

Article

Satellite Imagery for Comprehensive Urban Morphology and Surface Roughness Analysis: Leveraging GIS Tools and Google Earth Engine for Sustainable Urban Planning

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Abstract: High-resolution remotely sensed data, which are characterised by their advanced spectral and spatial capabilities, provide unprecedented opportunities to monitor and analyse the dynamic structures of urban environments. Platforms like Google Earth Engine (GEE) enhance these capabilities, as they provide access to vast datasets and tools for analysing key urban parameters, including land use, vegetation cover, and surface roughness—all critical components in urban sustainability studies. This study presents a knowledge-based framework for processing high-resolution satellite imagery tailored to address the demands of sustainable urban planning in the Municipality of Kalamaria in Thessaloniki, Greece. The framework emphasises the extraction of essential urban parameters, such as the spatial distribution of built-up and green spaces, alongside the analysis of surface roughness attributes, including displacement height and roughness length. Unlike conventional methods, our framework enables a detailed intra-urban analysis as these surface roughness attributes are calculated within 200 m × 200 m sub-units. Surface roughness indicators offer essential insights into aerodynamic drag and turbulent air mixing, both of which are directly influenced by the structural characteristics of the urban landscape. Using this approach, ‘wake interference flow’ type was identified as the dominant airflow pattern in the study area. This type was observed in 105 out of 150 sub-units, suggesting that these areas likely suffer from poor air circulation and are prone to higher concentrations of air pollutants. The integration of Google Earth Engine offered a scalable and replicable solution for large-scale urban analysis making it easily adaptable to other urban areas, especially where detailed morphological datasets are unavailable. By providing a robust, scalable, and data-driven tool for assessing urban form and airflow characteristics, our study offers a significant advancement in sustainable urban planning and climate resilience strategies, with clear potential for adaptation in other cities facing similar data limitations.

Keywords: satellite imagery; sustainable urban planning; surface roughness; urban green; built-up density; Google Earth Engine



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1. Introduction

The urban environment is a dynamic and constantly evolving space that is shaped by several key components of social, economic, and environmental factors. As a result, critical morphological characteristics, such as building density, green spaces, land use,

and their spatial distribution, play important roles in their sustainability and resilience. All these factors impact citizens' well-being, and influence many urban aspects such as air quality, thermal comfort, and overall environmental conditions [1–4]. The United Nations has adopted the Agenda 2030 and its Sustainable Development Goals (SDGs) [5] to guide efforts towards a more sustainable development worldwide, as cities represent half of the world's population and two-thirds of the global economy [6]. To pursue the objectives of this agenda, understanding and analyzing urban morphology is becoming essential. Key features of sustainable urban life, including energy efficiency, air quality, thermal comfort, and overall environmental performance, are directly influenced by urban morphology [7–11], highlighting its critical role in fostering sustainable and livable cities. Wang et al. [12], for example, studied the correlation between water use, evapotranspiration, electric energy consumption, surface albedo, and vegetation activity with urban Land Surface Temperature (LST) in twelve megalopolises in China, revealing a positive correlation, and highlighting that building areas played a more important role in LST in cities with less surface water distribution. In their research, Zhang et al. [13] revealed that urban morphology has a strong influence on outdoor thermal comfort in Beijing China. Santamouris [14] presented quantitative information on the energy penalties, mortality rates, and environmental degradation induced by urban warming. Stone Jr. [15] analysed urban and rural temperature trends in proximity to large cities in the United States of America from 1951–2000, revealing the decadal rate of change in Urban Heat Island (UHI) intensity. The analysis of UHI intensity, as a direct result of the observed increase in impermeable surfaces that replace vegetation and evaporating surfaces, has been thoroughly examined in previous years [16–20].

One particularly important aspect of urban morphology analysis is the study of surface roughness parameters. The concept of surface roughness can be defined across different disciplines, as the general idea is that every process occurring at the Earth's surface both interacts with and generates rough surfaces [21,22]. Consequently, diverse methods for evaluating roughness have been developed, with unique approaches emerging in different fields; meteorology [23], hydrology [24], forestry [25], and aerodynamics [26], to name a few. Conceptualizing roughness as a 'resistance to flow' [21] in urban environments, surface roughness can be defined as 'the set of obstacles that wind can encounter in a structured environment' [27], which in this case is the building stock. This surface roughness influences several environmental and climatic factors that shape urban comfort, including UHI effects, air circulation, and energy balance. By analyzing the three-dimensional structure of an urban area, researchers can better understand how different surfaces interact with atmospheric processes, heat retention, and solar radiation absorption. This knowledge is crucial for urban planning, as it supports sustainable development strategies, energy-efficient building design, and improved microclimatic conditions [28–30].

Specifically, two key parameters that are commonly used to determine the surface roughness of an urban landscape are the zero-plane displacement height (z_d) and the roughness length (z_o) [23,27,31,32]. In the work of [27], the first parameter is defined by the average height of roughness elements alongside building density, while the second parameter is defined by the average height of roughness elements alongside the density of buildings' facades. These parameters are generally determined either with morphological methods, which use algorithms with logarithmic wind profiles that link aerodynamic parameters with terrain morphology [22,33–36], or with micrometeorological methods [37], which rely on field measurements of wind and turbulence to determine the wind profile within the urban fabric. The first approach has the advantage of not requiring any field measurement equipment, which results in time and cost savings. However, the main drawback of this method is that the parameter calculations are based on empirical re-

relationships derived from wind simulation laboratories, which cannot fully replicate the actual urban environment. The second method, which is based on field measurements, can be applied to any urban environment. However, its major disadvantage lies in the high cost and complexity of the measurements. Initially, studies of air circulation within an urban environment focused on airflow around buildings [38,39]. Nevertheless, with advancements in high-performance computing, the scope expanded to larger geographical areas, though it remained limited to a portion of a typical city, covering an area of several hundred meters [40,41]. Various studies focused on investigating the wind characteristics within the urban boundary layer [42]. In the study by Ng et al. [43], a frontal area density (FAD) map at 200 m resolution was created to depict the surface roughness of urban Hong Kong, using a mapping method that takes into account the dense urban morphology. Drew et al. [44] in 2013 and Kent et al. [45] in 2018 observed the vertical wind speed profiles over several urban areas in London, using the morphological data of the available Digital Surface Model (DSM). Edward Ng [46], in his study, explored the feasibility of establishing some protocols to assess the effects of major planning and development proposals on external air movement for achieving an acceptable macro wind environment. However, the practical difficulties in estimating or directly observing air wind conditions present a significant challenge, as such studies require accurate and detailed morphological data to produce reliable results [47].

To respond to the growing interest in defining urban airflow profiles, this study focuses on providing surface form characteristics with low computational costs and relatively high accuracy, by leveraging advanced technologies such as Remote Sensing and Geographic Information Systems (GIS) and using the open access platform of Google Earth Engine (GEE). With the applied methodology, the surface roughness parameters are calculated for a whole administrative urban area of Northern Greece, allowing estimations for wind profiles within the study area. In this way, we aim to address crucial considerations regarding data availability on a city level and computational barriers by using freely available satellite imagery on a cloud-based platform. Although several previous studies have used Remote Sensing to explore the urban characteristics that shape urban form [19,48–55], only a few have utilized Remote Sensing techniques to define the surface roughness parameters, focusing primarily on soil surface roughness [56–58]. Our primary research question is: (i) How do various spatial features within a dense urban area impact wind profile?, and (ii) Can Remote Sensing offer meaningful insights to support decision-making and promote sustainable urban development? To the best of our knowledge, similar research studies have not been carried out in Greece, thus making the applied methodology a useful tool for Greek policy makers, as the advantage of this methodology is its adaptable analysis; it can be easily adjusted and processed in various regions of Greece. Furthermore, we developed a new classification scheme for breaking down the examined urban area into sub-units. Unlike administrative boundaries, this approach transitions from analyzing the entire city to examining specific neighborhoods in greater detail. This is crucial for implementing urban sustainability practices in micro-geographies where they can be most relevant and effective.

2. Materials and Methods

2.1. Study Area and Data

The study area of this research is the Municipality of Kalamaria in the city of Thessaloniki, Greece. Kalamaria is among the most densely populated suburbs in Thessaloniki, and is located about 7 km (4 miles) southeast of the downtown area, with a population of 92,248 [59] (Figure 1). Kalamaria presents a typical Greek urban fabric in the national panorama, with a dense urban development in its centre, and a series of peripheral ex-

pansion areas that have resulted in an increase in occupied space over the last decades. Kalamaria has experienced significant growth in recent years due to a population shift from both rural and urban areas to suburban regions, which has resulted in expansion of its impervious surface characteristics. The Hellenic Statistical Authority (ELSTAT) [60], reported a 69% population increase between the 1981 and 2001 censuses, and from 2001 to 2021, the population grew by 5%. Kalamaria's climate is warm and temperate, with an average annual air temperature of 17.1 °C, according to the European Centre for Medium-Range Weather Forecasts (ECMWF) database [61].

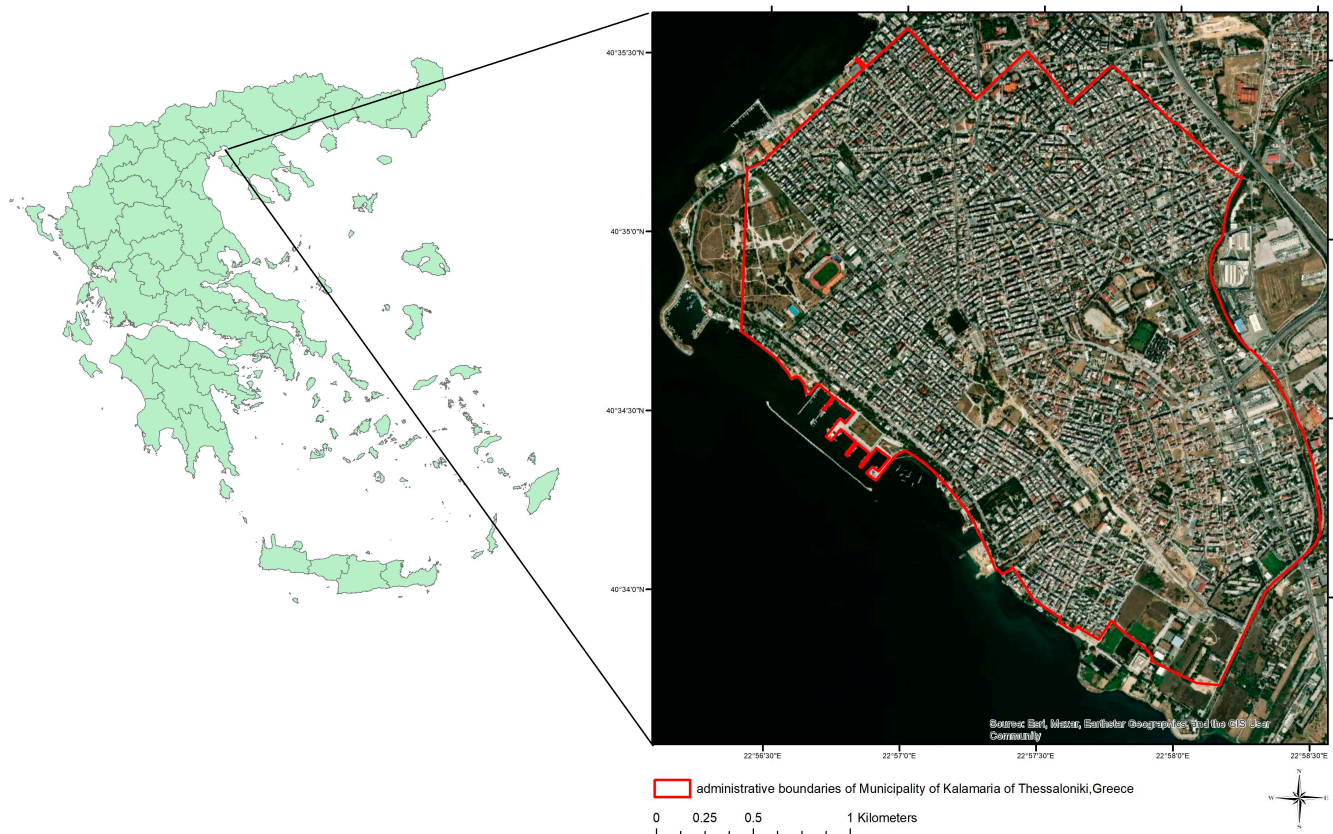


Figure 1. Study area of Municipality of Kalamaria in Thessaloniki, Greece (base map: National Geographic and Maxar Earthstar Geographic, ESRI).

The GEE platform provides an extensive collection of satellite images, such as data provided by Landsat sensors of the United States Geological Survey (USGS) and high-resolution optical images from Sentinel-2A and 2B of the European Commission's Copernicus program. For this study, we used the Sentinel-2A products, which provide atmospherically corrected surface reflectance data, making them more suitable for land cover classification. The Sentinel-2 mission offers a combination of systematic global coverage of land and coastal areas, a high revisit rate of five days under the same viewing conditions, and a high spatial resolution. The multispectral observations include 13 bands in the visible, near infrared, and short-wave infrared range of the electromagnetic spectrum [62]; thus, it is useful for identifying land surface characteristics. To improve the classification processes, a high-resolution WorldView-2 image was used and imported into the GEE platform. As the first high-resolution commercial satellite with 8-band multispectral capabilities, WorldView-2 operates at a 770 km altitude, offering 46 cm resolution for panchromatic imagery and 1.85 m for multispectral data [63].

The study area's administrative boundaries were downloaded from the Greek National Open Data Catalogue [64], a central repository that provides nationwide access to a broad

collection of publicly available geospatial data. Vector datasets containing information on building storeys of the study area were also employed.

2.2. Land Use Extraction

In large-scale land cover mapping, such as the Municipality of Kalamaria, processing large volumes of data and obtaining cloud-free images may pose significant challenges. GEE, which is a cloud-based computing platform, can effectively address these issues as it allows users to analyze remotely sensed images directly through a web-based Integrated Development Environment (IDE) without the need to download data to a local computer. The following steps were implemented in GEE to prepare the Sentinel-2A dataset for analysis:

1. Image collection selection: A Sentinel-2A image collection was loaded for the defined study area using the COPERNICUS/S2 dataset.
2. Temporal filtering: To ensure temporal consistency and minimize seasonal variation, the collection was filtered to include only images acquired during the summer months—June, July, and August of 2024.
3. Cloud cover filtering: The image collection was further filtered by selecting scenes with less than 20% cloud cover, using the CLOUDY_PIXEL_PERCENTAGE property available in the Sentinel-2 metadata.
4. Cloud masking (optional but recommended): To further reduce residual cloud effects, cloud and shadow pixels were masked using the Sentinel-2 QA60 band.
5. Image compositing: To derive a representative, noise-reduced dataset, a median composite image was then constructed, reducing residual cloud contamination and any radiometric inconsistencies.
6. Output for analysis: The resulting median served as the basis for subsequent analyses.

Two key spectral indices were computed to establish an initial differentiation between pervious and impervious surfaces in the study area: the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI). NDVI was utilized to identify vegetated areas, while NDBI facilitated the detection of impervious surfaces. These indices were then employed for the classification and masking of pervious and impervious surfaces across the study area. The impervious surface of the study area, identified through the NDBI, was subsequently masked in the high-resolution WorldView-2 image, while the green areas identified through the NDVI were utilized to mask pervious surfaces. To classify land cover types with greater accuracy, a Random Forest (RF) classification algorithm was applied.

The Random Forest classifier [65] is a widely used machine-learning algorithm that operates by constructing multiple decision trees during training. Each tree is trained on a random subset of the data, and the final classification is determined through majority voting, where the most frequently predicted class among all trees is assigned to a given pixel [66]. This approach enhances classification accuracy and reduces overfitting, making it particularly suitable for remote sensing applications [67]. In this study, the RF classifier was trained using a set of reference samples that correspond to different land cover types, ensuring that the model could effectively distinguish between various impervious and pervious surfaces. The spectral information from the WorldView-2 image was used, taking advantage of its high spatial and spectral resolution to improve the delineation of urban features. During this process, specific training sites were selected within the image to represent the target land cover classes. These training sites corresponded to areas that exhibited relatively uniform spectral characteristics, as determined by their similarity in tone or color. Following a thorough visual examination of the image, seven land cover categories were identified: (1) buildings with tiled roofs, (2) buildings with cement roofs,

(3) buildings with light-colored roofs, (4) dense vegetation, (5) sparse vegetation, (6) road infrastructure, and (7) shaded zones. To ensure optimal class separability, the training sites were carefully chosen to maximize the spectral distinctiveness of each land cover category (Figure 2).

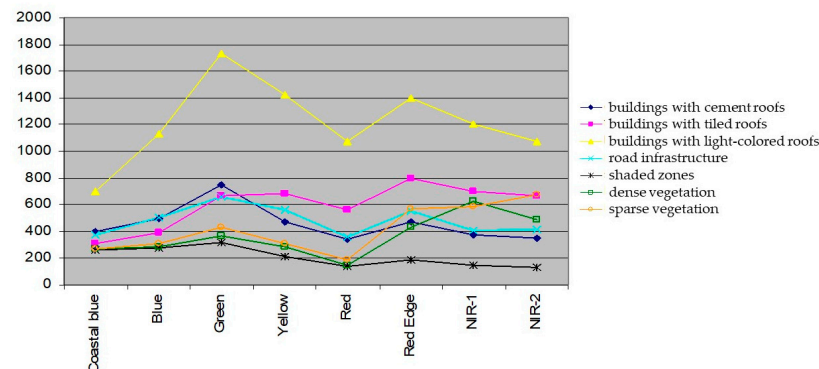


Figure 2. Spectral signatures of the identified land cover classes in the WorldView-2 image. X Axis represents the eight spectral bands while Y Axis presents the corresponding DN values of every class.

These land cover class samples were collected using a stratified sampling approach, ensuring that samples from the same class were spatially dispersed to minimize spatial autocorrelation. The collected samples were then categorized into the identified land cover classes: (1) buildings with tiled roofs—151 samples, (2) buildings with cement roofs—165 samples, (3) buildings with light-colored roofs—147 samples, (4) dense vegetation—200 samples, (5) sparse vegetation—152 samples, (6) road infrastructure—100 samples, and (7) shaded zones—53 samples. Only two thirds of the samples were used for building the model, while the remaining one third was reserved for validation.

Various studies have investigated the sensitivity of the RF classifier to the number of trees [68–70] and showed that this parameter has minimal influence on the classification results. However, in this study, multiple trials were conducted with tree counts ranging from 100 to 250 to determine the optimal configuration for the study area. To evaluate classification performance, an error matrix was generated, and accuracy metrics, including overall accuracy and the Kappa coefficient, were computed. These metrics quantify the reliability of the classification process, with the results presented in Table 1.

Table 1. RF Classification accuracy results with different numbers of trees.

Number of Trees in RF	Overall Classification Accuracy	Overall Kappa Statistics
100	86.40%	0.84
150	88.43%	0.88
200	87.02%	0.86
250	86.79%	0.85

The results indicated that employing 150 trees achieved the highest classification accuracy, leading to the extraction of land cover classes from this classification schema. The classification accuracy obtained in this study falls within the commonly accepted thresholds for urban land cover classifications, as established in previous studies [67,71–73]. This level of accuracy provides a reliable foundation for conducting further spatial analyses. Furthermore, potential misclassifications in mixed-use or transitional areas are unlikely to significantly affect the overall outcomes, particularly given the spatial resolution and analytical scope of the study [74].

Figure 3 illustrates the extracted building polygons categorized by roof type: (1) buildings with tiled roofs, (2) buildings with cement roofs, (3) buildings with light-colored roofs.



Figure 3. Classification of buildings with the RF classifier: (a) the WorldView-2 image, (b) the buildings classified by their roof types; (1) buildings with tiled roofs, (2) buildings with cement roofs, (3) buildings with light-colored roofs.

2.3. Extraction of Surface Roughness Parameters

Conceptualizing surface roughness as the set of obstacles of the building stock that wind can encounter in the study area, the zero-plane displacement height (z_d) and the roughness length (z_o) were calculated using only the extracted classes of buildings (namely buildings with cemented roofs, buildings with light-colored roofs, and buildings with tiled roofs). Building height data for the building stock were derived from a point-based vector file containing the number of storeys for buildings within the study area. Given that the minimum floor height, as defined by the official Greek General Code of Construction Practice, is 2.40 m, the total building height was calculated accordingly. Thus, after delineating the urban built-up boundaries, these height data were linked to the attribute table of the building layer using zonal statistics within the ArcGIS 10.4.1 platform. The resulting geodatabase for the study area compiled detailed information on the building stock. Specifically, it included data on the geographical location of each individual building (x and y coordinates), the rooftop area in square meters, the rooftop surface material, and the height of each building. In total, the final geodatabase contained over 5000 records.

The mathematical formulas for the calculation of the two parameters z_d and z_o are given as follows [22,75]:

$$z_o = (\bar{z}_H - z_d) \exp\left(-\sqrt{\frac{0.4}{\lambda_F}}\right), \quad (1)$$

$$z_d = \bar{z}_H \lambda_p^{0.6}, \quad (2)$$

where:

z_H is the mean building height within an area.

λ_p is the plan area density and is calculated as the ratio of the total building footprint area (A_T) within the study area to the total surface area (A_p) of the study area (A_T/A_p).

λ_F is the frontal area density and is calculated as the ratio of the total frontal area of the buildings (A_F) within a given area to the total surface area (A_p) of the study area (A_F/A_p).

Grimmond and Oke [35], comparing their results with values derived from field measurements, proposed the following simplified equations for calculating the parameters z_d and z_o :

$$z_d = f_d \bar{z}_H, \quad (3)$$

$$z_o = f_o \bar{z}_H, \quad (4)$$

where:

f_d is an empirical coefficient that depends on the building and vegetation density and f_o is an empirical coefficient that depends on the frontal area density of the buildings.

Various studies have proposed representative values for these coefficients. Garratt [76], in his atmospheric boundary layer review, suggests that $f_d \sim 0.67$ and $f_o \sim 0.10$ are good overall mean values for land surfaces. Hanna and Chang [77] suggest that $f_d \sim 0.5$ and $f_o \sim 0.1$ are useful approximations, and Grimmond and Oke [35] propose f_d with a value of 0.5 for sparsely built-up areas, 0.6 for moderately to densely built-up areas, and 0.7 for densely built-up areas, with f_o value 0.1 for urban areas, as seen also in [40,78].

Table 2 describes the three types of urban environments that can be defined based on roughness properties [35]. The first category refers to a residential area with low building density. This category includes areas where buildings and urban green spaces are sparsely distributed, typically consisting of one to two storey houses with open green spaces and without industrial zones. In this category, the airflow pattern usually corresponds to Type A—isolated roughness flow. Wind flows relatively freely around individual structures, resulting in minimal disruption, and therefore the air dispersion is allowed [35]. The second category refers to areas with moderate to high building density, where the airflow pattern mostly belongs to Type B—wake interference flow. This category typically includes urban areas with buildings of two to four storeys and densely arranged city blocks with residential use, commercial shops, churches, schools etc. The close proximity of buildings in this urban form leads to overlapping wind wake and potentially results in turbulent flow and reduced ventilation. This interaction between adjacent structures significantly hinders the dispersal of air pollutants, making Type B the most critical case scenario in terms of air quality, as it tends to trap pollutants close to ground level. This type refers to a flow regime where the wakes generated by individual buildings interfere with one another, leading to reduced airflow and potentially higher concentrations of air pollutants in the affected areas [35]. Finally, the third category includes areas with high building density, characterized by very densely built environments, narrow streets, and typically corresponds to city centers. In these areas, the airflow pattern almost always corresponds to Type C—skimming flow. This type of flow is characterized by strong winds that can effectively “clean” the surface, but also helps the dispersion of air pollutants [35].

Table 2. Typical nondimensional roughness properties of homogeneous zones in urban areas [35].

Urban Density-Flow Regime	Mean Building Height z_H (m)	Zero-Plane Displacement Height z_d (m)	Roughness Length z_o (m)
A: Low density—Isolated flow	5–7	2–4	0.3–0.8
B: Medium density—Wake interference flow	7–11	3.5–8	0.7–1.5
C: High density: Skimming flow	12–20	7–15	0.8–1.5

For the examined area, the surface roughness parameters were calculated based on Equations (3) and (4), using the values of $f_d = 0.5$ and $f_o = 0.1$ for sparsely built-up areas, $f_d = 0.6$ and $f_o = 0.1$ for moderately to densely built-up areas, and $f_d = 0.5$ and $f_o = 0.1$ for densely built-up areas. The definitions of these three urban density types were established by calculating the urban density with the following formula:

$$\lambda = \frac{A_p \text{ Built up area (m}^2\text{)}}{A_T \text{ total amount of land (m}^2\text{)}}, \quad (5)$$

λ is the ratio of the area covered by the built environment, expressed in square meters, to the total area of the geographical region under study. Using this formula, the building density of certain surface unit (A_T) area can be calculated and the urban environment can be classified as: (a) low-density urban environment, with λ values ranging from 0.05 to 0.2, (b) moderate-density urban environment, with λ values between 0.2 and 0.4, and (c) high density urban environment with λ values between 0.4 and 0.8.

Classification Schema of Sub-Units of the Examined Urban Area

The definition of the sub-unit A_T is crucial, since it sets the horizontal scale range of the roughness elements under study. In our case, the calculation of building density was based on the implementation of a grid with a cell size of $200 \text{ m} \times 200 \text{ m}$, covering the entire geographical area of the Municipality of Kalamaria. This approach effectively defines a minimum spatial analysis unit that meets specific criteria, namely:

- The division of the study area into small geographical units that include typical features of an urban neighborhood, such as two to three building blocks, road networks and intersections, urban green spaces, etc.
- Consideration of the spatial resolution of the available imagery to ensure that these urban characteristics can be adequately identified; in our case the spatial resolution of the available WorldView-2 image of 0.5 m.
- The ability to produce detailed results suitable for high-scale maps, such as 1:5000 to 1:1000.

The selection of the grid size was determined after several experimental trials (see Figure 4) to identify a spatial unit capable of fulfilling the above criteria. Dividing the study area into cells of $200 \text{ m} \times 200 \text{ m}$ returned the most satisfactory results. This spatial unit size was found to effectively represent small sections of the Greek urban fabric, typically comprising two or three building blocks, road segments and intersections, and urban greenery. By adopting this intermediate grid size, the existing urban structure and its spatial characteristics were more accurately depicted.

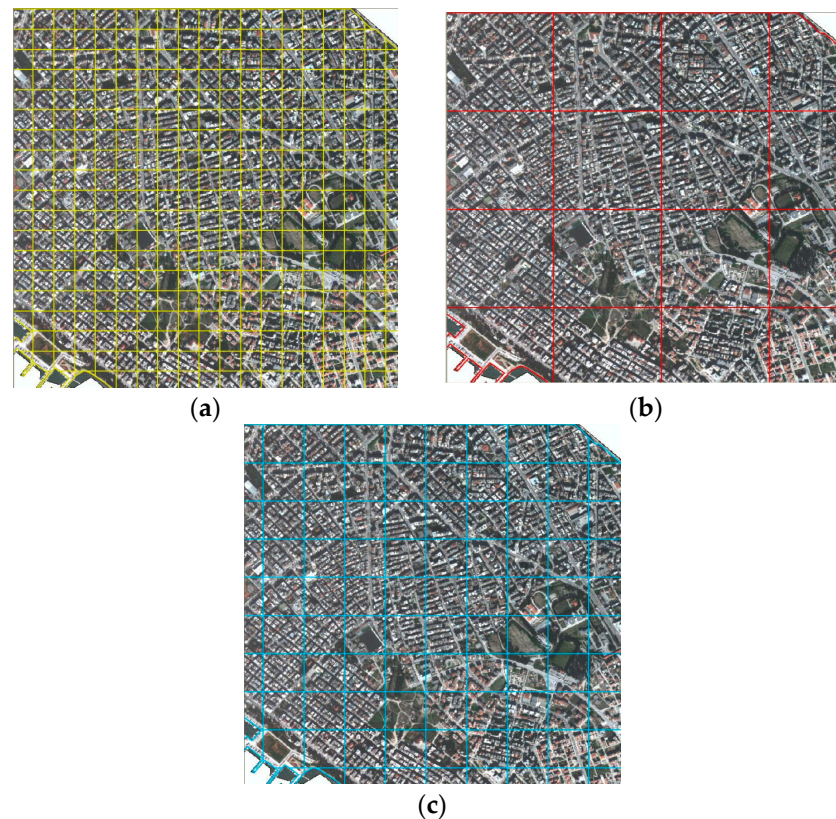


Figure 4. Dividing the study area into cells of (a) $100\text{ m} \times 100\text{ m}$, (b) $500\text{ m} \times 500\text{ m}$, (c) $200\text{ m} \times 200\text{ m}$, which best meet the selection criteria. This grid size represents a small section of the urban fabric, typically comprising two to three building blocks, road segments and intersections, and urban greenery.

3. Results

3.1. Classification of Urban Sub-Units Based on Built-Up Density

Figure 5 illustrates the classification of the $200\text{ m} \times 200\text{ m}$ sub-units within the study area according to the computed urban built-up density.

The classification analysis of the 150 urban land sub-units within the study area revealed distinct patterns of built-up density distribution. Specifically, 10 sub-units were classified as high-density, with λ values ranging from 0.4 to 0.8, highlighting the significant concentration of built structures. The majority of sub-units based on this classification, 73 in total, fell into the moderate-density category, with λ values between 0.2 and 0.4, while 67 sub-units were identified as low-density areas, characterized by λ values below 0.2. Spatial analysis of these classifications indicates that the majority of moderate- and high-density sub-units are concentrated in the historical center of the Municipality of Kalamaria, where urbanization has been long established. On the other hand, the newly developed areas in the southeastern part of the study region predominantly fall into the low-density category, suggesting a more dispersed urban fabric with improved spatial planning regarding built-up density.

The examination of proportional charts illustrated the distribution of greenery and built-up areas within each sub-unit. In this way, we can more accurately identify the significant deficiency of green spaces in areas classified as high and moderate density. This observation aligns with urban development patterns in Greece, where older and more compact urban cores often exhibit limited green infrastructure. In contrast, the newer residential neighborhoods demonstrate a more balanced urban design that incorporates greater green space coverage.

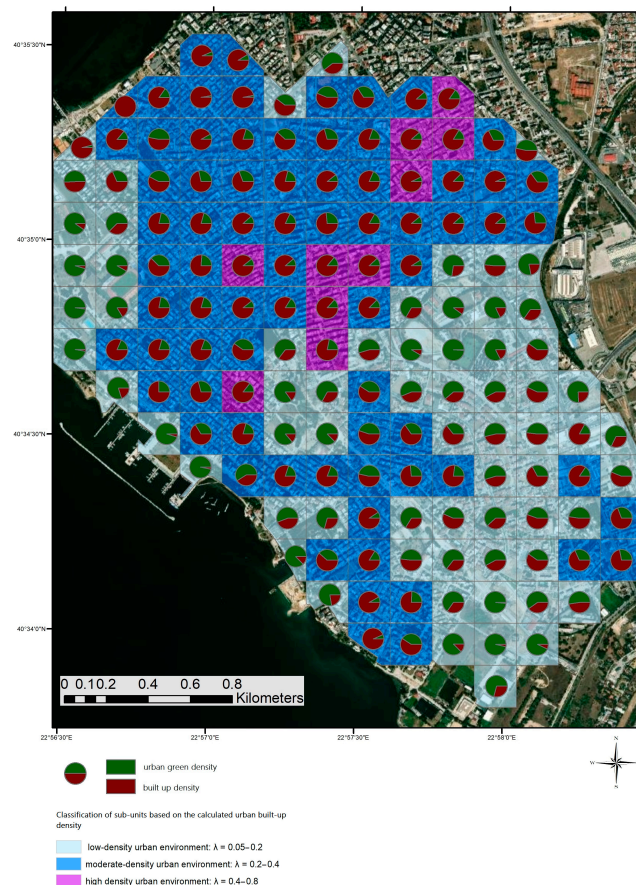


Figure 5. Classification results for the $200\text{ m} \times 200\text{ m}$ sub-units of the study area based on the computed urban built-up density. The generated classification scheme overlaid with proportional charts representing the percentages of the identified greenery and built-up areas within each unit.

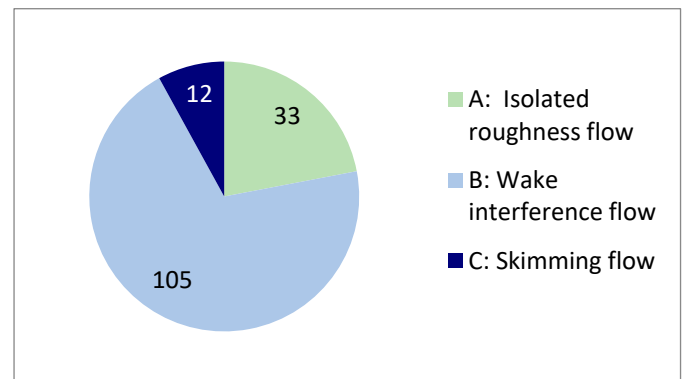
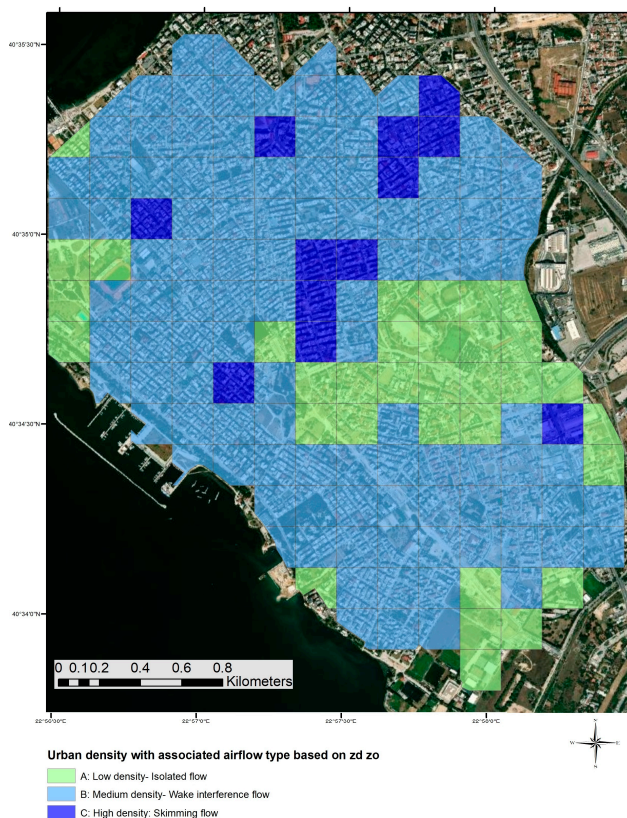
3.2. Classification of Urban Sub-Units Based on Identified Airflow Type

Figure 6 presents a different approach to classifying the $200\text{ m} \times 200\text{ m}$ sub-units within the study area, based on calculated urban built-up density. This time, the classification was determined by associating each sub-unit with a specific airflow type, derived from surface roughness parameter estimates.

The updated classification schema of the study area, which is based on characterizing urban density from the identified wind flow patterns, differs from the previous classification. Under this new framework, 12 zones have been identified as high-density built-up areas. Notably, the number of medium-density sub-units has significantly increased to 105, while low-density sub-units now account for only 33.

This refined classification enhances the understanding of airflow behaviour across the study area. According to the new classification, Type B—wake interference flow is the predominant airflow type in the study area. This could present an alarming concern for environmental health, as areas characterized by poor air circulation, such as those dominated by wake interference flow, tend to experience elevated concentrations of air pollutants, including nitrogen dioxide (NO_2) and other emissions from traffic and urban activities. At the same time, these air conditions contribute to thermal discomfort and Urban Heat Island (UHI) effects, intensifying the environmental stress in densely built-up areas. Therefore, the visual inspection of the study area, combined with the spatial identification of zones requiring intervention, provides critical insights to guide the development of specific measures, by prioritizing areas where mitigation measures, such as enhancing ventilation

corridors, optimizing building configurations, or introducing green infrastructure, can be most effective.



(a)

(b)

Figure 6. (a) Classification results for the 200 m × 200 m sub-units of the study area based on the computed urban built-up density. This time, the classification was determined by associating each sub-unit with a specific airflow type, derived from surface roughness parameter estimates. (b) Chart depicting the overall identified airflow types in the study area.

3.3. Classification of Urban Sub-Units Based on Built-Up Volume and Porosity Index

By calculating the available air volume or air void, it is also possible to assess the degree of airflow permeability within an urban area. The urban built-up environment and its relationship to urban air voids can provide essential morphological insights, contributing to a deeper understanding of the urban form and its functional dynamics. This can be achieved using the ratio of the available air volume to the total built volume within the study area. In this study, average building height (h) has been adopted as the vertical boundary for each sub-unit. This assumption provides a practical and consistent approximation of the built environment's three-dimensional extent and provides a more standardized evaluation of the ratio between available air volume and total built volume. This ratio represents the porosity of the urban fabric [79], and is determined using the following equation:

$$P_h = \frac{A_T \times h - V}{A_T \times h}, \quad (6)$$

where:

P_h : Urban porosity (airflow permeability of the urban area)

A_T : Total area of the study region

h : Average building height above ground within the sub-unit (calculated based on the floor heights of the buildings it contains)

V: Total built volume within the study area

This metric offers valuable insight into the degree of permeability of the urban environment to airflow, which is a key factor in determining the effectiveness of natural ventilation across the built landscape. Higher porosity values typically facilitate smoother wind penetration, which result in the more efficient dispersion of air pollutants and overall improvement in micro-climatic conditions such as thermal comfort and humidity levels. Conversely, areas with low porosity values, characterized by dense, compact building arrangements and limited void spaces, can restrict airflow, leading to elevated pollutant concentrations and intensified UHI effects. As such, this metric is instrumental in assessing urban form from both an environmental performance and public health perspective.

Figure 7 demonstrates the classification results of the study area based on the computed urban built-up volume and the derived porosity index that defines the airflow permeability of the study area, while Table 3 presents the classification of urban permeability based on these values.

Table 3. Porosity index values and classification of urban permeability [35].

Porosity Index Values	Classification	Urban Permeability Rationale
$p < 0.50$	Low Porosity	Restricted airflow
$0.50 \leq p < 0.70$	Medium Porosity	Moderate air circulation
$0.70 \leq p < 0.99$	High Porosity	Good ventilation potential

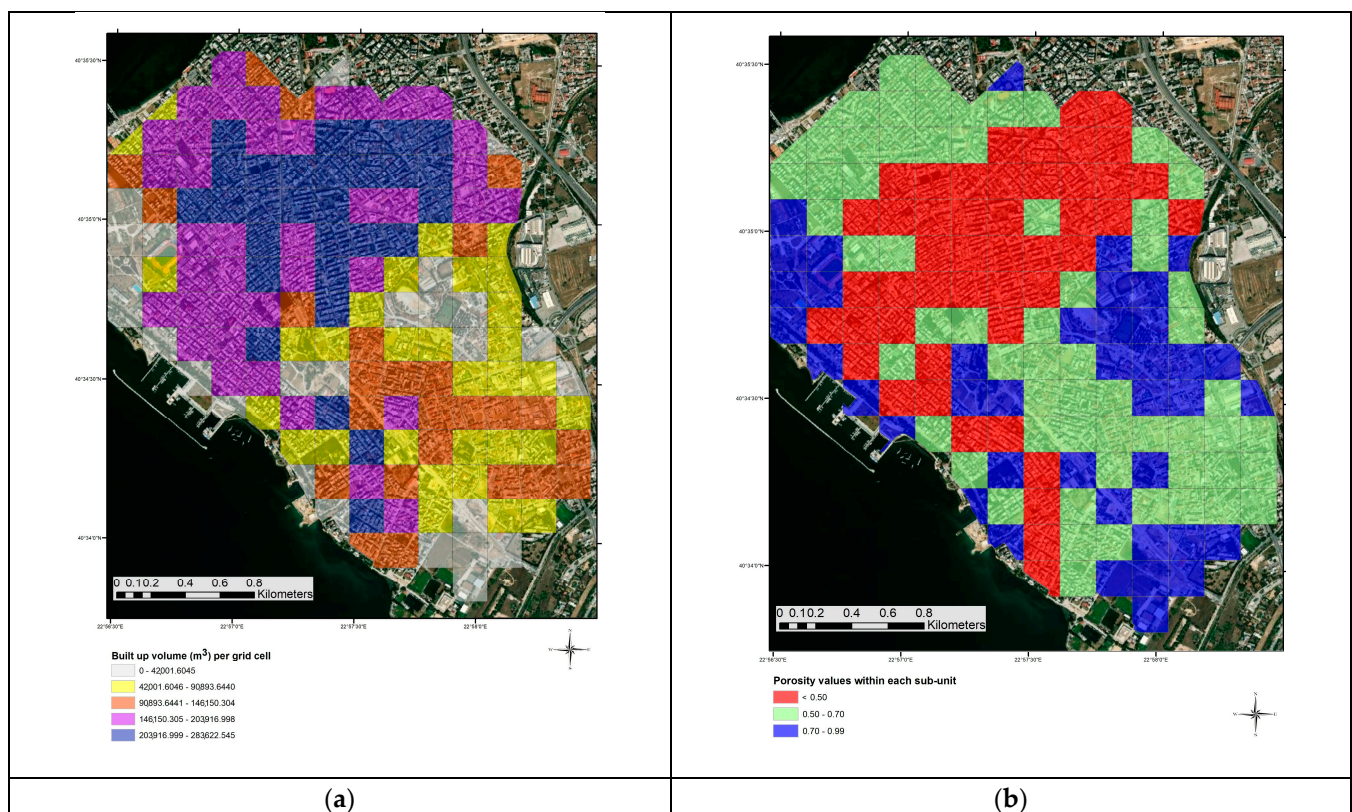


Figure 7. Cont.

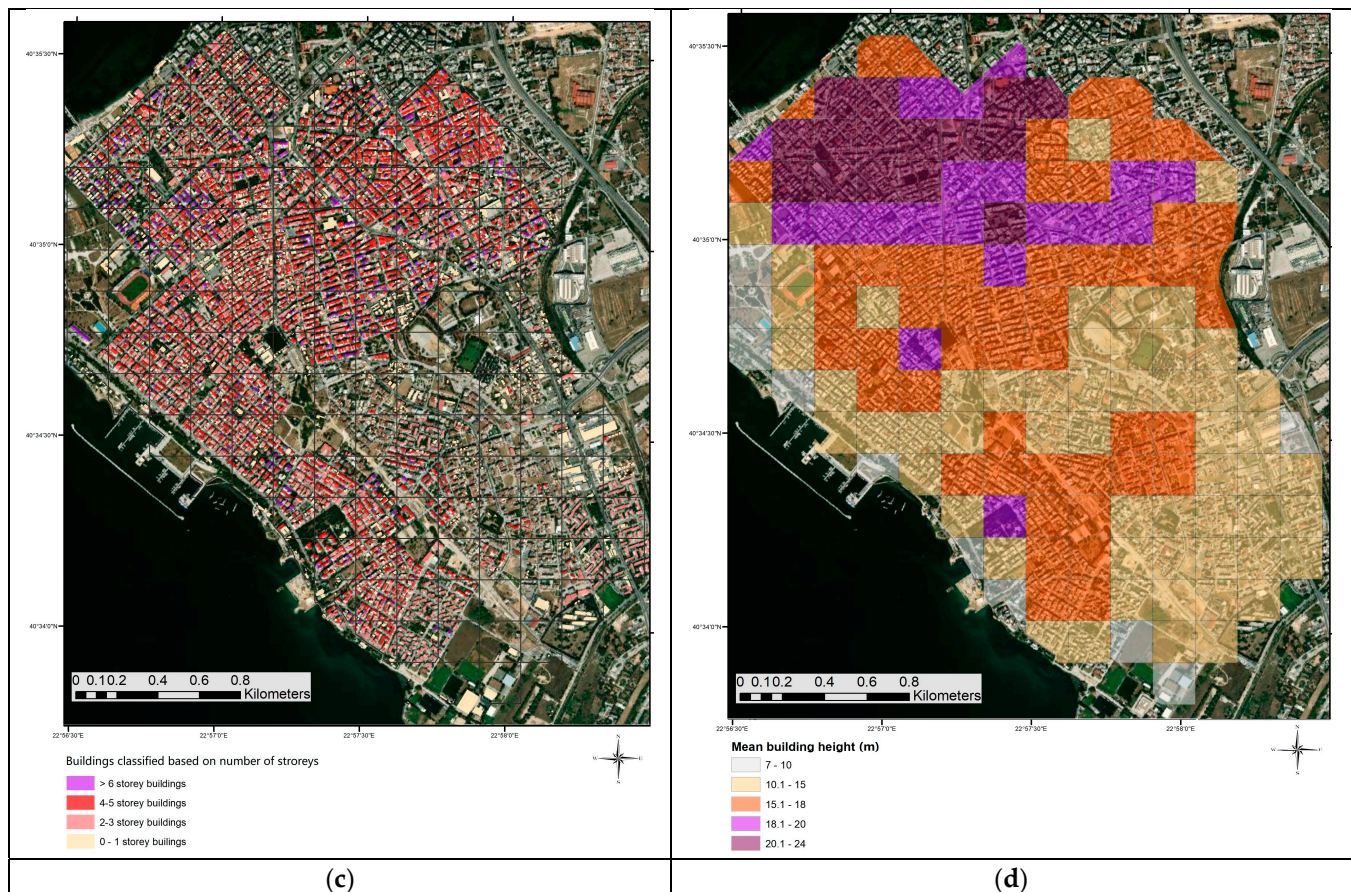


Figure 7. (a) Classification results for the $200\text{ m} \times 200\text{ m}$ sub-units of the study area based on the computed urban built-up volume in m^3 . (b) The generated classification scheme of the porosity index within each sub-unit. (c) Classified buildings based on number of storeys and (d) classification of sub-units based on mean building height.

The classification of the sub-units based on the porosity index values revealed that 46 out of the 150 sub-units exhibit low porosity values, which are indicative of restricted airflow. These areas are more likely to experience poor ventilation and increased pollutant accumulation. A total of 63 sub-units were found to have medium permeability, with porosity values ranging from 0.50 to 0.70. These areas usually represent a balance between built and open spaces that allow moderate airflow. Lastly, 41 sub-units were classified as having high porosity values, which are indicative of greater permeability. These areas, with more open space relative to built-up volume, facilitate better air circulation and potentially have improved microclimatic conditions with enhanced environmental quality.

To better understand the built-up volume and the associated airflow type, boxplots were calculated (Figure 8).

The box plots illustrate the distribution of the percentage of built-up volume found within $200\text{ m} \times 200\text{ m}$ grid cells across three flow types in the study area. The results of this analysis reveal that the sub-units that are classified as Type A have a wide range of values, ranging from 0% to approximately 18%, indicating high variability in building volume distribution. Type B sub-units show an increase in both central tendency and consistency, with a median near 27% and a range between roughly 18% and 34%. In contrast, Type C sub-units demonstrate the highest and most consistent built-up volumes, with both the mean and median around 35% and a narrow spread between approximately 33% and 39%. Overall, this boxplot confirms the upward trend in the percentage of built-up volume from Type A to Type C sub-units, with variability decreasing in Type C sub-units, suggesting

that areas characterized by skimming flow tend to have denser and more uniformly built-up environments.

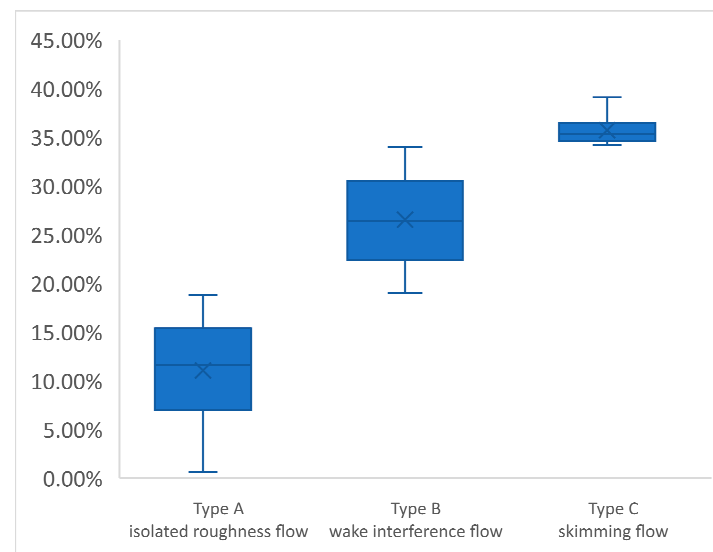


Figure 8. Boxplots presenting the distribution of the percentage of built-up volume found within 200 m × 200 m grid cells across the three airflow types identified in the study area.

This analysis offers a new perspective on the impact of obstacles (i.e., buildings and structures) that wind encounters within the study area. It highlights how vertical urban occupation, specifically the arrangement and density of buildings, affects airflow patterns and, consequently, the urban microclimate. By analyzing the relationship between porosity and airflow, we gain insights into how the built environment influences air quality, thermal comfort, and overall livability in urban spaces.

3.4. Associations Between the Built-Up Area, Airflow Type, and Porosity Index Across Urban Subunits

Conducting an association analysis between built up area, airflow type, and porosity index, which has been calculated in every sub-unit, was another measure for understanding the spatial relationships and interactions among key morphological and aerodynamic characteristics of the urban fabric under study. By examining these associations, we intended to highlight how variations in building density and air porosity influence airflow patterns within the urban grid of the study area. This insight is essential for assessing the impact of urban form on microclimatic conditions, particularly in terms of natural ventilation and thermal comfort. Moreover, such analysis can effectively support the development of evidence-based urban planning strategies that aim at enhancing environmental performance and resilience in densely built areas, which is a very common case scenario in Greek urban centres.

For this statistical analysis, the Spearman's rho correlation coefficient [80] was calculated as the normality test, which was initially conducted using the Kolmogorov–Smirnov method, which had revealed that these variables are not normally distributed. Spearman's rho (ρ) is a non-parametric method that evaluates how strongly two variables are related, even when that relationship is not perfectly linear. It is especially well-suited for urban morphology research, where variables such as porosity and built-up area often do not conform to the assumptions required for parametric tests. Unlike Pearson's correlation, Spearman's rho works by ranking values rather than relying on the raw data, which makes it more resilient to outliers and non-linear trends. In essence, it tells us whether increases in one variable are generally associated with increases or decreases in another. The results of

this association analysis, focused on built-up area, porosity, and airflow type, are presented in Table 4.

Table 4. Spearman’s rho correlation coefficient results.

Correlations					
			Built-Up Area	Airflow Type	Porosity
Spearman's rho	Built-up area	Correlation Coefficient	1.000	0.641 **	−0.731 **
		Sig. (2-tailed)		0.000	0.000
		N	150	150	150
	Airflow type	Correlation Coefficient	0.641 **	1.000	−0.582 **
		Sig. (2-tailed)	0.000		0.000
		N	150	150	150
	Porosity	Correlation Coefficient	−0.731 **	−0.582 **	1.000
		Sig. (2-tailed)	0.000	0.000	
		N	150	150	150

** Correlation is significant at the 0.01 level (2-tailed).

The Spearman’s rho correlation matrix confirmed the significant relationships among the studied variables based on a sample of 150 sub-units of the study area. All correlations are statistically significant at the 0.01 level. There is a strong positive association between built-up area and airflow ($\rho = 0.641$). This is another indication that as the built-up area within a grid cell increases, the airflow tends to shift toward more obstructed patterns, namely, airflow types B and C. In contrast, porosity is negatively correlated with built up and airflow type. The strongest negative association is with built-up area ($\rho = -0.731$), meaning that as the built-up area increases, porosity decreases, a logical outcome given that higher building density reduces open spaces. Porosity also shows a moderate negative association with airflow ($\rho = -0.582$). These results confirm that higher porosity is associated with airflow type A in the study area. Overall, this analysis highlights and confirms the complex relationships between urban form and aerodynamic behavior, underlining the importance of not only porosity but also spatial arrangement and building geometry when assessing urban ventilation performance.

4. Discussion

By utilizing satellite imagery, this paper analyzes how the composition of urban land cover affects urban ventilation in the region of Kalamaria Municipality in Thessaloniki, Greece. A combination of satellite imagery from Sentinel-2 and WorldView-2, along with vector spatial data, were used in the GEE platform. The study area was segmented into $200\text{ m} \times 200\text{ m}$ sub-units; thus, the analysis achieved a higher spatial analysis, facilitating a more detailed examination of urban morphology within the urban fabric. In many studies [81–83] on urban morphology analysis, the urban density is usually characterized using demographic indicators like population density, or utilizing administrative boundaries, such as district boundaries or city boundaries. These metrics are typically selected due to their broad availability across urban areas, rather than their relevance to the specific environmental challenges cities face nowadays, or their physical or morphological characteristics. As a result, the lack of consistency and comparability across different urban regions makes their use in scientific analysis not adequate.

We propose a spatial framework and classification schema for defining urban areas into sub-units that, in contrast to conventional administrative boundaries, are derived from objective metrics of the built and natural environment. This approach enables meaningful comparisons both within and across urban regions and captures structural heterogeneity

that population density alone fails to reflect. In our research, we analysed the study area at a neighborhood level, and calculated critical morphological parameters such as the built-up area, the urban density, and the surface roughness parameters z_d and z_o , revealing the associated airflow type, the porosity index, and the built-up and the air void volumes. All these parameters were derived using, as a primary source of data, the results of the satellite imagery processes with the combination of the available vector height data of the study area. The spatial analysis of these data allowed us to calculate all these parameters for every sub-unit of the study area and to create a geodatabase that contains all these valuable information (Figure 9).

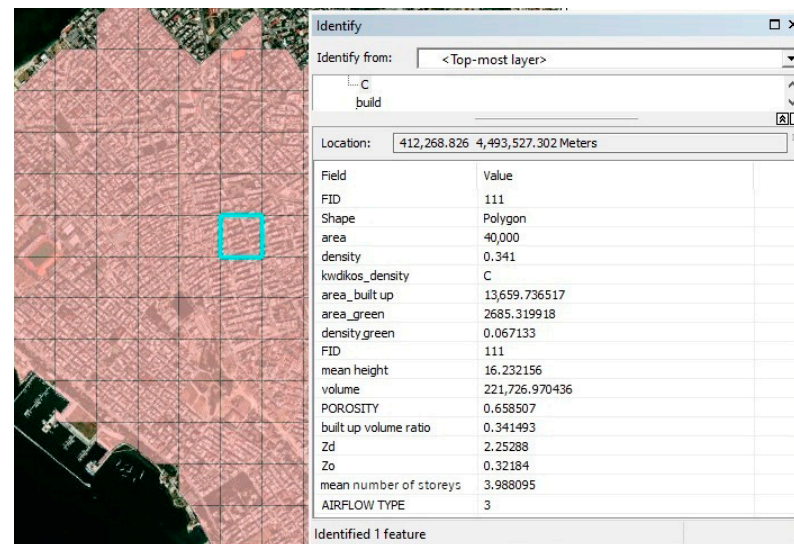


Figure 9. Dividing the study area into cells of 200 m × 200 m, the created geodatabase includes information of all calculated critical morphological parameters in every sub-unit such as: the built-up area, the urban density, and the surface roughness parameters z_d and z_o , revealing the associated airflow type, the porosity index, and the built-up and the air void volume.

Our analysis demonstrates that, by integrating surface roughness parameters, the zero-plane displacement height (z_d), and roughness length (z_o), a total of 12 spatial units were reclassified as high-density built-up units. These areas are associated with airflow type C, corresponding to the skimming flow pattern, that is typically observed in compact urban forms, where building height and spacing obstruct the air movement. These zones exhibit a high built-up volume ratio, ranging from 34% to 40%, while the built-up density (calculated based solely on buildings footprints) varies between 0.21 and 0.34. Conversely, the vegetative cover density within these zones is low, ranging from 0.03 to 0.12. Furthermore, two sub-units initially categorized as medium-density were reclassified as high-density zones, while one sub-unit previously defined as low-density was also reassigned to type C, following the integration of z_d and z_o values. In contrast, the number of medium-density sub-units substantially increased to 105 in the updated classification, compared to the original categorization, making it the predominant urban density type in the study area. Among these, 23 areas were formerly low-density, and one transitioned from high to medium density. Built-up density within these areas spans from 0.01 to 0.36, while green density displays values up to 0.79. Built-up volume across these sub-units also presents significant variability, ranging from 1.25% to 37%. Lastly, 33 areas are now classified under type A, indicative of low-density development patterns. These zones exhibit a built-up density ranging from 0 to 0.22, while vegetative density reaches up to 0.79. Interestingly, built-up volume in these low-density areas fluctuates from 22% to 66%, reflecting heterogeneity in vertical construction intensity. Finally, two sub-units originally

identified as medium-density were reclassified as low-density (type A) based on refined assessments incorporating surface roughness parameters.

Our findings indicate that the majority of sub-units classified as type C and B are located within the older, more compact urban areas of the Municipality of Kalamaria (Figure 10).



Figure 10. The boundaries of the broader area of Kalamaria’s city center (red rectangle). The area is characterized by dense building configurations, narrow street networks, and limited open or green spaces.

This finding is consistent with the known characteristics of these zones, which have historically exhibited high built-up coverage and limited green infrastructure. However, our approach provides a quantifiable assessment that enables the identification of specific areas that are more prone to urban environmental degradation. On the other hand, this analysis identified that newer residential neighborhoods display a more balanced urban design, characterized by increased green space coverage. A key advantage of this methodology is that it relies solely on satellite-derived data, spatial datasets, and spatial analysis techniques. This approach may introduce some degree of error, particularly in the classification of land use types. With the spatial resolution of WorldView-2 (0.5 m), mixed land use areas may not be fully captured, which could lead to misclassifications in the derived polygons. Nonetheless, this level of spatial resolution is considered high for Remote Sensing applications and is generally sufficient to produce a reasonably accurate representation of current land use patterns [44]. This allowed us to capture critical spatial patterns and conduct a detailed neighborhood-level assessment, rather than limiting the study to a city-wide overview. Such localized analyses are essential for the implementa-

tion of urban sustainability practices in micro-geographies, where interventions can be most impactful.

Another notable strength of our approach lies in its use of freely available and easily accessible data sources. By avoiding the need for in situ measurements, we propose an efficient and adaptable method for analyzing urban morphology, one that can be readily applied across different urban environments in Greece. The GEE platform has contributed significantly to achieving this, as it provides access to a vast archive of satellite imagery and enables the consistent application of custom algorithms across any area of interest. In Greece, where reliable morphological datasets are often lacking, this approach offers significant potential. The GEE platform facilitates broad urban coverage and allows researchers to analyze diverse geographic regions and different time periods. This capability supports a deeper understanding of urban dynamics that offers valuable insights into how various cities evolve and respond to ongoing environmental pressures.

Limitations and Future Directions

It is important to acknowledge the limitations of this study. First, as the applied methodology relies on satellite imagery acquired during the summer of 2024, this limits its ability to capture the effects of seasonal variations on surface roughness and airflow dynamics. Seasonal factors, such as building heating during winter and vegetation leaf fall, can influence airflow patterns and thermal characteristics. However, our analysis focused specifically on the role of permanent, man-made structures that remain stable across seasons. For the same reason, vegetation was intentionally excluded as a wind obstacle to isolate the aerodynamic effects of urban infrastructure. A spatio-temporal analysis would provide a more comprehensive understanding of urban microclimates, and we consider this to be an important direction for future research. Furthermore, the inclusion of on-site measurements, such as wind speed, pollutant concentrations, and temperature, would significantly strengthen the empirical basis of the findings. Due to the unavailability of such in-situ data during the study period in Greece, direct validation of modelled airflow and pollutant accumulation was not feasible. The only accessible data are from the Hellenic National Meteorological Service, which provides measurements at a city-wide scale. Such data lack the spatial resolution needed for a detailed analysis of wind profiles in our study area. Collaborating with environmental monitoring teams to incorporate field-based measurements is a key direction for our future research. In addition, we are continuing our investigation using GEE to extract surface temperature data across multiple seasons. This work aims to further explore the interactions between LST, land use, and wind profile patterns in the study area. These planned enhancements will not only expand the temporal dimension of our analysis but also improve the accuracy and applicability of our findings.

Finally, another limitation could concern the applicability of the empirical coefficients f_d and f_o , (refer to Section 2.3). While these coefficients are widely used in urban climate studies, they were originally developed in urban contexts that might differ from a typical Mediterranean setting, thus it is advisable to require further validation. Due to the absence of locally calibrated parameters for our study area we adopted the suggested values for these coefficients. Our intention is to fine-tune our results in the future using calibrated and experimentally validated data and on-site measurements of wind speed and pollutant concentrations to strengthen the credibility of these findings.

Despite the aforementioned limitations and drawbacks of the applied methodology, our approach, relying solely on freely available satellite and GIS data, ensures methodological consistency and enhances the applicability of this method in urban areas with limited data availability. As such, our findings should be interpreted as indicative rather

than definitive; they could offer a spatially informed overview of airflow patterns based on urban morphology, rather than direct meteorological validation.

5. Conclusions

To promote the sustainability of urban centers, a systematic investigation of the factors that define the complex urban environment is essential. Urban climates are steadily deteriorating, posing increasing challenges to healthy living conditions [48,84]. As cities keep growing and changing, it is more important than ever to take timely action to protect both the environment and the health of the people who live there. One way to support this effort is by using Remote Sensing, which has become an incredibly useful tool for understanding how cities are structured and how they function. By helping us monitor features like urban form and surface texture, Remote Sensing gives us valuable insight into the elements that define and influence the urban landscape.

Based on our findings, several targeted actions can be proposed to enhance the urban environment of the Municipality of Kalamaria. In high-density zones (Type C), where built-up volume is high and green cover is minimal, it is essential to prioritize the integration of green infrastructure through pocket parks, rooftop gardens, and vertical greening [19,85,86]. Urban greening strategies could include the introduction of vertical greenery systems and pocket parks in underutilized spaces, as well as the use of light-colored roofing materials to mitigate heat accumulation. These interventions can improve local microclimates and mitigate the effects of poor ventilation associated with skimming airflow patterns. For transitional medium-density areas (Type B), urban design guidelines should promote balanced development by enforcing minimum green space requirements and encourage mixed-use planning. Creating ventilation corridors that align with prevailing wind directions, based on localized wind flow modeling, can also play a crucial role in enhancing microclimatic conditions and overall urban comfort. Additionally, it is advisable to update the current urban regulations to preserve open spaces and require minimum setbacks for new developments that could enhance natural ventilation. These recommendations could be supported by design guidelines at the municipal level, ensuring alignment with local building typologies and environmental conditions. In low-density zones (Type A), where green density remains high but built-up volumes are increasing, protective measures should be implemented to preserve existing green spaces and support sustainable land-use practices. Furthermore, microclimate-sensitive urban design should be promoted across all density types by enhancing urban ventilation through the creation of airflow corridors and the use of reflective and permeable materials to combat urban heat stress. Our proposed data-driven approach could be adapted by local urban planning policy makers to continuously monitor morphological factors. The use of our proposed classification schema can support more informed and localized decision-making and ensure that urban sustainability strategies are both targeted and effective.

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Agency available database and are openly available at <https://earth.esa.int/eogateway/missions/worldview-2>. Accessed: 11 April 2025. [Online].

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