-state conditions is described by governing equations applied to the composed system vegetation-air-building. The Second Law of Thermodynamics allows us to compute entropy variations resulting from the building's heat exchange and solar energy gains, as shown in the flowchart (branches 5–6 of Figure 1). Energy balance at the leaf surface is based on the method proposed in [48], which combine contributions of solar radiation, infrared emission, convection and evapotranspiration:

$$GHI \cdot \alpha_l = \varepsilon_l \cdot \sigma \cdot (T_l + 273)^4 + k_1 \left(\frac{v_w}{D_l} \right)^{0.5} (T_l - T_a) + L_l \left(\frac{\rho_{vl} - RH_a \rho_{va}}{r_l + k_2 \frac{D_l^{0.3} W_l^{0.2}}{v_w^{0.5}}} \right) \quad (1)$$

GHI is the global horizontal solar radiation on a specific site [W/m^2], T_l and T_a are, respectively, the surface temperature of the leaves and the ambient temperature [$^{\circ}\text{C}$]; v_w is the wind velocity [m/s] and RH_a is the relative humidity of the air [-]. σ is the Stefan-Boltzmann constant [$5.67 \times 10^{-8} \text{ W}/\text{m}^2 \text{ K}^4$]. Parameters such as absorption coefficient α_l [-], emissivity ε_l [-] and evaporation resistance of leaves r_l [s/m], latent heat of vaporization L_l [kg/m^3], vapor density at the surface leaves' temperature (ρ_{vl}) and at the ambient temperature (ρ_{va}) [kg/m^3], the characteristic dimension of leaves, in the direction transverse (W_l) and parallel (D_l) [m] to the wind, and empirical coefficients k_1 [$\text{J m}^{-2} \text{ s}^{-1/2} ^{\circ}\text{C}^{-1}$] and k_2 [$\text{s}^{1/2} \text{ m}^{-1}$] are taken from the literature experimental evidence [48].

Starting from the knowledge of the leaves' surface temperature, the green coverage is considered as an infinitely extended flat surface neglecting its thickness.

Therefore, the simplified energy balance in absence and presence of green coverage is expressed by the following equations (from Equations (2)–(5)). In particular, in Equations (2) and (3), the quantity of heat released into the air under the green coverage is considered. In Equations (4) and (5), the same quantity is described without greenery.

In the absence of green cover:

$$\alpha_a GHI + h_g (T_g - T_{a-g}) + \varepsilon_{effective} \sigma (T_g^4 - T_{a-g}^4) - mc_p (T_{a-g} - T_a) = 0 \quad (2)$$

$$(1 - \alpha_a) \alpha_g GHI - h_g (T_g - T_{a-g}) - \varepsilon_{effective} \sigma (T_g^4 - T_{a-g}^4) = 0 \quad (3)$$

In the presence of the green coverage:

$$\varepsilon_{effective} \sigma (T_l^4 - T_{a-g}^4) - h_g (T_{a-g} - T_g) + h_l (T_l - T_{a-g}) - mc_p (T_{a-g} - T_a) = 0 \quad (4)$$

$$\varepsilon_{effective} \sigma (T_l^4 - T_g^4) + h_s (T_{a-g} - T_g) + \varepsilon_{effective} \sigma (T_{a-g} - T_g) = 0 \quad (5)$$

with

$$m = v_w \rho_a \quad (6)$$

The meaning of the physical parameters used is α_a air adsorption coefficient, assumed 0.2 [48] in the visible range, while in the infrared wavelength range is taken equal to the emissivity ε_a 0.9; h_s is the heat transfer coefficient by convection between the ground and the air above [$\text{W}/\text{m}^2 \text{ } ^\circ\text{C}$] (calculated through dimensionless numbers and their connected empirical correlations); T_g is the ground surface temperature [$^\circ\text{C}$]; T_{a-g} is the air temperature above the ground [$^\circ\text{C}$]; $\varepsilon_{effective}$ is the effective emissivity between two bodies/surfaces as a function of the emissivity of each: $\varepsilon_{effective} = \left(\frac{1}{\varepsilon_1} + \frac{1}{\varepsilon_2} - 1 \right)^{-1}$ (e.g., for radiative heat exchange between the ground and the air above it, ε_1 and ε_2 are referred to them; $\varepsilon_{effective}$ is different for each term); m is the air flow rate on the considered surface as a function of wind velocity [$\text{kg}/\text{s m}^2$]; ρ_a is the air density at ambient temperature [kg/m^3]; T_a is the air temperature according to climate data [$^\circ\text{C}$]; α_g is the ground adsorption coefficient [-] (e.g., 0.85 for asphalt, and the same value is used for emissivity ε_g [48]); and T_l is the leaves' surface temperature [$^\circ\text{C}$] from Equation (1); h_l is the heat transfer coefficient by convection between the leaves and air below [$\text{W}/\text{m}^2\text{K}$] (for natural convection as a function of dimensionless numbers and connected correlations [49]).

The balances iteratively solved allow for determining the air temperature, affected by the presence of green cover, and the sunny ground without greenery, replacing, respectively, T_e and T_{e-G} of Equations (7) and (8). For this computation the overall average over summer hours of all the parameters must be considered. Due to the boundary conditions of central hours of some summer days, the leaf temperature can be lower than that one of the surrounding environment. Taking into account this phenomena, the outside air temperature values tend to decrease. The heat exchange of the building (branch 5 of the flowchart in Figure 1) in the absence (Q_b) and presence of greenery (Q_{b-G}), can be calculated as follows:

$$Q_b = U A_b (T_e - T_i) \quad (7)$$

$$Q_{b-G} = U A_b (T_{e-G} - T_i) \quad (8)$$

where T_e is the external air temperature without the green covering, T_{e-G} is the external air temperature with greenery and T_i the internal design temperature of the building (28°C) in compliance with [50,51], A_b is the total dispersing surface and U the overall heat exchange coefficient that depends on the type of construction and average age of each building provided in [52]. In particular, the overall heat transfer coefficient U is related to the type of construction and materials used, which depend on the building's age. It significantly affects the amount of heat exchanged between the building and environment, mutual radiative heat exchange, increasing the overall entropy.

Considering the most significant climatic condition, i.e., summer, the total heat transfer occurs from the external environment to the internal one of building. Assuming a seasonal coefficient of performance of 2.7 (SCOP) the heat released to the external environment via a cooling system can be calculated in the absence and presence of greenery (Equations (9) and (10)), from the First Law of Thermodynamics:

$$Q_{b_rel} = Q_b \frac{(1 + SCOP)}{SCOP} \quad (9)$$

$$Q_{b-G_rel} = Q_{b-G} \frac{(1 + SCOP)}{SCOP} \quad (10)$$

Referring to the Second Law of Thermodynamics (branch 6 of the flowchart in Figure 1), the entropy variation [J/K] of a building at real environmental conditions, in the absence and presence of greenery, can be calculated with the following equations:

$$\Delta S_b = Q_{b_rel} \left(\frac{1}{T_e} \right) \quad (11)$$

$$\Delta S_{b-G} = Q_{b-G_rel} \left(\frac{1}{T_{e-G}} \right) \quad (12)$$

with T_e and T_{e-G} in Kelvin.

Using temperatures T_e , T_{e-G} , and Q_{Sun} (i.e., horizontal global solar radiation), A_{urban} is the total surface and α_m the mean absorption coefficient of the urban area (the latter is usually 0.6); the Sun entropy that naturally exists can be assessed by Equations (13) and (14):

$$\Delta S_{Sun, e} = \alpha_m A_{urban} \left(\frac{Q_{Sun}}{T_e} \right) \quad (13)$$

$$\Delta S_{Sun, e-G} = \alpha_m A_{urban} \left(\frac{Q_{Sun}}{T_{e-G}} \right) \quad (14)$$

Applying the Second Law of Thermodynamics, two entropy footprints (hereinafter referred to ef and ef^*) can be calculated. ef and ef^* are, respectively, the entropy weight of the urban built-up area in the absence and presence of greenery. They are expressed by the ratio between the entropy variation in buildings and the entropy variation due to the solar energy gain of the area. They provide a measure of the irreversibility produced in the environment and are calculated as follows:

$$ef = \frac{\Delta S_b}{\Delta S_{Sun, e}} \quad (15)$$

$$ef^* = \frac{\Delta S_{b-G}}{\Delta S_{Sun, e-G}} \quad (16)$$

Finally, a new irreversibility indicator can be defined by the ratio between ef and ef^* . This ratio expresses the building's entropy contribution when greenery is present compared to that generated in the absence of greenery.

2.2. Modeling Approach, Data Sources, and Pre-Processing

The proposed method, applied to a real urban area (Florence, Italy), is structured and follows the flowchart provided in Figure 1. The thermo-hygrometric modeling incorporates microclimatic influences and vegetation contributions inside the Urban Canopy Layer (UCL)—defined as the volume between the ground and the top of buildings and vegetation [53].

This region, where urban climate dynamics directly affect human comfort and energy demands [54], is characterized through high-resolution climate modeling and vegetation assessment. The modeling process includes remote sensing, meteorological data, and GIS-based building classification. Our research focuses on UCL-UHI because it is commonly characterized by field measurements and is the zone where thermal-hygrometric comfort, environmental quality, and people well-being are assessed [54]. Climatic inputs are derived from historical records and future projections using regional climate models. The climate change scenarios are based on the Very High-Resolution PROjections for Italy (VHR_PRO_IT) under RCP4.5 and RCP8.5 pathways [55,56]. These models provide hourly data at 2.2 km resolution for five datasets: historical (1981–2005), near-term, and long-term projections under both RCP4.5 and RCP8.5 forcing scenarios (Appendix A.1.). Starting from

the modeling of past and future climate scenarios, five datasets are obtained: (i) historical years 1981–2005, (ii) RCP4.5 years 2006–2038, (iii) RCP4.5 years 2039–2070, (iv) RCP8.5 years 2006–2038, and (v) RCP8.5 years 2039–2070.

Each dataset includes air temperature, humidity, wind speed, and solar radiation that are collected with hourly frequency, for the entire time span over which they are defined. To apply entropy balances, a typical weather year (TWY) is generated for each dataset, condensing 30-year data into an annual sequence while maintaining representativeness (Appendix A.2). Details on climatological modeling and climate change scenarios construction are provided in Appendix A.1.

The characterization of greenery can be carried out by a dedicated modeling (branch 1 of the flowchart in Figure 1). Green cover surfaces and structural characteristics of urban vegetation (e.g., different species, total height, and diameter at breast height) can be collected either through the public tree census (which provides information on trees located in public areas) or by using optical and LiDAR remote sensing data, when census information is not available. This is the case of private green areas (i.e., private gardens), which still play a pivotal role in the total share of urban green surfaces. Moreover, each plant, with all its properties for specific species, can easily be referenced and connected to the urban area with GIS techniques.

In particular, to characterize green surface and tree species, the individual tree crown segmentation algorithm (ITC), based on the Canopy Height Model (CHM) have to be applied, using a variable moving window size [57]: treetops of trees in the upper canopy strata are identified through the local maxima algorithm [58] with a variable window filter [59]. The moving window [60] is used to scan the CHM so that any cell found to be the highest within the window can be classified as a treetop. The Marker-Controlled Watershed Segmentation algorithm [61] is then applied to delineate urban tree canopies.

In particular, the ITC algorithm allows for the quantification of the (i) number of urban trees (also including those not covered by the public tree census), and (ii) their canopy extent. Using available in situ data, or from Green-Trees Census and Municipal Green Plans, it is possible to classify each ITC-based canopy into broadleaved/conifer with very high-resolution imagery, by means of the application of machine learning models (e.g., Random Forest [62]).

The model's accuracy have to be assessed using out-of-bag (OOB) samples [63,64], which consist of data points that are not included in the bootstrap sample used to train a given tree [65]. These samples are used as a validation set for each decision tree in the Random Forest [66]. The OOB error is computed by aggregating the predictions made by each tree on its respective OOB samples. This procedure is usually applied for model's performance evaluation, without requiring a separate validation set, and provides the accuracy assessment [62].

Practical application to any area, as that one studied, allows the characterization of the existing vegetation and identification of basic species-specific parameters (e.g., the emissivity coefficient in the infrared and the evaporation resistance and/or vapor permeability of leaves). Usually, these parameters are obtained through direct measurement [67] or derived from dedicated studies carried out under local conditions [68]. For example, Tiralla et al. [69] collected information on ϵ for many different trees, shrubs, and herbaceous species, along with their standard deviation. Similarly, Mashabatu et al. [68] provided some useful information about the mean specific leaf resistance of five fruit tree orchard species. In Section 2.3, the above modeling method implementation is explained and adapted for the specific greenery of the urban area studied.

2.3. The Case Study: Typical Built-Up Urban Area of Florence

An urban area of the city of Florence (Figure 2), of Tuscany region (Italy), is the case study. The studied urban area belongs to the Municipal Environmental Energy Plan (PEAC) [70] (branch 3 of the flowchart in Figure 1). This built-up urban area is a representative of the city's urban development and includes buildings of different uses and construction periods (age classes of buildings) (Figure 2, in blue). In this area asphalt and green surfaces are present (Figure 2, in green).

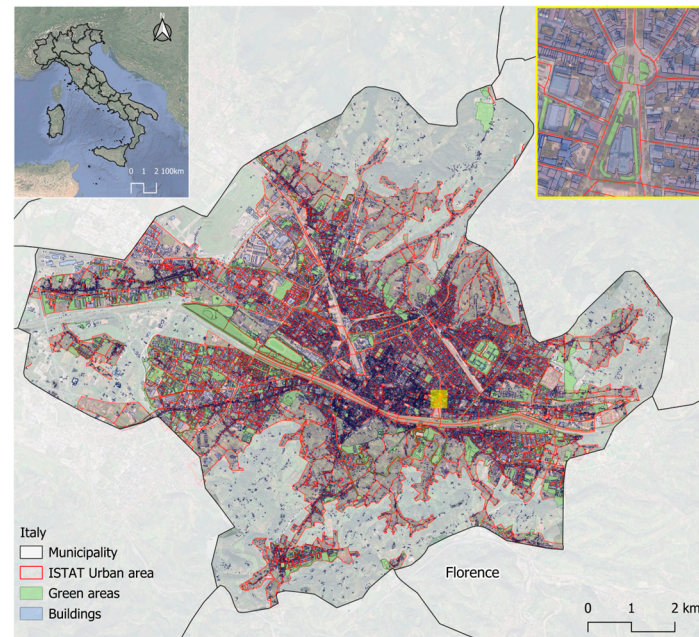


Figure 2. The area studied according to the boundaries defined by ISTAT for the urban area (in red). Green areas (in green) and buildings (in blue) refer to the Florence Municipality (in black).

The limits of this area were identified using the spatial boundary provided by the Italian National Institute of Statistics for the year 2011 [71], which includes the densely inhabited areas near recognized aggregation centers, i.e., squares and public complexes (Figure 2, in red). For this reason, the peripheral areas and those with low interaction between green system and built-up zones were excluded. All the necessary environmental parameters are derived from available databases/open-sources and census data from 2011 [71]. Georeferenced building data (i.e., three-dimensional geometry of buildings and their house number and construction age class, thermo-physical features, volume, height, base area, type of plant system, number of occupants, intended use, etc.) were extracted from PEAC [70,72]. By means of database interfacing and necessary information extraction, many useful data were derived from Tuscany Region GEOscopio (<https://www.regione.toscana.it/-/geoscopio> (accessed on 12 August 2025)) with QGIS software (version 3.40.1-Bratislava) post-processing [73].

The Florence Municipality covers 102.4 km², with a population of 352,622 in the urban area; the urban area case study is 6464 hectares (A_{urban}), with 115,000 buildings corresponding to 192 million m² total dispersing surface (A_b). The global heat exchange coefficient U [W/m² K] for all these buildings has an average value of 2.1 W/m²K. The intended use of most buildings is “residential”; then follows “services” and “commercial”.

The total dispersing surface of each building is connected with the global heat exchange coefficient as a function of the construction age class of each building, which takes into account the thermo-physical characteristics of the building envelope, as reported in

the PEAC database [70,72]. Table 1 shows the value of the global heat exchange coefficient deduced from PEAC.

Table 1. Global heat exchange coefficient by building construction age class [$\text{W}/\text{m}^2\text{K}$].

Age Class	<1940	1940–1970	1971–1980	>1980
U [$\text{W}/\text{m}^2\text{K}$]	2.4	1.9	1.8	1.2

For green areas computation (branch 1 of the flowchart in Figure 1), the ITC algorithm was applied on the specific CHM, provided by the Florence Municipality for the year 2023, with 0.5 m spatial resolution. Two thresholds were applied at resulting segmentation for filtering out the non-tree features. Selecting trees, with heights between 3 and 35 m, the mean Normalized Difference Vegetation Index (NDVI) was calculated for each identified tree crown (based on Sentinel-2 data composite for May–July 2023) using a minimum NDVI threshold of 0.5 [74]. Therefore, 273,528 trees, of public and private zones, were identified, for 9,858,840 m^2 total canopy cover, that is 15% of the total selected urban area.

This resulting total surface is used as the whole leaf-surface coverage (in Equation (1)) that is a square, with 3140 m side length, replacing the values for both the parameters D and W in Equation (1).

The specific trees classification was carried out: segmented tree crowns intersection with tree census points from the city of Florence, which provided a subset of 43,469 tree crowns for coniferous or broadleaf; five percentiles computation (10th, 30th, 50th, 70th, and 90th) based on four predictors and for each identified crowns [75] (i.e., the CHM and three bands from a high-resolution Florentine orthophoto; 0.2 m, for year 2023). Then, 20 predictors available for each tree crown were computed. Random Forest (RF) model [62] allowed for predicting tree species class (coniferous or broadleaf) using the above 20 predictors as input features. The Google Earth Engine RF classifier was exploited, setting the number of decision trees to 300. Modeling performance was evaluated by the OOB aggregating predictions and comparing reference data, and then constructing a confusion matrix. Due to the unbalance inside the dataset (i.e., 6269 coniferous trees vs. 37,200 broadleaves), the RF classification model performance was assessed by the Matthews Correlation Coefficient (MCC) [76,77] based on the confusion matrix. In detail, the MCC is a correlation measure between categorical predictions and observations: it equals 1 for perfect predictions, 0 for random agreement, and -1 when predictions and observations are entirely mismatched. The trained model was applied to the 273,528 tree crowns remaining, using the 20 predictors to classify all of them into coniferous and/or broadleaves, with a 0.83 MCC value. This classification provided a subset of 43,469 tree crowns (coniferous or broadleaf) according to the municipality's tree census.

Therefore, for the present study, the overall canopy coverage turned out 760,191 m^2 conifers and 9,098,648 m^2 broadleaves. Their mean emissivity values (inside the 8–14 μm interval) were derived from [78]: the emissivity was 0.982 ± 0.009 for conifers and 0.985 ± 0.010 for broadleaves; 0.985 emissivity mean value, weighted by the covering surface. Fundamental literature evidence [79] was used for the evaporation resistance of the oak leaves (i.e., 2000 s/m) that was applied to conifers and broadleaves trees. The used values of vapor diffusivity, despite not directly available for conifer species, and absorption coefficient of solar radiation 0.8, refer to [48].

Using to the aforementioned greenery parameters, and to the TWYs for each dataset, all the balances of Equations (1)–(5) were carried out for summer periods, i.e., from 01/04 to 31/10.

From the available hourly data, the hot hours (HHs) were selected, matching the following boundary conditions:

$$GHI > 200 \frac{W}{m^2} \quad 0.1 \frac{m}{s} < v_w < 10.7 \frac{m}{s} \quad T_a > 28 \text{ } ^\circ\text{C}$$

Those constraints identify the set of hot hour measurements, such that all the balances have physical meaning. The conditions on the solar radiation GHI and the exclusion of small values of v_w ensure thermodynamic balance validity [56]. Extreme wind conditions are avoided, taking into account the Beaufort wind force scale, i.e., an empirical scale that relates wind velocity to observed conditions at sea or on land: for the upper bound chosen, the scale indicates a condition of fresh breeze, characterized by the presence of wind that begins to move the large branches, but not the entire structure of the tree [79].

Filtering the summer data with the above boundary conditions, all the balances are solved for the two configurations (i.e., green presence and absence) in order to determine the hourly values of leaf temperature T_l , air volume temperature T_{a-g} , and ground temperature T_g . The average values of the external temperature with green coverage are

$$T_{e-G} = \langle T_{a-g}^{withG} \rangle_{HH}$$

and without green coverage

$$T_e = \langle T_{a-g}^{withoutG} \rangle_{HH}$$

where the $\langle \rangle_{HH}$ represents the average over the selected hours (HH).

The mean values are used to solve Equations (7)–(14) and calculate the entropy footprint of Equations (15) and (16). The average value of GHI over the HH subset was used for the solar radiation Q_{Sun} in Equations (13) and (14).

3. Results

All the balances of Section 2 are solved under the hypothesis and boundary conditions extensively described above, obtaining the main following results: hourly summer temperature for the leaf coverage T_l ; bottom mean air temperature T_{e-G} , i.e., between the leaf coverage and ground; mean air temperature above the ground without leaf coverage, T_e ; cooling energy need of buildings in the presence and absence of greenery, respectively (Q_{b-G} and Q_b); heat released to the external environment, in the presence and absence of greenery ($Q_{b-G,rel}$ and $Q_{b,rel}$); entropy increase, in the presence and absence of greenery, i.e., ΔS_{b-G} and ΔS_b ; entropy footprints ef and ef^* , due to the aforementioned thermodynamic process; and entropy increases due to the Sun radiation hitting the ground $\Delta S_{Sun, e-G}$ and $\Delta S_{Sun, e}$.

In particular, a preliminary global sensitivity analysis was carried out, in order to evaluate how much greenery properties (i.e., emissivity, vapor resistance, and absorption coefficients) impact the balances and affect results. This sensitivity analysis showed a variation in leaf temperature of no more than one hundredth of a degree, and therefore, an absolute error lower than 2%, also showing the method robustness and its applicability to different contexts. Therefore, in the ranges of all the possible values for parameters, the leaf temperature variation obtained is negligible compared to the contribution of the parameters related to the boundary conditions (solar radiation, wind velocity, relative humidity).

Table 2 shows the main parameters for the five investigated scenarios, referring to [80]: Standard TWY, Historical TWY, “RCP4.5 years 2006–2038” TWY, “RCP4.5 years 2039–2070” TWY, “RCP8.5 years 2006–2038” TWY, and “RCP8.5 years 2039–2070” TWY.

Table 2. Studied area results: main temperatures and entropy footprints with and without greenery.

	Standard TWY	Historical TWY	RCP4.5 2006–2038 TWY	RCP4.5 2039–2070 TWY	RCP8.5 2006–2038 TWY	RCP8.5 2039–2070 TWY
T_i [°C]			28.0			
A_{urban} [m ²]			64,645,324			
A_b [m ²]			192,582,468			
U [W/m ² K]			2.1			
T_e [°C]	31.8	32.5	33.0	33.1	32.7	33.8
$T_e - G$ [°C]	31.3	32.1	32.5	32.7	32.3	33.4
GHI [W/m ²]	641.3	610.6	606.4	589.6	597.0	581.3
Q_b [MWh]	1540	1831	2016	2085	1897	2337
$Q_b - G$ [MWh]	1347	1670	1844	1921	1731	2174
Q_{b_rel} [MWh]	2110	2509	2763	2857	2600	3202
$Q_b - G_{rel}$ [MWh]	1846	2289	2527	2633	2372	2979
$\Delta S_{Sun, e}$ [MJ/K]	293,658	278,941	276,589	268,791	272,575	264,473
$\Delta S_{Sun, e - G}$ [MJ/K]	294,117	279,303	276,973	269,146	272,942	264,819
ΔS_b [MJ/K]	24,925	29,566	32,510	33,597	30,620	35,578
$\Delta S_b - G$ [MJ/K]	21,836	27,008	29,777	31,001	27,967	35,006
ef [%]	8.5%	8.5%	9.7%	10.4%	9.1%	12.1%
ef^* [%]	7.4%	7.6%	8.7%	9.4%	8.1%	11.1%
ef/ef^* [%]	87.5%	89.1%	89.6%	90.6%	89.2%	91.8%

It must be noticed that the entropy footprints are already updated according to the weighted correction b found in Equation (A2), that is -0.021 . The calibration effect is provided by Figure 3 (top graph): entropy footprints for the different datasets, highlighting the distance between the entropy footprints value calculated in respect to the same period (1981–2005) but with different sources (Standard TWY vs. Historical TWY).

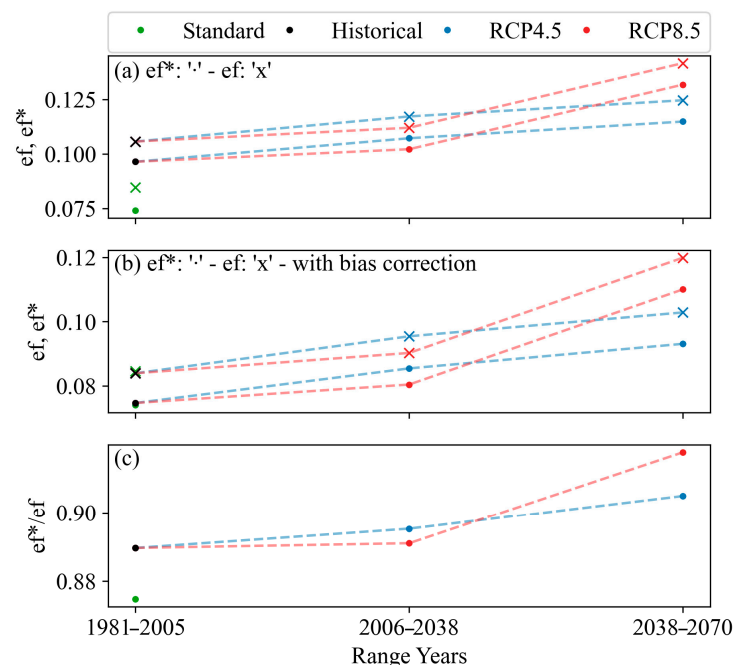


Figure 3. Entropy footprints [–] (a) without and (b) with bias correction. (c) Ratio between the entropy footprints for all the climatological datasets with bias correction. Standard refers to the dataset obtained from measured data from fixed station, while Historical refers to the dataset obtained from the historical model, and temporally overlapped to the Standard dataset. RCP4.5 and RCP8.5 indicate the two different projections considered for the impact analysis on future states (extensively explained in the text and appendixes).

After calibration, the entropy footprints value is shown in Figure 3 (center graph) that also provides results for the dataset of years 1981–2005, varied by 0.2% at maximum.

Comparing ef^* with ef , and considering their ratio, a drop in the entropy production can be found, due to the green coverage presence. All this acts by modifying the environmental constraints of temperature (only the humidity changes are considered in Equation (1) for leaf temperature calculation) creating cooler boundary conditions for the building plants, which can operate with a reduced external thermal load during summer.

For all the scenarios, the entropy decreases by almost 1% in respect to the contribution of the Sun radiation hitting the ground. The low value is due to that reference at the denominator, which is relatively high.

Using the percentage between the values of each entropy footprint (i.e., ef and ef^*), due to the green coverage, the entropy footprint is 9.2–12.5% depending on the considered scenario, but with lower changes resulting in the projections at different scales (Table 2). These trends are provided in Figure 3 and in the bar graph in Figure 4, with a more direct and easier way to understand and compare.

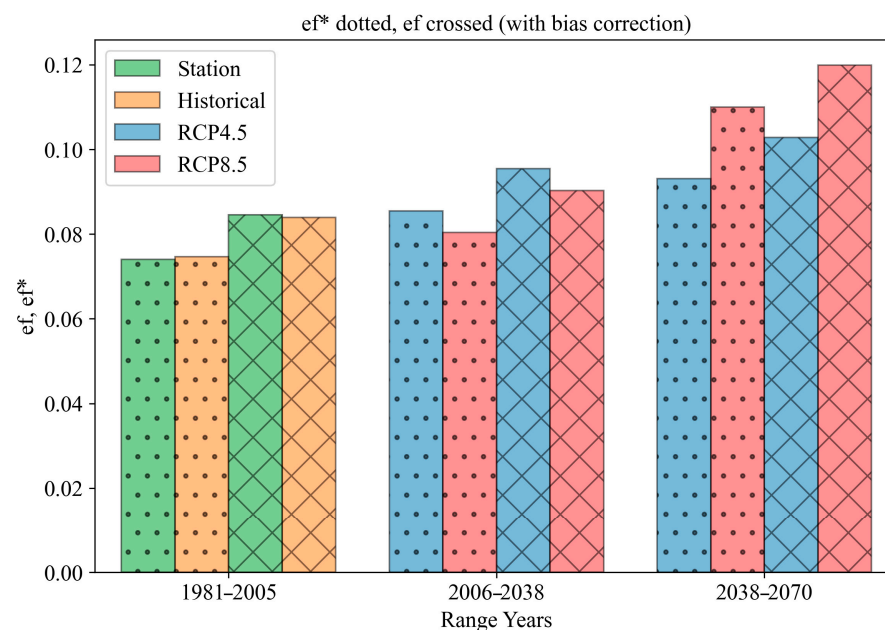


Figure 4. Bar graph of the entropy footprint [–] grouped by data range. ef^* is marked with dots in bars, while ef is marked with crosses. Each color indicates a different dataset: green for the Station dataset, orange for the Historical dataset, and blue and red for the two projections considered in the study, RCP4.5 and RCP8.5, respectively. To clarify the interpretation of the different impact of the greenery's contribution, under different Anthropocene forcings for the near and long-term, the two datasets obtained from the projections considered are shown with the same color.

It is important to note that differences between the values of the entropy footprints are small, but statistically significant and important. As a matter of fact, the entropy footprints are close to 10% because they refer to thermal energy coming from the Sun, which, precisely because it exists naturally, can be taken as a basic reference. This is relatively greater than the contribution that buildings and their plant-systems can provide. For this reason, a slight variation (at most 4.3%) in the entropy footprints can be noted.

On the other hand, Table 2 shows the absolute values of the entropy produced, which, for the cases examined alone, reaches the order of magnitude of 10^5 MJ/K. The difference between the scenarios with and without greenery is 3000 MJ/K for a standard TWY. This means that, if the study is extended to the whole urban area, the impact becomes

physically and statistically appreciable, confirming the importance of the presence of greenery, especially for those scenarios with more critical conditions.

The effectiveness of the greenery presence is more evident if the absolute value of the difference in entropy released in the environment by the built-up urban area with or without is considered.

In Table 3 the ambient temperature T_a that corresponds to the maximum temperature of each dataset is reported: these values were used to evaluate the entropy difference.

Table 3. Maximum temperature [°C] for each dataset.

Standard	Historical	RCP4.5 2006–2038	RCP4.5 2039–2070	RCP8.5 2006–2038	RCP8.5 2039–2070
36.8	40.0	42.9	41.9	43.3	43.7

ΔS , shown in Figure 5.

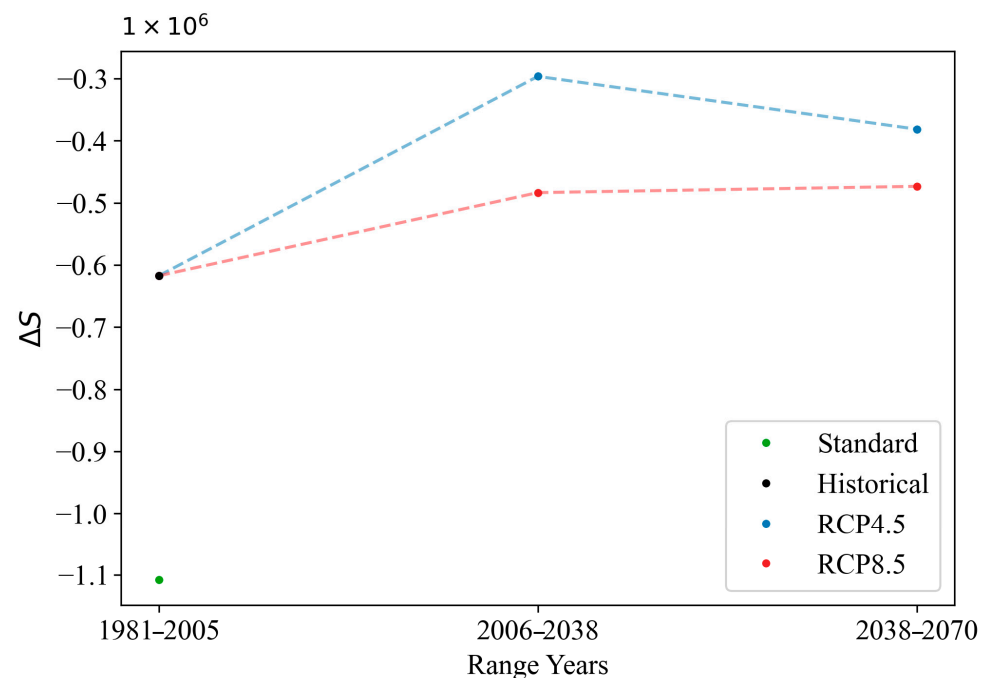


Figure 5. Entropy difference [MJ/kg] calculated for different periods and scenarios and for the hottest day.

As a matter of fact, for RCP4.5 there is a smaller increase in the maximum temperature compared to the RCP8.5 scenario, with a lower overheating effect of the buildings, a greater cooling effect by the plants and therefore a lower energy consumption of the heat pump system (HP) for cooling.

4. Discussion

This study proposes a useful tool, based on the physics of real systems, matching thermodynamics (of First and Second Law) with advanced modeling techniques for evaluating green systems effectiveness to counteract climate change and reduce the entropy of the urban built-up system, ensuring responsive resilience cities. The method can be applied at different urban scales.

The study offers crucial indicators based on thermodynamics, i.e., the entropy footprints, which can be used for quantifying sustainability in urban areas, supporting the

decision-making policies of local governments and public administrations for urban and energy planning oriented to sustainability and green energy transition.

Comparing the entropy footprint values of different zones of any urban built-up area, effective interventions can be directly oriented to entropy flows reduction in building–plant systems, in the presence and absence of greenery, referring to dynamic climate change scenarios. The entropy analysis of the urban area allows for energy–environmental sustainability evaluation, in terms of the low environmental impact, energy quality, and durability.

By the method application, quantification of energy–environmental benefits due to entropy flows reduction that effectively counteracts of climate change effects can be assessed: it allows a general but significant evaluation of the lower impact due to air conditioning systems when buildings are immersed in greenery (see Figure 4).

From this perspective, the methodological approach, based on entropy footprint, is innovative because, using the Second Law of Thermodynamics, allows the quantification of greenery presence effects on any urban system by a simplified and easy-to-implement approach without the need for large amounts of measured/detected data or obtained from the literature evidence and/or specific data sources. It is robust–rigorous, as it is validated and confirmed by the important relevant literature evidence that by means of energy analyses application to urban systems (i.e., First Law of Thermodynamics) show the real cooling demand reduction in buildings due to greenery presence (e.g., NBS integration, green roofs and green walls), remote sensing data on surface temperature drops, and measured air temperature differences between green and non-green areas in urban systems [54,81–89].

The innovative contribution of the method also lies in the fact that, through the quantification of the entropy footprints (ef and ef^*) and the indicator obtained from their ratio, a homogeneous scale, of physical significance, can be built, identifying the most critical and vulnerable areas on which to intervene as a priority. This allows us to use and apply a physical-entropy-informed criterion for controlling and planning interventions over time. As a matter of fact, results comparison (Table 2) shows that the contribution due to the greenery decreases for different scenarios referred to the different climatological dataset, but at the same time the increase in entropy becomes higher for the scenario with higher emissions (RCP8.5).

However, it must be considered that the proposed method is simplified because all the thermal properties of building materials are unified in the global heat exchange coefficient that is linked to the age class. Moreover, the present study aims at urban-level analyses rather than at the performance/design of building–plant systems and indoor scenarios assessment. In line with the two Laws of Thermodynamics, building energy balances for summer period, consider the temperature levels at which heat exchanges occur. Furthermore, any increase in greenery or energy efficiency interventions and NBS integration on buildings would certainly lead to a lowering of the ambient temperature together with a reduced energy consumption by the cooling systems. The latter, thanks to the energy efficiency of buildings, would entail significant improvements in environmental impacts decrease, i.e., the entropy production reduction (Table 3).

Another limitation/simplification of the method is due to a basic general evaluation of the overall heat exchange of buildings with the external environment as a function of their overall heat exchange coefficient and volume (disregarding their mass and thermal inertia and heat capacity of specific building materials, linked to the accumulation of heat due to solar radiation). This latter choice is motivated by the fact that most available databases and the literature do not provide specific information on the construction and thermo-physical characteristics of buildings.

However, the method proposed can be directly applied by public administrations, all stakeholders, and local governments in the perspective of planning the energy green and sustainability transition for livable and comfortable urban areas and resilient cities.

These aspects are also supported by the recent literature results [90] that show how at least three quarters of the current carbon storage of urban trees in Central and Southern Europe will be seriously threatened by 2070.

With adequate and available data, the entropy footprint evaluation can provide useful quantification of sustainability due to the current conditions of any urban area and effective analyses of different strategies to combat climate change, UHIs, and anthropogenic effects in cities, in the short and long term, considering that conversion of impervious surfaces into green areas has high costs and requires time [91].

In the sustainability, resilience, and transition perspectives, the method implementation could be used as predictive tool. Indeed, it provides a physical-entropy-informed support for practical applications at large scales, focused on selection of suitable species for NBS and integrated green systems, maintenance of urban functional diversity, and permeability [92,93].

More in general, results comparison, obtained at small scale, show that further applications of the method can be for the management, design, and implementation of energy and environmentally sustainable projects, considering the entropy footprints based on the necessary operating times in relation to the developments of climate change effects over the years.

Future research directions will concern the method's application to different urban realities, both in terms of complexity and infrastructures and the presence of different green areas and water surfaces (e.g., fountains, rivers, lakes, etc.) for different climatic contexts. A further interesting development of the research will concern the study of entropy footprint at regional level, in the local context, but also at a wider national level.

Starting from the entropy footprints connected to the different development of green areas, intensive vegetation and strong integration of NBS, and the choice of effective strategies in the medium to short term, the method foresees future developments, including its implementation at a large scale, and of an objective function to be minimized/maximized in relation to the decision-making policies and strategic environmental, energy, and proactive resilience choices of specific managerial groups and stakeholders (taking into account economic aspects).

In this perspective, the research will use AI and implement finalized machine learning techniques, especially oriented towards a detailed study of criticalities and vulnerability of the urban areas.

5. Conclusions

This study proposes an integrated method, simple and easy to implement, to quantify the energy–environmental sustainability of urban areas. The research links applied thermodynamics of Second Law to strategic modeling of biophysical thermo-hygrometric balances of leaf surfaces, high-resolution climate at urban scale, identification and characterization of plants for specific species and vegetation, and spatial georeferencing applied techniques for entropy exchanges evaluation within the urban context.

The focus, i.e., the entropy flow reduction and entropy impact of urban built-up areas assessment, with and without greenery, constitutes the innovative thermodynamic-entropy framework to quantify the benefits of urban greening.

The simple method proposed can thus be easily implemented for energy and entropy analyses on a small and large urban scale.

Given that most databases and the literature lack detailed thermo-physical data on buildings, but provide georeferenced and general attributes (e.g., age-based heat exchange coefficients, volume, surface area, height, system type, and use), the proposed simplified method relies on readily available information. It evaluates the energy and entropy balance of the built environment in relation to green space distribution, without accounting for detailed building-system thermo-physics. Thus, this method can be a crucial tool for energy planning and thermo-hygrometric comfort improvement in urban areas. It allows also programming activities of authorities, local municipal governments, disaster management authorities and the same citizens, to better understand the relationship between the potential for reducing anthropogenic impacts, the UHI mitigation, climate change adaptation, housing factors and urban areas development, urban forestry, and NBS and/or green systems integration. The method can be easily applied for quantifying proactive resilience and sustainability transition, as it provides a homogeneous scale of entropy footprints, i.e., irreversibility, as a measure of sustainability, and a rational criterion for comparing and integrating these evaluations. While not suited for deterministic modeling, this approach might serve as a decision-support tool for evaluating ex-ante and ex-post urban energy strategies, including energy savings, renewable integration, and nature-based solutions, through entropy-based assessment (with entropy footprints) of adaptive sustainability and resilience.

Nevertheless, basic limitations of the method concern its effectiveness and applicability, especially when moving from small scale to large scale (i.e., from single building to group of buildings, block and whole urban area, from city to regional scale). Its reliability depends on the availability, quality, and quantity of information and usable data (e.g., climate and local weather conditions, buildings' features and their air conditioning systems, greenery).

Despite the method, by means of the entropy footprints assessment, which can provide a rational criterion to compare complex innovative and sustainable technology solutions, capable of leading to important irreversibility reduction and energy efficiency increase, its application to different urban areas and then to larger scale of analysis (e.g., regional and national scale) can show possible implementation downsides mainly due to the reliability and typology of necessary data.

Author Contributions: C.B. (Carla Balocco); Writing, review and editing, Supervision, Funding acquisition, Conceptualization, Methodology, Investigation, G.P.; Writing, Methodology, Investigation, Validation, Software, Data curation, M.B.; Writing, Investigation, Validation, Software, Data curation, C.B. (Costanza Borghi); Writing, Investigation, Data curation, S.F.; Writing, Data curation, G.C.; Review and editing, S.M.; Review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the EU Project, LIFE Energy + LIFE Climate—Project 101157553-LIFE23-CCA-IT-LIFE ESCAPOS “Environmental energy for Strategic Capillary urban Policies”, funded by the European Union.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest and that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Nomenclature

A_b	dispersing surface of the buildings in the investigated area [m ²]
A_{urban}	urban area considered for the analysis [m ²]
b	correction factor for the entropy weights [-]
SCOP	mean coefficient of performance for heat pumps [-]
D_l	characteristic dimension of the leaves in the wind direction [m]
ef	entropy weight without the presence of the greenery [-]
ef^*	entropy weight with the presence of the greenery [-]
GHI	global horizontal irradiation on a specific site [W/m ²]
h_l	heat transfer coefficient by natural convection between leaves and the air below [W/m ² °C]
h_s	heat transfer coefficient of natural convection between ground and the air above [W/m ² °C]
k_1	empirical coefficient [J/m ² ·s ^{1/2} ·°C ¹]
k_2	empirical coefficient [s ^{1/2} ·m ¹]
L_l	latent heat of vaporization at the surface temperature of the leaves [J/kg]
m	air flow rate on the considered surface as a function of the wind velocity [kg/s m ²]
Q_b	cooling power for buildings in the summer period without the presence of greenery [W]
Q_{b-G}	cooling power for buildings in the summer period with the presence of greenery [W]
Q_{b_rel}	thermal power released to the environment without the presence of greenery [W]
Q_{b-G_rel}	thermal power released to the environment with the presence of greenery [W]
Q_{Sun}	total horizontal Sun radiation hitting the urban area in the summer period [W/m ²]
r_l	evaporation resistance of the leaves [s/m]
RH_a	relative humidity of the air [-]
T_a	ambient temperature [K]
T_{a-g}	air temperature above the ground [K]
T_e	external mean air temperature in the summer period without the presence of greenery [K]
T_{e-G}	external mean air temperature in the summer period with the presence of greenery [K]
T_g	temperature of the ground surface [K]
T_i	indoor temperature for the buildings in the summer period [K]
T_l	surface temperature of the leaves [K]
U	global heat exchange coefficient for the building (W/m ² K)
v_w	wind velocity [m/s]
W_l	characteristic dimension of the leaves in the direction transverse to the wind [m]

Geek symbols

α_a	adsorption coefficient of the air in the visible range [-]
α_g	adsorption coefficient of the ground across the entire spectrum [-]
α_l	absorption coefficient [-] for the leaves across the entire spectrum [-]
α_m	mean absorption coefficient [-] for the urban area across the entire spectrum [-]
ΔS_b	entropy generation due to the buildings without the presence of greenery [J/K]
ΔS_{b-G}	entropy generation due to the buildings with the presence of greenery [J/K]
$\Delta S_{Sun, e}$	entropy generation due to Sun radiation hitting the urban area without greenery [J/K]
$\Delta S_{Sun, e-G}$	entropy generation due to Sun radiation hitting the urban area with greenery [J/K]
ε_a	emissivity coefficient of the air in the infrared range [-]
$\varepsilon_{effective}$	emissivity between two bodies/surfaces as a function of the emissivity of each [-]
ε_g	emissivity coefficient for the ground in the infrared range [-]
ε_l	emissivity coefficient of leaves in the infrared range [-]
ρ_a	density of the air at ambient temperature [kg/m ³]
ρ_{va}	vapor density at the ambient temperature [kg/m ³]
ρ_{vl}	vapor density at the surface temperature of the leaves [kg/m ³]
σ	Stefan–Boltzmann constant [W/m ² K ⁴]

Appendix A

Appendix A.1

In the application of the present method, the VHR_PRO_IT tool is used, a climatological model with very high spatial and temporal resolution, obtained as a dynamic downscaling starting from an ensemble of climatological projections within the Med-CORDEX project (<http://cordex.org/domains/region-12-mediterranean/> (accessed on 15 August 2025)).

In order to quantify the different responses to the different strategies that can be implemented to counteract climate change, two different possible scenarios are considered and defined by the RCP. Those different scenarios, formally adopted by the IPCC, quantify different paths to describe future greenhouse gas concentrations. Over the years, several possible scenarios have been identified, represented by a reduction in greenhouse gas emissions, up to a continuous increase in the same. This translates into a different response to climate change, and the average values of greenhouse gas emissions correspond to a greater increase in the average surface temperature. These pathways are tabulated and based on the expected changes in the radiative forcing values. For this case study, we considered the RCP4.5 and RCP8.5 scenarios, therefore corresponding to an average increase in radiative forcing (4.5 W/m^2) and the most extreme condition (8.5 W/m^2), respectively. The first scenario foresees an increase in emissions that reaches its peak around 2040: that is the most likely a baseline, as it does not take into account strong containment policies at a global level, but only the exhaustible nature of fossil fuels. The RCP8.5 scenario, on the other hand, foresees a continuous increase in emissions throughout the 21st century. Although, since the publication of the IPCC Fifth Assessment Report [83] this hypothesis has been criticized for overestimating coal production, and considered an unreliable and unrealistic long-term scenario, it is still interesting for quantifying climatological trends in the near future (up to 2050) and the impact of the socio-political choices for recent years.

In particular, to evaluate the medium and long-term impact, the two scenarios, available for the years 2006–2070, are divided into two different datasets, namely between the years 2006–2038 and 2039–2070.

On the other hand, when the climate model outputs (e.g., temperature, precipitation) are compared in historical mode and real-word measurements from fixed weather stations, systematic discrepancies often arise. These differences, known as bias, occur due to imperfect parametrization, missing physical process, or limitations in model resolution. As a matter of fact, model data, which describe an average behavior over the area defined by the resolution of the model, generally fails to describe the hyperlocal nature of the atmospheric dynamic characteristics of the zone where the fixed station is located.

To quantify these differences, a data processing approach is applied in historical mode, aligning model outputs temporally with the records from weather stations. Although the model data used has a spatial resolution of 2.2 km, this method enables a direct comparison with the time-synchronized data aggregated in the standard TWY file.

This model data allows the quantification of different responses to the balance equations, in particular the estimated temperature above the ground, T_{a-g} . This step is crucial, because a bias in these temperatures is directly transmitted into the evaluation of the entropy footprints ef and ef^* which strictly depend on T_{a-g} . To address this bias and having projection results comparable to what is measured by the weather stations, a bias correction process to the values of ef and ef^* obtained in the TWY file from the model data, is implemented. This procedure is based on correcting the estimated entropy footprints by a value b that considers the differences in entropy footprints between the historical and

weather station datasets. The correction is performed by shifting the entropy footprints estimated from the model data by a factor b :

$$ef_{model} = ef_{model} + b \quad (A1a)$$

$$ef_{model}^* = ef_{model}^* + b \quad (A1b)$$

where the subscript model in the two equations indicates the different modes: historical, RCP4.5 and RCP8.5. The bias correction b was obtained as a weighted average between the differences in the entropy footprint in the presence and absence of green cover between the two temporal overlapping datasets, i.e.,

$$b = \frac{ef_{station} - ef_{historical}}{2} + \frac{ef_{station}^* - ef_{historical}^*}{2} \quad (A2)$$

Before applying the balances and quantifying the average entropic contributions in the different configurations (with green and without green), for each dataset, it was necessary to generate a specific TWY, so as to transform a dataset with an average duration of 30 years, into an annual dataset, but with the typical characteristics of the different years. A detailed description of the procedure used to generate the TWY is provided in Appendix A.2.

Appendix A.2

The typical weather year, i.e., the TWY weather data, is composed of 12 separate months of data, each chosen to be the most “typical” month from the total years of data. TMY data selection is carried out using the Sandia method [84] which is an empirical approach that selects individual months from different years of the period of record. Given a range of N_y data years, we analyze all the m -th months in the N_y years. For instance, suppose $m = 1$, January, all the N_y Januarys are examined and the one judged “most typical” is selected to be included in the TMY. The other months of the year are treated in a similar manner, and then the 12 selected typical months are concatenated to create a complete year. The typical month is selected based on nine daily indices consisting of the maximum, minimum, and mean dry bulb and dew point temperatures; the maximum and mean wind velocity; and the total global horizontal solar radiation. For each month of the calendar year, we select the year with cumulative distribution functions (CDFs) for the daily indices that are the closest to the long-term CDFs, computed considering all the m -th of all years in the dataset. The CDF gives the proportion of values that are less than or equal to a specified value of an index. Candidate monthly CDFs are compared to the long-term CDFs by using the following Finkelstein-Schafer (Δ) statistics for each index:

$$\Delta^{(j)} = \frac{1}{n} \sum_{i=1}^N \delta_i^{(j)} \quad (A3)$$

where $\delta_i^{(j)}$ is the absolute difference between the long-term CDF and the candidate month, n is the number of daily readings in a month and the index j runs over the different variables. Because some indices are judged more important than others, a weighted sum of the $\Delta^{(j)}$ statistics, obtained considering all the different variables, is used to select the candidate month that has the lowest weighted sums:

$$W = \sum_j w_j \cdot \Delta^{(j)} \quad (A4)$$

where w_j is the weighting factor, listed in Table A1.

A typical month is then selected by choosing the months of the year with the lowest w values, e.g., the one with the smallest deviation from the long-term CDF is applied.

Table A1. Weighting factors used to compute the weighted sum W .

Weather Index	w_j	Weather Index	w_j
Maximum dry bulb temperature	1/24	Mean dew bulb temperature	2/24
Minimum dry bulb temperature	1/24	Maximum wind velocity	2/24
Mean dry bulb temperature	2/24	Mean wind velocity	2/24
Maximum dew bulb temperature	1/24	Total horizontal solar radiation	11/24

In particular, the external air vapor content per unit kg of dry air (also known as absolute humidity) was calculated because it provides information on the air enthalpy variation in presence or in absence of greenery and the connected work of the air conditioning systems.

In Figure A1 the probability distribution of the absolute humidity of the air for the hot hours (HH) values in the different datasets, is shown.

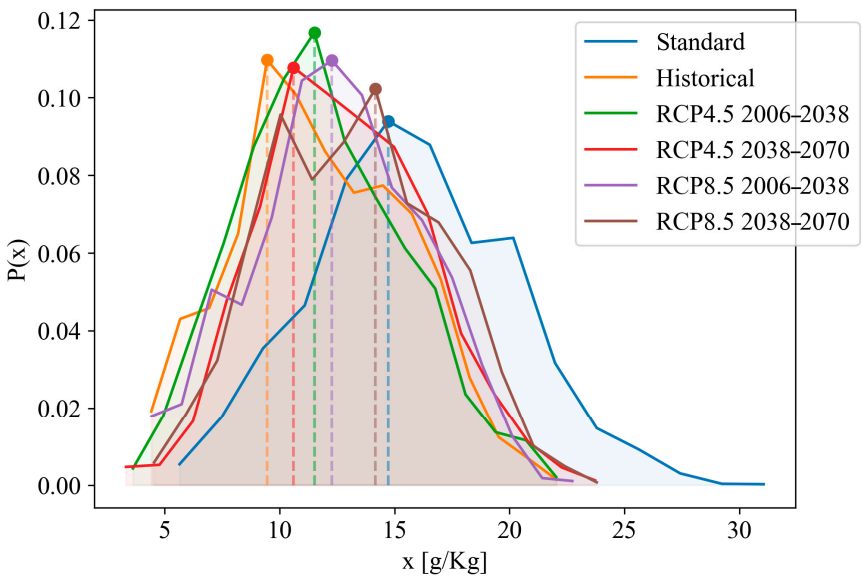


Figure A1. Probability distribution of the air absolute humidity for HH values in different datasets.

If the modes of the probability distributions (marked with a vertical dashed line in Figure A1) are compared, it is possible to notice the important trend of the absolute humidity distribution which has increasingly increasing values for the different models and over time.

References

1. Tamang, B. Global Climate Change: Challenges, Opportunities, and Multilateral Strategies for Sustainable Development. *NPRC J. Multidiscip. Res.* **2024**, *1*, 65–76. [\[CrossRef\]](#)

2. Afifa; Arshad, K.; Hussain, N.; Ashraf, M.H.; Saleem, M.Z. Air Pollution and Climate Change as Grand Challenges to Sustainability. *Sci. Total Environ.* **2024**, *928*, 172370. [\[CrossRef\]](#) [\[PubMed\]](#)

3. Malakar, K.D.; Kumar, M.; Anand, S.; Kuzur, G. Climate Crisis and Socio-Ecological Sustainability. In *Climate Change and Socio-Ecological Transformation*; Springer: Singapore, 2023; pp. 439–494.

4. Cornell, S.E.; Gupta, A. Is Climate Change the Most Important Challenge of Our Times? In *Contemporary Climate Change Debates*; Routledge: Oxfordshire, UK, 2019; pp. 6–20.

5. Meerab, K. Addressing the Global Environmental Crisis: A Comprehensive Review of Current Strategies and Challenges. *Int. Res. J. Arts Soc. Sci.* **2023**, *11*, 1–4. [\[CrossRef\]](#)

6. Francini, S.; Chirici, G.; Chiesi, L.; Costa, P.; Caldarelli, G.; Mancuso, S. Global Spatial Assessment of Potential for New Peri-Urban Forests to Combat Climate Change. *Nat. Cities* **2024**, *1*, 286–294. [\[CrossRef\]](#)

7. Gao, J.; O'Neill, B.C. Mapping Global Urban Land for the 21st Century with Data-Driven Simulations and Shared Socioeconomic Pathways. *Nat. Commun.* **2020**, *11*, 2302. [CrossRef] [PubMed]
8. IISD. International Day of Forests. Available online: <https://sdg.iisd.org/events/international-day-of-forests-2018/> (accessed on 12 August 2025).
9. Netto, V.M.; Meirelles, J.; Ribeiro, F.L. Cities and Entropy: Assessing Urban Sustainability. In *Sustainability Assessment of Urban Systems*; Cambridge University Press: Cambridge, UK, 2020; p. 438. Available online: <https://www.cambridge.org/core/books/abs/sustainability-assessment-of-urban-systems/cities-and-entropy-assessing-urban-sustainability-as-a-problem-of-coordination/83D93195E53A8B8579E974CEF9AEEB81#chapter> (accessed on 12 August 2025).
10. Purvis, B.; Mao, Y.; Robinson, D. Entropy and Its Application to Urban Systems. *Entropy* **2019**, *21*, 56. [CrossRef]
11. Schneider, E.D.; Kay, J.J. Life as a Manifestation of the Second Law of Thermodynamics. *Math. Comput. Model.* **1994**, *19*, 25–48. [CrossRef]
12. Roach, T.N.F. Use and Abuse of Entropy in Biology: A Case for Caliber. *Entropy* **2020**, *22*, 1335. [CrossRef]
13. Zhao, S.; Ren, Y.; Mao, C.; Yue, A. Are Cities Healthy? A City Health Diagnose Framework from the Perspective of Living Organism. *Ecol. Indic.* **2024**, *160*, 111834. [CrossRef]
14. Modonesi, C.; Serafini, S.; Giuliani, A. Urban Systems Between the Environment, Human Health and Society: An Overview. *Systems* **2025**, *13*, 487. [CrossRef]
15. Zhang, Y.; Yang, Z.; Li, W. Analyses of Urban Ecosystem Based on Information Entropy. *Ecol. Modell.* **2006**, *197*, 1–12. [CrossRef]
16. Rondinel-Oviedo, D.R.; Keena, N. Entropy and Cities: A Bibliographic Analysis towards More Circular and Sustainable Urban Environments. *Entropy* **2023**, *25*, 532. [CrossRef]
17. Al Mashagbah, A.F. The Use of GIS, Remote Sensing and Shannon's Entropy Statistical Techniques to Analyze and Monitor the Spatial and Temporal Patterns of Urbanization and Sprawl in Zarqa City, Jordan. *J. Geogr. Inf. Syst.* **2016**, *8*, 293–300. [CrossRef]
18. Gaur, A.; Eichenbaum, M.K.; Simonovic, S.P. Analysis and Modelling of Surface Urban Heat Island in 20 Canadian Cities under Climate and Land-Cover Change. *J. Environ. Manag.* **2018**, *206*, 145–157. [CrossRef]
19. Mohajerani, A.; Bakaric, J.; Jeffrey-Bailey, T. The Urban Heat Island Effect, Its Causes, and Mitigation, with Reference to the Thermal Properties of Asphalt Concrete. *J. Environ. Manag.* **2017**, *197*, 522–538. [CrossRef] [PubMed]
20. Wu, Q.; Huang, Y.; Irga, P.; Kumar, P.; Li, W.; Wei, W.; Shon, H.K.; Lei, C.; Zhou, J.L. Synergistic Control of Urban Heat Island and Urban Pollution Island Effects Using Green Infrastructure. *J. Environ. Manag.* **2024**, *370*, 122985. [CrossRef] [PubMed]
21. Kleidon, A.; Malhi, Y.; Cox, P.M. Maximum Entropy Production in Environmental and Ecological Systems. *Philos. Trans. R. Soc. B Biol. Sci.* **2010**, *365*, 1297–1302. [CrossRef] [PubMed]
22. Aoki, I. Entropy Budgets of Deciduous Plant Leaves and a Theorem of Oscillating Entropy Production. *Bull. Math. Biol.* **1987**, *49*, 449–460. [CrossRef]
23. Chen, Y.; Wang, J.; Feng, J. Understanding the Fractal Dimensions of Urban Forms through Spatial Entropy. *Entropy* **2017**, *19*, 600. [CrossRef]
24. Free, G.; Poikane, S.; Solheim, A.L.; Bussettini, M.; Bradley, C.; Smith, J.; Caroni, R.; Bresciani, M.; Pinardi, M.; Giardino, C.; et al. Climate Change and Ecological Assessment in Europe under the WFD—Hitting Moving Targets with Shifting Baselines? *J. Environ. Manag.* **2024**, *370*, 122884. [CrossRef]
25. Repo, A.; Albrich, K.; Jantunen, A.; Aalto, J.; Lehtonen, I.; Honkaniemi, J. Contrasting Forest Management Strategies: Impacts on Biodiversity and Ecosystem Services under Changing Climate and Disturbance Regimes. *J. Environ. Manag.* **2024**, *371*, 123124. [CrossRef]
26. Pelorosso, R.; Gobattoni, F.; Leone, A. The Low-Entropy City: A Thermodynamic Approach to Reconnect Urban Systems with Nature. *Landsc. Urban Plan.* **2017**, *168*, 22–30. [CrossRef]
27. Fistola, R.; Gargiulo, C.; La Rocca, R.A. Rethinking Vulnerability in City-Systems: A Methodological Proposal to Assess “Urban Entropy”. *Environ. Impact Assess. Rev.* **2020**, *85*, 106464. [CrossRef]
28. Fistola, R. Urban Entropy vs Sustainability: A New Town Planning Perspective. In Proceedings of the 7th International Conference on Urban Regeneration and Sustainability, Ancona, Italy, 7 May 2012; pp. 195–204.
29. Sun, X. Green City and Regional Environmental Economic Evaluation Based on Entropy Method and GIS. *Environ. Technol. Innov.* **2021**, *23*, 101667. [CrossRef]
30. Prigogine, I.; Stengers, I. La Nouvelle Alliance: Métamorphose de La Science. *Contemp. Fr. Civiliz.* **1979**, *7*, 305.
31. Pulselli, M.R.; Tiezzi, E. *Città Fuori Dal Caos*; Donzelli Editor, Series: Essays; Nature and Artifact: Rome, Italy, 2008; ISBN 9788860362582.
32. Zuo, S.; Dai, S.; Ju, J.; Meng, F.; Ren, Y.; Tian, Y.; Wang, K. The Importance of the Functional Mixed Entropy for the Explanation of Residential and Transport CO₂ Emissions in the Urban Center of China. *J. Clean. Prod.* **2022**, *380*, 134947. [CrossRef]
33. JRC. Urban Heat Islands: Managing Extreme Heat to Keep Cities Cool. Available online: https://joint-research-centre.ec.europa.eu/jrc-news-and-updates/urban-heat-islands-managing-extreme-heat-keep-cities-cool-2024-07-22_en (accessed on 22 July 2024).

34. Ghanghermeh, A.; Roshan, G.; Orosa, J.A.; Costa, Á.M. Analysis and Comparison of Spatial–Temporal Entropy Variability of Tehran City Microclimate Based on Climate Change Scenarios. *Entropy* **2018**, *21*, 13. [CrossRef]
35. Cabral, P.; Augusto, G.; Tewolde, M.; Araya, Y. Entropy in Urban Systems. *Entropy* **2013**, *15*, 5223–5236. [CrossRef]
36. Rapf, M.; Kranert, M. Irreversible Entropy to Account for Environmental Impacts and Sustainability. *Procedia CIRP* **2021**, *98*, 601–606. [CrossRef]
37. Giorgi, F.; Jones, C.; Asrar, G. Addressing Climate Information Needs at the Regional Level: The CORDEX Framework. *Organ. Bull.* **2009**, *58*, 175–183.
38. Jacob, D.; Petersen, J.; Eggert, B.; Alias, A.; Christensen, O.B.; Bouwer, L.M.; Braun, A.; Colette, A.; Déqué, M.; Georgievski, G.; et al. EURO-CORDEX: New High-Resolution Climate Change Projections for European Impact Research. *Reg. Environ. Change* **2014**, *14*, 563–578. [CrossRef]
39. Rizwan, A.M.; Dennis, L.Y.C.; Liu, C. A Review on the Generation, Determination and Mitigation of Urban Heat Island. *J. Environ. Sci.* **2008**, *20*, 120–128. [CrossRef]
40. Dee, D.P.; Uppala, S.M.; Simmons, A.J.; Berrisford, P.; Poli, P.; Kobayashi, S.; Andrae, U.; Balmaseda, M.A.; Balsamo, G.; Bauer, P.; et al. The ERA-Interim Reanalysis: Configuration and Performance of the Data Assimilation System. *Q. J. R. Meteorol. Soc.* **2011**, *137*, 553–597. [CrossRef]
41. Kotlarski, S.; Keuler, K.; Christensen, O.B.; Colette, A.; Déqué, M.; Gobiet, A.; Goergen, K.; Jacob, D.; Lüthi, D.; van Meijgaard, E.; et al. Regional Climate Modeling on European Scales: A Joint Standard Evaluation of the EURO-CORDEX RCM Ensemble. *Geosci. Model Dev.* **2014**, *7*, 1297–1333. [CrossRef]
42. Boberg, F.; Christensen, J.H. Overestimation of Mediterranean Summer Temperature Projections Due to Model Deficiencies. *Nat. Clim. Change* **2012**, *2*, 433–436. [CrossRef]
43. Colmet-Daage, A.; Sanchez-Gomez, E.; Ricci, S.; Llovel, C.; Borrell Estupina, V.; Quintana-Seguí, P.; Llasat, M.C.; Servat, E. Evaluation of Uncertainties in Mean and Extreme Precipitation under Climate Change for Northwestern Mediterranean Watersheds from High-Resolution Med and Euro-CORDEX Ensembles. *Hydrol. Earth Syst. Sci.* **2018**, *22*, 673–687. [CrossRef]
44. Derdour, S.; Ghenim, A.N.; Megnounif, A.; Tangang, F.; Chung, J.X.; Ayoub, A.B. Bias Correction and Evaluation of Precipitation Data from the CORDEX Regional Climate Model for Monitoring Climate Change in the Wadi Chemora Basin (Northeastern Algeria). *Atmosphere* **2022**, *13*, 1876. [CrossRef]
45. Prein, A.F.; Langhans, W.; Fossler, G.; Ferrone, A.; Ban, N.; Goergen, K.; Keller, M.; Tölle, M.; Gutjahr, O.; Feser, F.; et al. A Review on Regional Convection-permitting Climate Modeling: Demonstrations, Prospects, and Challenges. *Rev. Geophys.* **2015**, *53*, 323–361. [CrossRef] [PubMed]
46. IPCC. Emission Scenarios. Available online: <https://www.ipcc.ch/report/emissions-scenarios> (accessed on 7 March 2025).
47. Balocco, C.; Grazzini, G. Thermodynamic Parameters for Energy Sustainability of Urban Areas. *Sol. Energy* **2000**, *69*, 351–356. [CrossRef]
48. Gates, D. *Physical Processes in Ecosystems*; University of Washington Center for Quantitative Science: Seattle, WA, USA, 2020.
49. Holman, J.P. *Heat Transfer*; McGraw-Hill: New York, NY, USA, 2010; ISBN 0-07-352936-2.
50. Gazzetta Ufficiale. Norme per L’attuazione Del Piano Energetico Nazionale in Materia Di Uso Razionale Dell’energia, Di Risparmio Energetico e Di Sviluppo Delle Fonti Rinnovabili Di Energia. 1991. Available online: <https://www.gazzettaufficiale.it/gunewsletter/dettaglio.jsp?service=1&datagu=2010-04-21&task=dettaglio&numgu=92&redaz=010G0078&tmstp=1273049012988> (accessed on 12 August 2025).
51. Gazzetta Ufficiale. Regolamento Recante Norme per la Progettazione, L’installazione, l’esercizio e La Manutenzione Degli Impianti Termici Degli Edifici Ai Fini Del Contenimento Dei Consumi Di Energia 1993. Available online: <https://www.gazzettaufficiale.it/eli/id/1993/10/14/093G0451/sg> (accessed on 12 August 2025).
52. UNI UNI/TS 11300-1:2014; Energy Performance of Buildings-Part 1: Evaluation of Energy Need for Space Heating and Cooling. British Standards Institution (BSI): London, UK, 2014.
53. WMO. *Guidance to Measuring, Modelling and Monitoring the Canopy Layer Urban Heat Island*; WMO: Geneva, Switzerland, 2023; ISBN 9789263112.
54. Pena Acosta, M.; Vahdatikhaki, F.; Santos, J.; Dorée, A.G. A Comparative Analysis of Surface and Canopy Layer Urban Heat Island at the Micro Level Using a Data-Driven Approach. *Sustain. Cities Soc.* **2023**, *99*, 104944. [CrossRef]
55. Raffa, M.; Adinolfi, M.; Reder, A.; Marras, G.F.; Mancini, M.; Scipione, G.; Santini, M.; Mercogliano, P. Very High Resolution Projections over Italy under Different CMIP5 IPCC Scenarios. *Sci. Data* **2023**, *10*, 238. [CrossRef] [PubMed]
56. CMCC DDS. Climate Projections RCP4.5 and RCP8.5 Downscaled @2.2 Km over Italy. Available online: <https://doi.org/10.25424/CMCC-J90A-5P12> (accessed on 7 August 2025).
57. Douss, R.; Farah, I.R. Extraction of Individual Trees Based on Canopy Height Model to Monitor the State of the Forest. *Trees For. People* **2022**, *8*, 100257. [CrossRef]

58. Mohan, M.; Leite, R.V.; Broadbent, E.N.; Wan Mohd Jaafar, W.S.; Srinivasan, S.; Bajaj, S.; Dalla Corte, A.P.; do Amaral, C.H.; Gopan, G.; Saad, S.N.M.; et al. Individual Tree Detection Using UAV-Lidar and UAV-SfM Data: A Tutorial for Beginners. *Open Geosci.* **2021**, *13*, 1028–1039. [\[CrossRef\]](#)
59. Popescu, S.C.; Wynne, R.H. Seeing the Trees in the Forest. *Photogramm. Eng. Remote Sens.* **2004**, *70*, 589–604. [\[CrossRef\]](#)
60. Mohan, M.; Mendonça, B.A.F.; de Silva, C.A.; Klauberg, C.; de Saboya Ribeiro, A.S.; Araújo, E.J.G.; de Monte, M.A.; Cardil, A. Optimizing Individual Tree Detection Accuracy and Measuring Forest Uniformity in Coconut (*Cocos nucifera* L.) Plantations Using Airborne Laser Scanning. *Ecol. Modell.* **2019**, *409*, 108736. [\[CrossRef\]](#)
61. Yu, K.; Hao, Z.; Post, C.J.; Mikhailova, E.A.; Lin, L.; Zhao, G.; Tian, S.; Liu, J. Comparison of Classical Methods and Mask R-CNN for Automatic Tree Detection and Mapping Using UAV Imagery. *Remote Sens.* **2022**, *14*, 295. [\[CrossRef\]](#)
62. Breiman, L. Random Forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
63. Francini, S.; Schelhaas, M.-J.; Vangi, E.; Lerink, B.; Nabuurs, G.-J.; McRoberts, R.E.; Chirici, G. Forest Species Mapping and Area Proportion Estimation Combining Sentinel-2 Harmonic Predictors and National Forest Inventory Data. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *131*, 103935. [\[CrossRef\]](#)
64. Francini, S.; Coccozza, C.; Hölttä, T.; Lintunen, A.; Paljakka, T.; Chirici, G.; Traversi, M.L.; Giovannelli, A. A Temporal Segmentation Approach for Dendrometers Signal-to-Noise Discrimination. *Comput. Electron. Agric.* **2023**, *210*, 107925. [\[CrossRef\]](#)
65. Hermosilla, T.; Bastyr, A.; Coops, N.C.; White, J.C.; Wulder, M.A. Mapping the Presence and Distribution of Tree Species in Canada's Forested Ecosystems. *Remote Sens. Environ.* **2022**, *282*, 113276. [\[CrossRef\]](#)
66. Lindquist, M.A. The Statistical Analysis of FMRI Data. *Stat. Sci.* **2008**, *23*, 439–464. [\[CrossRef\]](#)
67. Fuchs, M.; Tanner, C.B. Infrared Thermometry of Vegetation 1. *Agron. J.* **1966**, *58*, 597–601. [\[CrossRef\]](#)
68. Mashabatu, M.; Ntshidi, Z.; Dziki, S.; Jovanovic, N.; Dube, T.; Taylor, N.J. Deriving Crop Coefficients for Evergreen and Deciduous Fruit Orchards in South Africa Using the Fraction of Vegetation Cover and Tree Height Data. *Agric. Water Manag.* **2023**, *286*, 108389. [\[CrossRef\]](#)
69. Tiralla, N.; Panferov, O.; Kreilein, H.; Olchev, A.; Ali, A.A.; Knohl, A. Quantification of Leaf Emissivities of Forest Species: Effects on Modelled Energy and Matter Fluxes in Forest Ecosystems. *Geogr. Environ. Sustain.* **2019**, *12*, 245–258. [\[CrossRef\]](#)
70. Comune di Firenze Piano Strutturale e Piano Operativo. Available online: <https://www.comune.fi.it/dalle-redazioni/piano-operativo-e-piano-strutturale-2023> (accessed on 7 March 2025).
71. Istat. Basi Territoriali: Anni 1991, 2001, 2011 E 2021. Note Legali: Responsabilità E Licenza. 2024. Available online: <https://www.istat.it/wp-content/uploads/2024/07/Descrizione-dei-dati-Basi-territoriali.pdf> (accessed on 7 March 2025).
72. Grazzini, G.; Gonnelli, A. Il Piano Energetico Ambientale Comunale di Firenze. In Proceedings of the II Congresso Nazionale AIGE, Pisa, Italy, 4–5 September 2008.
73. Regione Toscana Geoscopio—Cartoteca. Available online: <https://www502.regione.toscana.it/geoscopio/cartoteca.html> (accessed on 7 March 2025).
74. Martinez, A.; de la, I.; Labib, S.M. Demystifying Normalized Difference Vegetation Index (NDVI) for Greenness Exposure Assessments and Policy Interventions in Urban Greening. *Environ. Res.* **2023**, *220*, 115155. [\[CrossRef\]](#)
75. Hawryło, P.; Francini, S.; Chirici, G.; Giannetti, F.; Parkitna, K.; Krok, G.; Mitelsztedt, K.; Lisańczuk, M.; Stereńczak, K.; Ciesielski, M.; et al. The Use of Remotely Sensed Data and Polish NFI Plots for Prediction of Growing Stock Volume Using Different Predictive Methods. *Remote Sens.* **2020**, *12*, 3331. [\[CrossRef\]](#)
76. Chicco, D.; Jurman, G. The Advantages of the Matthews Correlation Coefficient (MCC) over F1 Score and Accuracy in Binary Classification Evaluation. *BMC Genomics* **2020**, *21*, 6. [\[CrossRef\]](#)
77. Matthews, B.W. Comparison of the Predicted and Observed Secondary Structure of T4 Phage Lysozyme. *BBA—Protein Struct.* **1975**, *405*, 442–451. [\[CrossRef\]](#)
78. Rubio, E. Emissivity Measurements of Several Soils and Vegetation Types in the 8–14, Mm Wave Band: Analysis of Two Field Methods. *Remote Sens. Environ.* **1997**, *59*, 490–521. [\[CrossRef\]](#)
79. Turner, N.C.; Heichel, G.H. Stomatal Development and Seasonal Changes in Diffusive Resistance of Primary and Regrowth Foliage of Red Oak (*Quercus rubra* L.) and Red Maple (*Acer rubrum* L.). *New Phytol.* **1977**, *78*, 71–81. [\[CrossRef\]](#)
80. WMO. Comité Météorologique International, Procès-Verbaux de La Session de Paris; Imprimerie La Concorde: El Baten, Tunisia, 1–12 July 1946.
81. Du, H.; Cai, W.; Xu, Y.; Wang, Z.; Wang, Y.; Cai, Y. Quantifying the Cool Island Effects of Urban Green Spaces Using Remote Sensing Data. *Urban For. Urban Green.* **2017**, *27*, 24–31. [\[CrossRef\]](#)
82. Arellano, B.; Roca, J. Assessing Urban Greenery Using Remote Sensing. In Proceedings of the SPIE—The International Society for Optical Engineering, Conference: SPIE Optical Engineering + Applications, San Diego, CA, USA, 21–26 August 2022. Proceedings Volume 12232, Earth Observing Systems XXVII.
83. Sharmin, M.; Tjoelker, M.G.; Pfautsch, S.; Esperon-Rodriguez, M.; Rymer, P.D.; Power, S.A. Tree Crown Traits and Planting Context Contribute to Reducing Urban Heat. *Urban For. Urban Green.* **2023**, *83*, 127913. [\[CrossRef\]](#)

84. Speak, A.; Montagnani, L.; Wellstein, C.; Zerbe, S. The Influence of Tree Traits on Urban Ground Surface Shade Cooling. *Landsc. Urban Plan.* **2020**, *197*, 103748. [[CrossRef](#)]
85. He, T.; Hu, Y.; Guo, A.; Chen, Y.; Yang, J.; Li, M.; Zhang, M. Quantifying the Impact of Urban Trees on Land Surface Temperature in Global Cities. *ISPRS J. Photogramm. Remote Sens.* **2024**, *210*, 69–79. [[CrossRef](#)]
86. Jin, J.; Chen, W.Y.; Jia, B.; Wang, C. Cooling Effect of Urban Greenery: A Bibliometric Analysis. *Urban For. Urban Green.* **2024**, *99*, 128453. [[CrossRef](#)]
87. Morakinyo, T.E.; Dahanayake, K.W.D.K.C.; Ng, E.; Chow, C.L. Temperature and Cooling Demand Reduction by Green-Roof Types in Different Climates and Urban Densities: A Co-Simulation Parametric Study. *Energy Build.* **2017**, *145*, 226–237. [[CrossRef](#)]
88. Meili, N.; Zheng, X.; Takane, Y.; Nakajima, K.; Yamaguchi, K.; Chi, D.; Zhu, Y.; Wang, J.; Qiu, Y.; Paschalis, A.; et al. Modeling the Effect of Trees on Energy Demand for Indoor Cooling and Dehumidification Across Cities and Climates. *J. Adv. Model. Earth Syst.* **2025**, *17*, e2024MS004590. [[CrossRef](#)]
89. Mohammed, A.; Khan, A.; Khan, H.S.; Santamouris, M. Cooling Energy Benefits of Increased Green Infrastructure in Subtropical Urban Building Environments. *Buildings* **2023**, *13*, 2257. [[CrossRef](#)]
90. Lloyd, G.; Ossola, A.; Burley, H.; Evans, K. Climate Change Threatens Carbon Storage in Europe’s Urban Trees. *Urban For. Urban Green.* **2024**, *101*, 128532. [[CrossRef](#)]
91. Croeser, T.; Garrard, G.E.; Visintin, C.; Kirk, H.; Ossola, A.; Furlong, C.; Clements, R.; Butt, A.; Taylor, E.; Bekessy, S.A. Finding Space for Nature in Cities: The Considerable Potential of Redundant Car Parking. *NPJ Urban Sustain.* **2022**, *2*, 27. [[CrossRef](#)]
92. Pattnaik, N.; Honold, M.; Franceschi, E.; Moser-Reischl, A.; Rötzer, T.; Pretzsch, H.; Pauleit, S.; Rahman, M.A. Growth and Cooling Potential of Urban Trees across Different Levels of Imperviousness. *J. Environ. Manag.* **2024**, *361*, 121242. [[CrossRef](#)] [[PubMed](#)]
93. Sjöman, H.; Watkins, H.; Kelly, L.J.; Hiron, A.; Kainulainen, K.; Martin, K.W.E.; Antonelli, A. Resilient Trees for Urban Environments: The Importance of Intraspecific Variation. *Plants People Planet* **2024**, *6*, 1180–1189. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.