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Using GEOBIA and Vegetation Indices to Assess Small Urban Green Areas in Two Climatic Regions

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Abstract: The importance of small urban green areas has increased in the context of rapid urbanization and densification of the urban tissue. The analysis of these areas through remote sensing has been limited due to the low spatial resolution of freely available satellite images. We propose a timeseries analysis on 3 m resolution Planet images, using GEOBIA and vegetation indices, with the aim of extracting and assessing the quality of small urban green areas in two different climatic and biogeographical regions – temperate (Bucharest, Romania) and mediterranean (Athens, Greece). Our results have shown high accuracy (over 91%) regarding the extraction of small urban green areas in both cities, across all analysed images. The timeseries analysis showed consistency in location for around 55% of the identified surfaces throughout the entire period. The vegetation indices registered higher values in the temperate region, due to the vegetation characteristics and the planning of the two cities. For the same reasons, the increase in vegetation density and quality, as a result of the distance from the city centre and the decrease in the density of built-up areas is more obvious in Athens. The proposed method provides valuable insights in the distribution and quality of small urban green areas at city level and can represent the ground basis for many analyses, currently limited by poor spatial resolution.

Keywords: small urban green areas; GEOBIA; NDVI; MSAVI2; Planet

1. Introduction

The rapid urbanization that characterizes society today comes with two main trends in urban development – densification of the urban area with the aim of creating compact cities and expansion in the peripheral areas, often through urban sprawl. Both models are currently being critically analysed from the perspective of sustainable urban development, one of the main goals of the HABITAT Agenda [1] and The United Nations Sustainable Development Goals [2]. Cities are facing a wide range of challenges, which have an effect on environmental quality and the wellbeing of residents [3].

One of the main challenges for achieving sustainable, resilient and inclusive cities [4] is ensuring the optimum amount of available and accessible high quality urban green areas. The expansion of cities has resulted in the existing green spaces being hard to reach from the new residential areas developed in the urban outskirts [5], while the increase in density has multiplied the pressures to which they are subjected [6]. Due to the lack of undeveloped public open spaces inside cities, many of the new larger green areas are located on the outskirts [7,8]. Therefore, small urban green spaces have become a viable solution for increasing the presence of vegetation in cities [9,10] since they are easier to plan than the larger spaces, due to their surface and the diversity of existing approaches, both traditional (street alignments, residential gardens, pocket parks) and modern (green roofs, green walls, rain gardens).

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Small urban green areas are patches covered by vegetation within cities. The accepted size for a small green area is debatable, with many studies focusing on the category rather than on the surface. Among the proposed threshold values, one of the most used is 0.5 ha [5,11], but depending on the object of the analysis or the legislative context, researchers have also opted for other limits. In Romania, for example, the Green Areas Law enforces a surface of a minimum of 1 ha, in order for a green area to be acknowledged as a park and a maximum of 1 ha for an area to be regarded as a green square [12].

Small urban green spaces represent stepping stones in the green infrastructure [13] and provide cumulative benefits correlated with the network's density. As with all urban green spaces, the small ones contribute to increasing environmental quality through aspects such as climate change mitigation [14], pollution and noise control, regulation of the hydrological circuit or the creation of habitats [15]. Moreover, they positively impact both physical and mental health [16] and help increase human wellbeing and the quality of life [17].

Research has mainly concentrated on large urban green areas [18], especially urban parks and forests, since they are very important elements at urban level and provide a wide range of benefits. Research in the field of small urban green areas is still scarce and their distribution and quality have generally been neglected, even if as a whole, they represent a high percentage of the vegetation in cities. Studies focusing on small urban green areas usually focus on their use [5], their importance in terms of population health and the perception the population has in relation to their design [10] or associated benefits [19]. There is also a category of technical studies which focuses, in particular, on exploring the characteristics of modern, small urban green areas, such as green roofs [11], green walls or rain gardens and quantifying their input in terms of improving environmental quality.

Remote sensing is widely used in the assessment of urban green areas but it especially targets large areas [20], as they are easier to assess by means of automatic and semi-automatic methods. Research studies so far have mainly focused on the distribution and dynamics of urban green areas [21,22] and their characteristics, such as species composition [23] and the quality and health of vegetation in cities [24,25].

Remote sensing analysis is conditioned by the resolution and characteristics of available images, their spatial and temporal coverage and access to data [18]. The most used images for the extraction of urban green areas are NASA's Landsat [22,26] and ESA's Sentinel [27,28], due to their long-term coverage. Yet, their spatial resolution of 30 m, respectively 10 m, does not support the accurate extraction of small patches of vegetation. New imagery developed over the last few years, such as Pleiades [28,29] and Planet have allowed researchers to dive into the analysis of the distribution and quality of small urban green areas. Furthermore, high resolution images (under 1 m spatial resolution) like IKONOS, GeoEye, World View 3 and 4 are difficult to use on a large scale in research due to their cost.

The extraction and analysis of small green areas through remote sensing also faces methodological challenges. OBIA, one of the most widely used methods in the field, can create irregular shapes for the objects through the segmentation process [30]. To solve this problem, it has been suggested that an appropriate segmentation scale and a multi-temporal analysis of object-based classification be used [31]. Another issue in the classification of small urban green areas is the presence of shadows on the imagery [18], since they very often occupy the areas near buildings which can't be properly seen. Hyperspectral images are recommended in this situation since different combinations of bands can help better distinguish the elements [32].

In a recent study, Shahtahmassebia et al. [18] realized a review regarding the remote sensing of urban green spaces and highlighted the need for a more detailed investigation of small urban green areas. They recommended developing timeseries analysis and thematic applications, among others. Our study contributes to filling this gap by trying to respond to three research questions: (1) Is GEOBIA method applied to Planet images suitable for extracting small urban green areas? (2) Is the method suitable irrespective of the biogeographical region to which is applied? (3) Does the method provide valuable results in terms of the quality of small urban green areas regardless of the biogeographical region?

In order to respond to these questions, we tested the method on two cities located in different climatic and biogeographical regions – Bucharest (Romania) and Athens (Greece). In line with the proposed research questions, the study proposed two objectives:
(1)to determine whether small urban green areas can be extracted using GEOBIA on Planet timeseries in two different biogeographical and climatic regions.
(2)to compare the quality of small urban green areas in two different biogeographical and climatic regions.

2. Data and Methodology

2.1. Study area

The proposed method was developed and tested using two European capitals as case studies: Bucharest, the capital of Romania, situated in a plain area and Athens, the capital of Greece, located in a hollow area, edged by the Saronic Gulf (Aegean Sea) (Figure 1). Both cities are the largest in their respective countries, Bucharest having 2 million inhabitants and an area of 240 km^2 [33], meanwhile the number of inhabitants in the Greater Athens Area has reached 3.1 million in an area of 360 km^2 [34].

The two study areas are characterized by different climatic conditions which influence the quality and quantity of urban green spaces. Bucharest has a temperate-continental climate with a transition effect [35], meanwhile Athens enjoys a typical Mediterranean climate, with hot, dry summers and mild, rainy winters (Table 1). Over the last few years, both areas have been affected by heatwaves. Both cities contain large, dense built-up areas and are affected by urban sprawl and intense air pollution which, combined with the destruction of peri-urban forests by wildfires or changes in land cover, have generated an urban heat island effect with an intensity as high as 10^{o}C in Athens [36], compared with an average of 5^{o}C in Bucharest [37].

Table 1. Climatic characteristics of Bucharest and Athens.

City	Annual mean temperature	Temperature amplitude	Minimum monthly average temperature	Maximum monthly average temperature	Annual average amount of precipitation	Reference
Bucharest	10.5^{o}C	26^{o}C	-3^{o}C in January	23^{o}C in July	585 mm	ANM [38]
Athens	17.8^{o}C	19.5^{o}C	8.8^{o}C in January	28.3^{o}C in July	411.8 mm	Hellenic National Meteorological Service [39]

The planning systems in which the cities developed have considerably influenced the surface and morphology of green areas. Bucharest is a mix of socialist neighbourhoods, containing all important public services (including green areas, both large and small), historical areas, usually represented by dense single-family residential, and modern projects, mainly represented by office spaces [40,41]. Over the past three decades, the city has experienced a chaotic development as a result of two key processes - urban sprawl and densification [42,43]. By contrast, Athens began to experience spontaneous, undesigned urban development in rural areas around its historical centre starting in the 1920s, with the uncontrolled and unplanned outward expansion of the urban tissue continuing to this day [44,45]. Consequently, both cities have limited public open spaces.

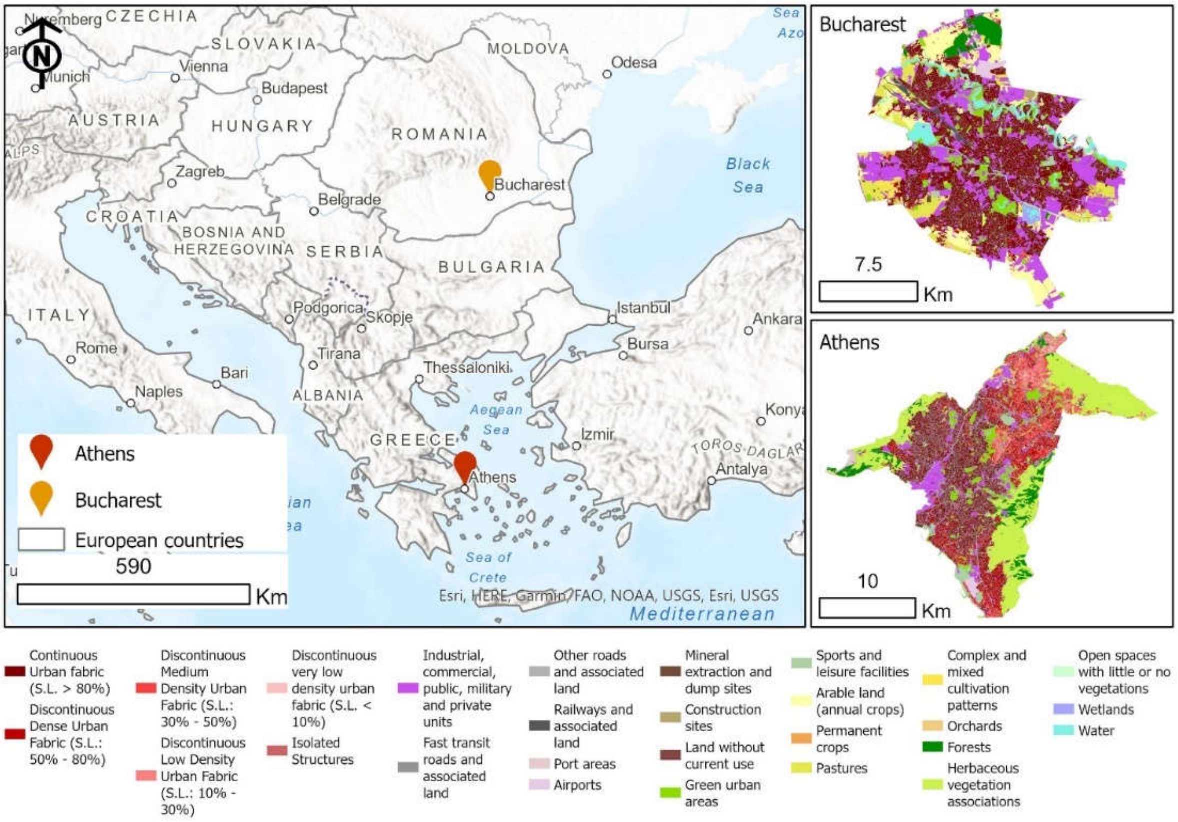

Figure 1. Location of the case studies and main land use categories, based on Urban Atlas data [46].

According to the European Environment Agency [47], Bucharest and Athens boast a low percentage of urban green and blue spaces, compared with the other European capitals and are ranked 31 and 36, respectively, out of the 37 analysed cities. The green space network in the two cities is represented both by large green areas (such as parks, cemeteries, sports areas, forests) and small urban green areas, such as pocket parks, residential and institution gardens, street alignments or green roofs, which represent a significant part of the total. National statistics may differ slightly from the European figures, since each country regulates their green space differently. Romania, for example, doesn't include green roofs or playgrounds but does include cemeteries and sports areas [12], which may contain extensive, impervious surfaces. Greece regulates green spaces along with other public areas, such as sidewalks, bike paths or playgrounds, which may not include green areas, and suburban green [48].

2.2. Extracting small urban green areas using GEOBIA

For the present study we used four-band Planet imagery with a 3 m spatial resolution [49] for the period 2018-2020. We selected summer images retrieved between 1st June and 15th July, when the vegetation season was at its height in both case study areas. We extracted small urban green areas using Geographic Object-Based Image Analysis (GEOBIA) [30,50,51]. In the segmentation step, the scale factor was chosen based on several trials with values between 18 and 20 [52,53]. Random forest classification was used to classify the objects obtained in the segmentation step into three main land use types (green, developed and water) [29,54,55]. The validation of the obtained classification was performed using confusion matrix to calculate the overall accuracy and Kappa index [28,37]. We classified four images for each city, all of which had an overall accuracy higher than 91%, which is considered very good [27] and a Kappa index higher than 0.84 (Table).

Table 2. Accuracy results for GEOBIA classification.

City	Image code	Acquisition date	Overall accuracy (%)	Kappa
Athens	A20180613	13 June 2018	94.80	0.9020
	A20190708	08 July 2019	91.80	0.8470
	A20200621	21 June 2020	93.40	0.8783
	A20200722	22 July 2020	92.87	0.8662
Bucharest	B20180610	10 June 2018	96.20	0.9267
	B20190613	13 June 2019	93.20	0.8739
	B20200626	26 June 2020	95.00	0.9080
	B20200715	15 July 2020	93.00	0.8700

As it was only required to maintain the small urban green areas in our database, we used the OSM 2021 data [56] to erase the land uses associated with large green areas, such as cemeteries, farmland, farmyards, forests, meadows, allotments, nature reserves, parks, recreation grounds and scrubs from the obtained classifications. Moreover, we also deleted the areas classified as green outside the built-up limit, which were not identified as green by OSM, but also did not represent urban green areas. Afterwards, we used the roads from the same database to split the remaining green areas into parcels and deleted those with an area over 2 ha. The resulted dataset was used in the next steps of the analysis, which focused only on the small urban green spaces.

2.3. Vegetation indices used for assessing the quality of small urban green areas

To analyse the small urban green areas, we selected two widely used vegetation indices - the Normalized Difference Vegetation Index (NDVI) [57] and the Modified Soil Adjusted Vegetation Index 2 (MSAVI2) [58]. Considering the visible spectrum and near infrared provided by the Planet images [59], we calculated NDVI and MSAVI2 using the formula in Table 3. NDVI is an indicator of vegetation, used for evaluating the abundance of vegetation and its characteristics, based on a scale from -1 to +1, where 0.2 is considered as a threshold for impervious areas [60,61]. MSAVI2 is considered to provide better results than NDVI in terms of distinguishing different canopy structures, as well as in the case of early stages of vegetation or types of vegetation which do not entirely cover the soil, even when they are fully developed [62]. Usually, these two indicators are used together for analysis purposes to obtain better information [29]. Due to objective considerations, such as the wavelength of the images, it was not possible to calculate indices referring to water, nitrogen or carbon [63–65].

In the context of the current study, we refer to quality of small urban green areas from the point of view of the information provided by the two indicators – NDVI and MSAVI2. Therefore, through quality we understand the density and health of vegetation, since the assessed indicators are strongly correlated to photosynthetic activity, biomass, plant and soil moisture and plant stress [66,67].

Table 3. Vegetation indices used in the analysis [68].

Index code	Index	Formula
MSAVI2	Modified Soil Adjusted Vegetation Index 2	$\frac{2 \times NIR + 1 - \sqrt{(2 \times (NIR + 1)^2 - 8(NIR - Red)}}{2}$
NDVI	Normalized Difference Vegetation Index	$\frac{(NIR - Red)}{(NIR + Red}$

An optimized hot spot analysis was performed based on the Getis-Ord GI z-scores [69,70] for NDVI and MSAVI2, to identify statistically significant spatial clusters of high values (hot spots) and low values (cold spots) [71].

2.4. Factors influencing the quality of small urban green spaces

In order to understand the spatial variations in the quality of small urban green areas, as indicated by the two calculated indicators (NDVI and MSAVI2), we performed statistical analysis which helped in quantifying the variations. Based on scientific literature, we selected three indicators which proved useful when assessing the characteristics of urban green spaces, in order to assess the spatial distribution of the quality of small urban green areas. The three selected indicators were the distance from the main roads [65] (as defined in the OSM database), the distance from the city centre [62] and built-up density [72] (calculated using OSM data for a fishnet of 100x100m). The small urban green areas extracted in the previous step were clipped using the same fishnet and for each resulted patch (with a surface of maximum 1 ha) we calculated the distance from the closest main road, the city centre and the built-up density. For each patch we also applied spatial statistics and calculated the z-score for NDVI and MSAVI2 [73].

After calculating the three indicators for each patch of small urban green area in the two cities, we identified the minimum and maximum values. For each indicator and each city, we created five classes using the equal interval method. For the built-up indicator, the values ranged from 0 (no built-up areas in the analysed cell) to 1 (the cell was entirely occupied by the built-up area).

One-way ANOVA was performed using SPSS [74] in order to compare the effect of the three indicators on the quality of small urban green areas. The average value of NDVI and MSAVI2 per patch of small urban green area were used as dependent variables. As independent variables, we used the three indicators: distance from the green patch to the main roads – *Class_roads*, distance from the city centre – *Class_centre* and built-up density – *Class_built*.

Furthermore, we tested the differences in average NDVI and MSAVI2 values between the five classes established for each indicator. We performed post hoc tests (Tukey HSD test) [75] in order to identify the different classes between which differences were registered. The calculation of the vegetation indexes, the zonal statistics and the hot spot analysis were optimized by developing Python scripts.

3. Results

3.1. Distribution and dynamics of small urban green areas

The analysis highlighted that a considerable share of the green areas in the cities are represented by small patches. The extraction of green features through GEOBIA revealed that, on average, 49% of Bucharest and 68% of Athens are covered by vegetation (including tree canopy overlapping built areas and infrastructure, agricultural land, protected areas and abandoned surfaces covered by vegetation in the peripheral area of the cities). Between 36% (in the case of Athens) and 47% (in the case of Bucharest) of the surface identified as vegetation is represented by small urban green areas, which mainly include residential gardens (both public and private), pocket parks, street trees and gardens of institutions. Analysing the dynamics of the small urban green areas between 2018 and 2020, we observed that in Bucharest, these showed variations between 21% and 28% of the city's surface with a slightly increasing trend (Figure 2a), meanwhile in Athens they registered a gradual decrease from 29% to 23% (Figure 2b).

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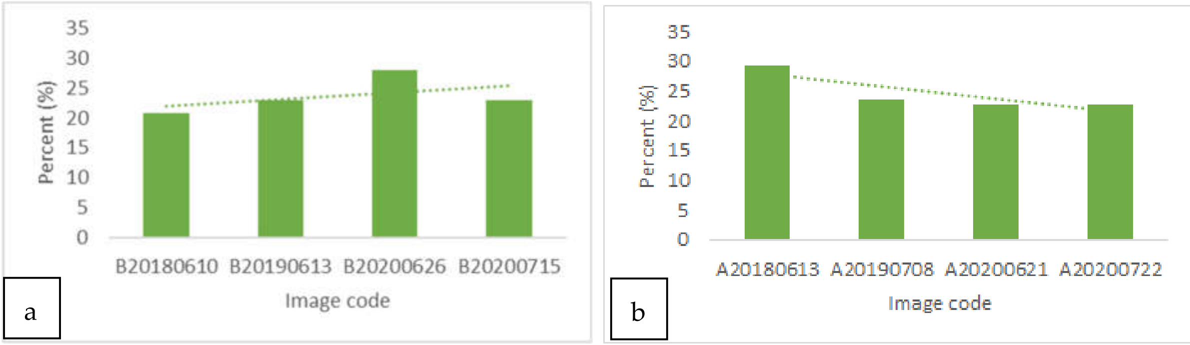

Figure 2. Variations of small urban green areas per image for Bucharest (a) and Athens (b).

The dynamics of the small urban green areas was analysed by overlapping the four images for each city. In Bucharest, 37.11% of the surface of small urban green areas is identified as green on all four images (100% overlap), 18.57% overlaps on three images (>50% overlap), 18.87% on two images (<50% overlap), while 25.44% of the green surface only appears on one of the classified images (Figure 3a). In Athens, 36.5% of the surface of identified small urban green areas are distributed in this category in all four analysed moments, 15.67% are classified as green on three images (>50% overlap), 22.41% on two images (<50% overlap) and 25.41% appear on only one image (Figure 3b).

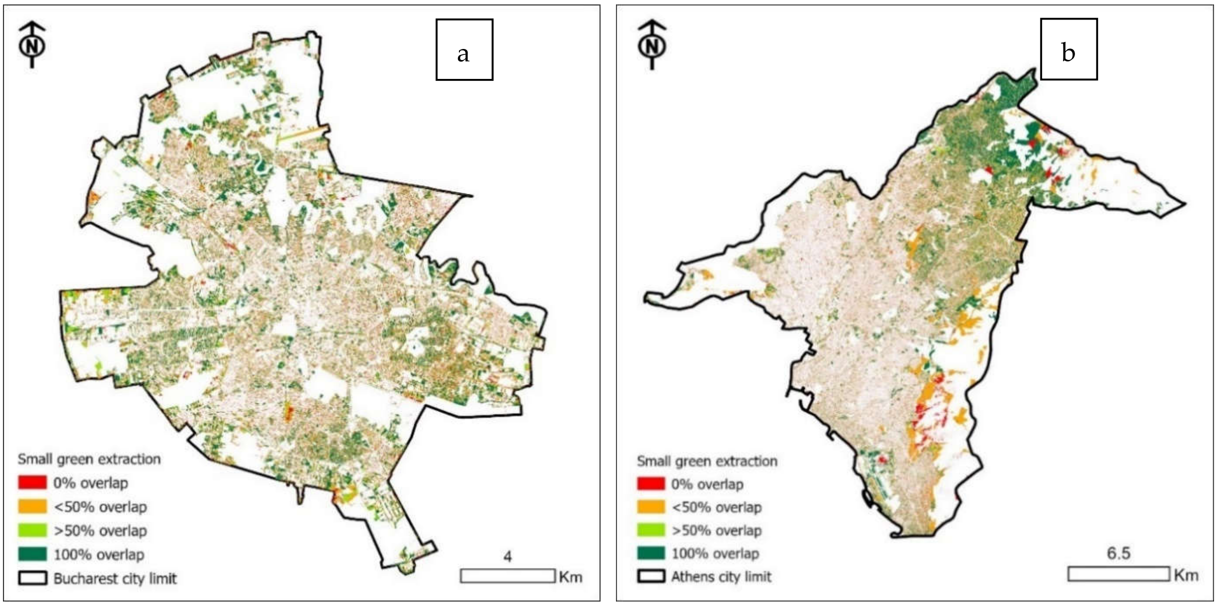

Figure 3. Small urban green area distribution for Bucharest (a) and Athens (b), 2018-2020.

The percentage of overlaps highlights the certainty of the presence of small urban green areas in those locations. In the case of both cities, around 55% of the identified small green areas remain in this category almost across the entire analysed timeframe. The areas with a high percentage of overlaps have different distributions across the two cities. Meanwhile Bucharest has high overlap mainly in the peripheral socialist neighbourhoods, in Athens those areas are mostly located in the hills in the north-eastern part of the city where neighbourhoods consisting of villas belonging to the higher class are located.

3.2. Quality of small urban green areas

The values of NDVI and MSAVI2 highlight the characteristics and quality of small urban green spaces in the two cities. At city level, Bucharest has higher values than Athens in the analysed timeframe, even if the latter contains a larger surface of green areas, the same tendency exists when analysing only the small urban green areas. The average values for NDVI of identified small urban green areas, calculated for the analysed timeseries, are 0.53 for Bucharest and 0.29 for Athens; meanwhile, the average value of MSAVI2 for the same surfaces is 0.69 for Bucharest, compared to 0.44 for Athens. The highlighted tendency is explained by the different types of vegetation characterizing the two cities.

In the case of Bucharest, the average values of NDVI, calculated for the small urban green areas, vary between 0.48 in 2018 and 0.59 in 2019. Meanwhile, Athens is characterized by smaller variations, with a minimum average of 0.26 in 2018 and a maximum average of 0.30 for the other three images. According to the registered values, the small urban green areas in Bucharest have denser and healthier vegetation than those in Athens. The values above 0.66 show that these small patches contain mature trees with a dense canopy, a situation which is characteristic of Bucharest, whereas those between 0.33 and 0.66 suggest the presence of bushes or scarcer vegetation, as may be found in Athens.

The highest values of NDVI within small green patches in Bucharest are associated with the wealthier neighbourhoods in the north, followed by some of the largest socialist neighbourhoods in the city, Titan (in the east), Berceni (in the south) and Militari and Drumul Taberei (in the west) (Figure 4a). In Athens, the highest values are around 0.66 and characterize the north-eastern region of the city (Kifisia, Ekali), an area inhabited by the wealthier class (Figure 4b).

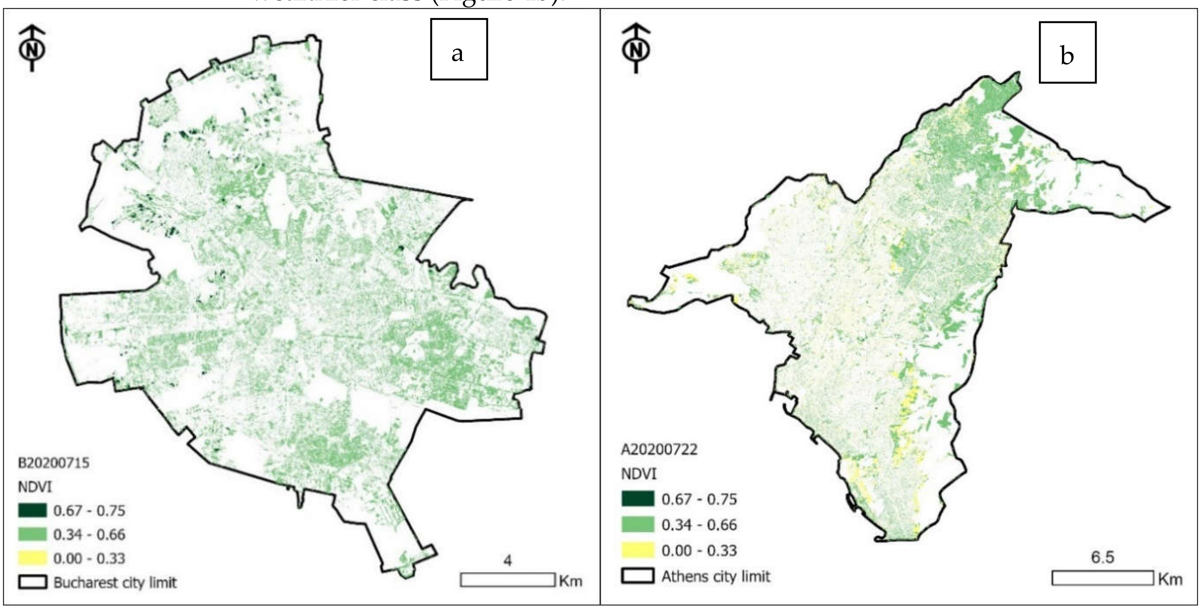

Figure 4. NDVI distribution of small urban green areas for July 2020 in Bucharest (a) and Athens (b).

In Bucharest large urban green areas (as forests and parks) are characterized by higher values of NDVI than small green patches throughout the entire analysed timeframe. In 2019, we registered the highest values of NDVI with 67% of the large urban green areas and 45% of the small urban green areas having values over 0.66. In Athens, few areas have NDVI values above 0.66, regardless of whether they are large or small.

The MSAVI2 average values, calculated for small urban green areas, varied between 0.64 in 2018 and 0.74 in 2019 in Bucharest and between 0.4 in 2018 and 0.46 in 2019 in Athens, with very similar values for 2020. Both the spatial distribution and the temporal dynamics of MSAVI2 are similar to those of NDVI. In Bucharest, almost all surfaces identified as small green areas have average values over 0.6 (Figure 5a), indicating that the vegetation is sufficiently dense to cover the soil. However, in Athens, the registered average values for MSAVI2 above 0.6 were between 6% in 2019 and 31% in July 2020. The majority of the small urban green areas in the city have average values between 0.4 and 0.6 (Figure 5b) highlighting the scarcity of Mediterranean vegetation. The spatial distribution of the values of MSAVI2 points to both city centres as lacking appropriate green coverage.

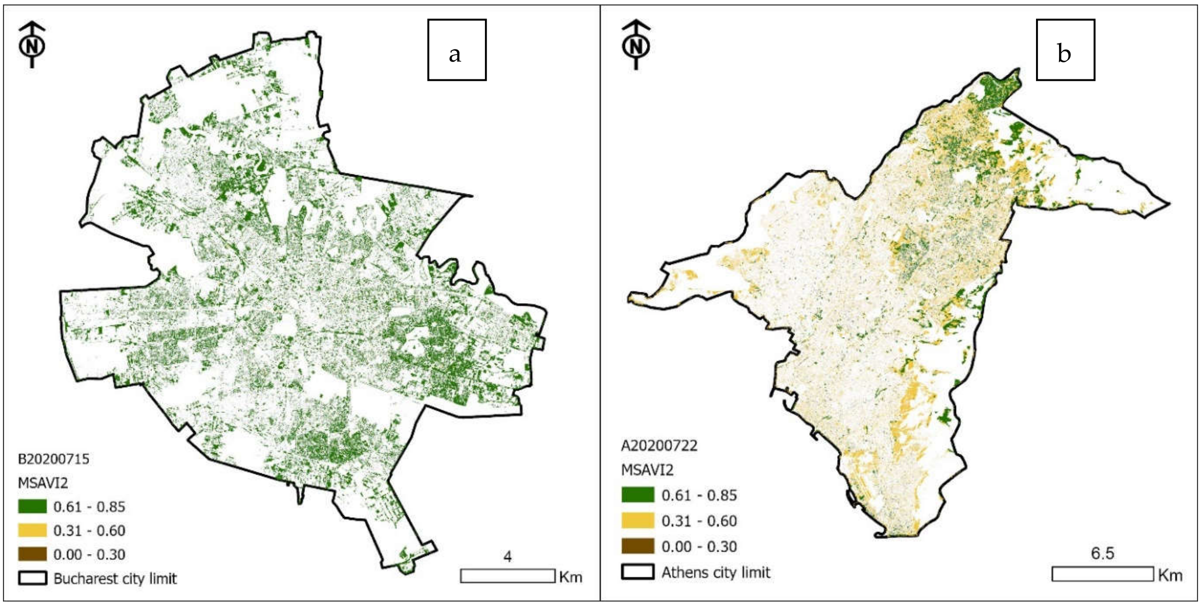

Figure 5. MSAVI2 distribution of small urban green areas for July 2020 in Bucharest (a) and Athens (b).

3.3. Spatial distribution of the quality of small urban green areas

The Optimized Hot Spot Analysis showed the same spatial characteristics for both indicators and all four images analysed for each city. The average values of NDVI and MSAVI2 for small urban green areas showed that strong spatial clustering, marked as hot spots in the northern and western part of Bucharest exists (Figure 6a), whereas the centre and the eastern regions are identified as cold spots. In Athens, the clustering shows hot spots in the northern and eastern parts of the city (Figure 6b). In both cities, there is a tendency to create hot spots in areas near the forests (in the north in Bucharest and the north-east in Athens) and cold spots in the central area. Small urban green areas tend to have higher average values, if they are in the proximity of large green areas.

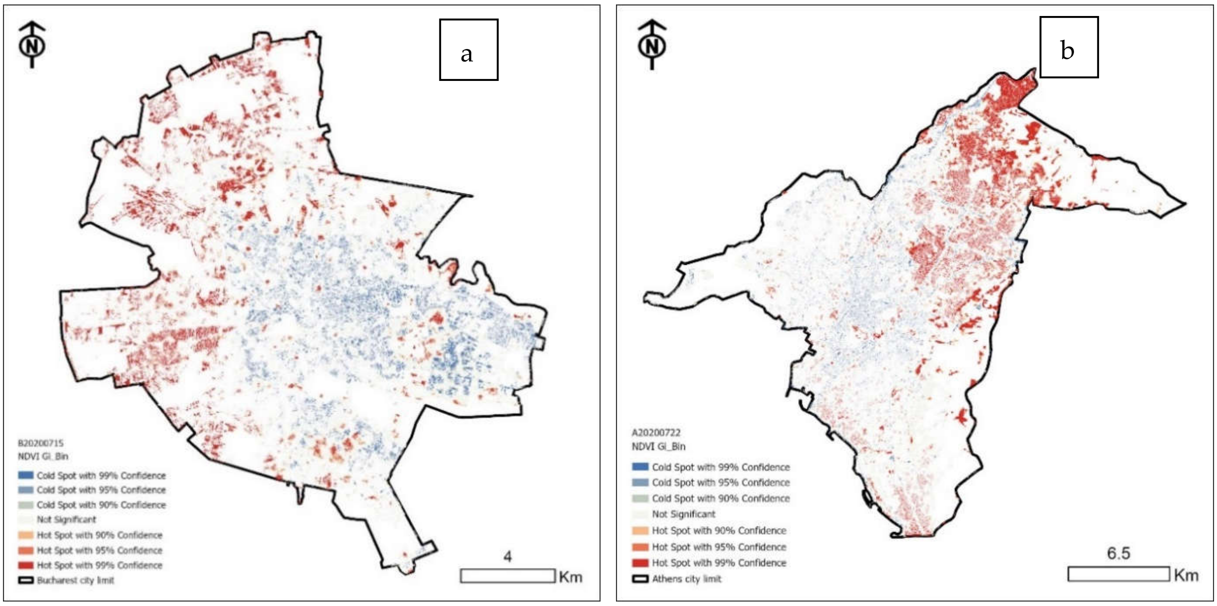

Figure 6. Optimized hot spot distribution of NDVI for July 2020 Bucharest (a) and Athens (b).

Testing the spatial distribution of the quality of small urban green areas highlighted similar tendencies for NDVI and MSAVI2 in both cities. The ANOVA tests revealed significant statistical differences between the quality of small urban green areas (measured

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through NDVI and MSAVI2) for all three tested indicators – distance from main roads, distance from the city centre and built-up density (Table 4) in both cities. The only exception was the image of Bucharest from 2018 in which we were unable to identify significant differences between the NDVI classes in relation to the built-up surface.

Table 4. ANOVA test results for mean values of NDVI and MSAVI2 for Bucharest and Athens.

Image code	Df between groups	Df within groups	F-statistic/ p-value	Class_roads NDVI	Class_roads MSAVI2	Class_center NDVI	Class_center MSAVI2	Class_built NDVI	Class_built MSAVI2
A20180613	4	223966	F	357.03	348.71	4778.36	4580.19	4203.57	4347.13
			p	0.00	0.00	0.00	0.00	0.00	0.00
A20190708	4	149844	F	428.16	413.18	2975.23	2984.12	2841.54	3006.98
			p	0.00	0.00	0.00	0.00	0.00	0.00
A20200621	4	181283	F	385.94	369.83	5220.60	5085.26	4531.01	4743.90
			p	0.00	0.00	0.00	0.00	0.00	0.00
A20200722	4	242108	F	180.10	203.38	3548.11	3484.79	3789.40	3897.32
			p	0.00	0.00	0.00	0.00	0.00	0.00
B20180610	4	91753	F	34.32	63.79	5.83	256.52	1.34	42.52
			p	0.00	0.00	0.00	0.00	**0.25**	0.00
B20190613	4	92611	F	32.75	32.91	340.22	351.81	144.91	126.52
			p	0.00	0.00	0.00	0.00	0.00	0.00
B20200626	4	107680	F	26.87	26.24	230.55	217.16	116.02	107.57
			p	0.00	0.00	0.00	0.00	0.00	0.00
B20200715	4	100240	F	518.35	507.65	2274.74	2216.17	1206.33	1182.90
			p	0.00	0.00	0.00	0.00	0.00	0.00

The most relevant indicator was the distance of the small green areas from the centre of the city. The Tukey HSD test showed significant differences between all analysed classes in seven of the eight images. The image for Bucharest from 2018 only registered significant differences between some of the five classes. In the case of Athens, the quality of the small green areas exhibited a significantly clear increase from the city centre to the peripheral areas, with differences between 0.8 (2019) and 0.13 (July 2020) for the mean values of NDVI and between 0.9 (2019) and 0.14 (July 2020) for those of MSAVI2. Regarding Bucharest the values are much closer together with class 2 (located between 2.5 and 4.7 km from the city centre) only registering significantly higher values. This class is essentially located outside the inner-city ring of Bucharest and overlaps the large socialist neighbourhoods in the city.

As in the case of the first indicator, the built-up density is better illustrated in Athens than in Bucharest. The quality of the small urban green areas decreases as the built-up density increases; the differences are registered by the mean values for the five classes, varying between 0.11 (2018) and 0.17 (June 2020) for NDVI and between 0.15 (2018) and 0.22 (June 2020) for MSAVI2. The Tukey HSD test highlights that in Athens, there are significant differences between all classes except classes 4 (61-80% built-up) and 5 (81-100% built-up) in respect of the two images in 2020. For Bucharest, the results are similar with those registered for the distance from the city centre, with small variations between the means of the five classes and no consistent spatial pattern.

In the case of the distance from the main roads, the results are similar for both cities. The post-hoc tests showed several classes with no significant differences between them, especially those closer to the main roads compared with those farthest away. In both cities, the highest-class averages for NDVI and MSAVI2 were registered for the medium distances. Multiple comparisons showed that there is a correlation between the results obtained with Optimized Hot Spot Analysis and the differences between groups.

4. Discussions

4.1. Method efficiency for extracting small urban green areas

GEOBIA is an efficient method, widely used for extracting different types of land use at city level, including urban green areas [76,77]. We took one step further and calibrated this to efficiently extract the small urban green areas using high resolution images. Our data showed a high level of accuracy when identifying green areas (over 91% across all analysed images) in both the climatic and biogeographic regions analysed – mediterranean and temperate.

The small urban green areas we extracted from the images do not exactly represent the physical surface of the green areas, but the canopy for those which contain trees [18]. For this reason, combined with the resolution of images and the fact that the selected method allows the exclusion of artificial areas, which are included in green spaces [78] (e.g., large alleys in parks, roofs of sports areas), but also the inclusion of green areas which may not be considered as such in the legislation (e.g., informal green areas which may include, among others, the green roofs or private residential gardens [7]), the resultant green areas cannot be compared with the official statistics. Instead, these should be comparable with the data provided by Copernicus Land Monitoring Service and other similar databases since they use the same range of methods [37].

Image resolution is a positive aspect of our analysis. Sun *et al.* [79] demonstrated that urban green spaces can be successfully identified using images with spatial resolution between 2 m and 16 m. With a 3 m resolution, Planet images are the best available satellite images, provided freely for research by Planet. They offer the opportunity to study the small urban green areas, which was not possible with other widely used satellite imagery, like Landsat (30 m resolution) and Sentinel (10 m resolution). Research into urban green areas, using Planet images, is still in its infancy, however, the application of the latter is wide-ranging. For example, Pascual et al. [80] used these in order to predict the risk of tree mortality in a tropical eucalypt forest in Brazil.

Our analysis showed that very small green areas (such as the green patches on roundabouts) and linear elements (such as street alignments) have lower validation scores than pocket parks or residential gardens. To analyse these accurately, there is a need for images with a better resolution, technologies which may not be publicly available and a computational capacity which increases exponentially with the detail degree of the analysis [81].

The use of timeseries ensures validation [82], especially when analysing an element with high spatial dynamics, such as small urban green areas. In both case studies in more than 50% of the cases small urban green areas are identified as such on at least three of the four images. The rest of the surface may be identified as small green only on some images, due to the technical factors or changes in the land cover. Among the relevant technical factors, we highlight the quality of the images and the shadow effect, which especially affects the areas near high buildings where small green areas may be located [18]. Researchers have explored several methods in order to minimize this problem, such as the use of four masks (vegetation, height, shadow and distance) [83].

Land cover change is a significant aspect when analysing small urban green areas [82,84] since their surface and their often unclear legal status make them vulnerable to transformations [43]. For example, in Bucharest, in the context of a volatile legislative framework, many small green areas have been transferred into private property and transformed into other land uses [85,86]. Moreover, there are areas which are not actively managed and therefore, depending on the climatic conditions and the works that take place, these may be covered by ruderal vegetation [87], by bare soil or even urban waste. This might be the case in abandoned industrial or agricultural areas, brownfields or even different types of gardens depending on their management [26]. On a smaller scale, the differences between the images may be attributable to various reasons, such as artificial vs. natural grass on football fields, the construction or demolition of buildings, the clearing of grass on empty plots and the pruning of trees and bushes, which is not performed to the same extent every year.

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4.2. Insights into the quality of small urban green areas

In line with prior research [88], our findings highlighted higher values of NDVI in Bucharest, which has a temperate climate, than in Athens, which enjoys a mediterranean climate. This aspect is related to both the biogeographical characteristics of the two regions and the planning decisions implemented in the cities. The vegetation in Athens is mainly represented by evergreen species, such as oak and cypress, and in the peripheral areas there are olive groves [89]. Many urban green spaces in the city contain oleander, olive, lemon or orange trees. The vegetation in Bucharest mainly consists of deciduous species, such as linden, hornbeam, American maple and platanus.

Mediterranean vegetation is adapted to cope with drought stress and has a low water content [89] which explains the lower levels of NDVI in comparison with the vegetation in the temperate climate during summer. Meanwhile evergreen vegetation has similar NDVI values over the year [90]; deciduous species in the temperate zone register maximum values during late spring and early summer when the biomass and photosynthesis are at peak [67].

Our results showed that both cities have neighbourhoods with very well developed small urban green areas (Figure 7), but their share within the city is very different. In Bucharest, the socialist neighbourhoods (e.g. Drumul Taberei), which comprise the majority of the multi-family residential spaces, have very well developed small green areas, mainly represented by residential gardens, pocket parks and street alignments. These areas, which were planned during the socialist regime, along with the residential buildings they serve, have dense and well-developed vegetation (usually including mature trees which are 40-50 years old) rendering them NDVI hot spots at city level. In contrast, multi-family residential areas in Athens (e.g. Kalithea) have low values of NDVI, due to the scattered character of the vegetation which generates very low values of NDVI (around 0.3). The single-family residential areas have comparable NDVI values in Bucharest and Athens, but in the case of the latter, these cover small areas, usually in the eastern and north-eastern peripheries.

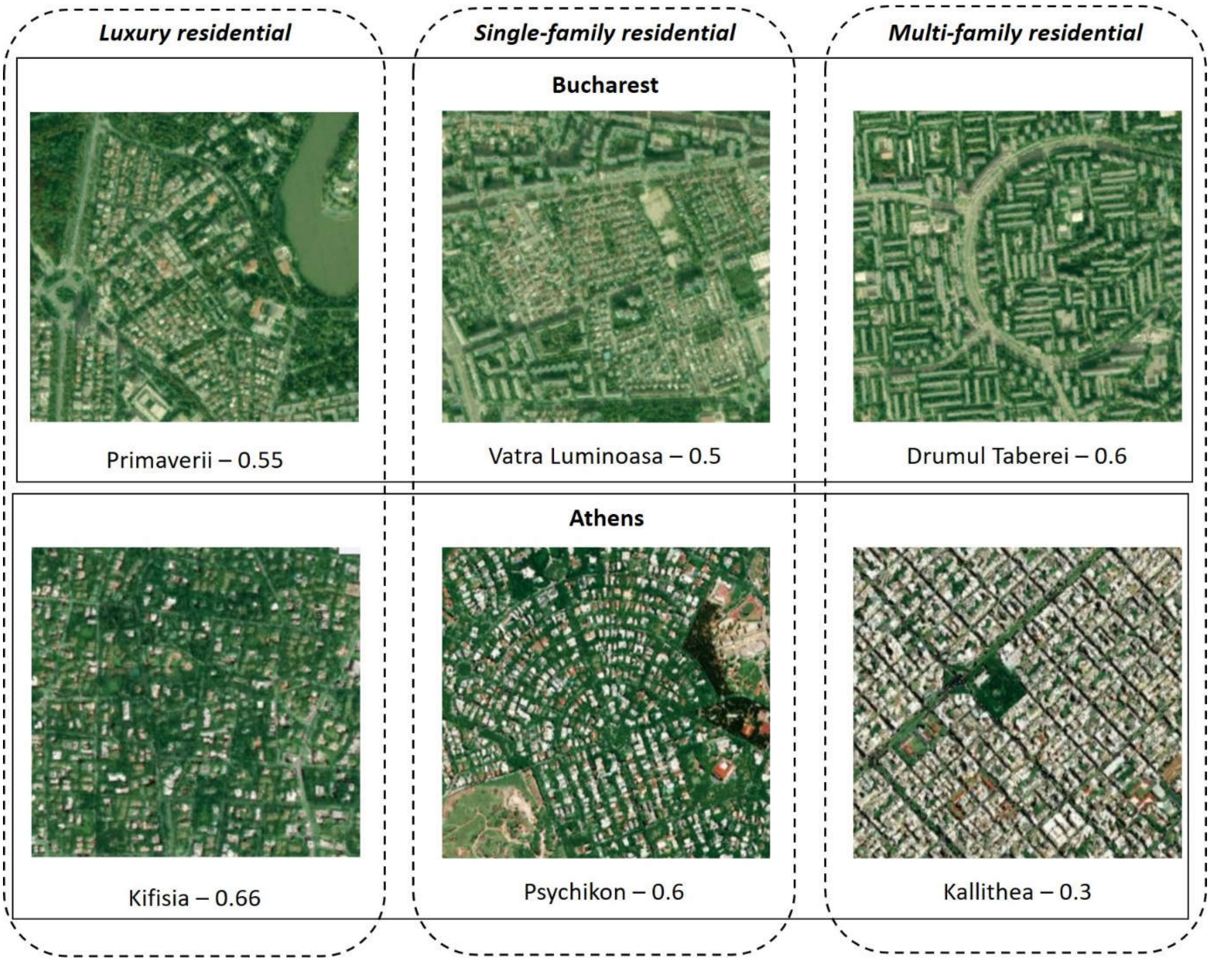

Figure 7. Sample of small green area with high NDVI values in Bucharest and Athens.

When assessing the quality of small green areas in relation to the distance from the city centre, the distance from roads and built-up density, there were smaller differences between the NDVI and MSAVI2 classes averages in Bucharest than in Athens. This is explained by the fact that in the urban core of Athens vegetation is very scarce and is dominated by individual trees; meanwhile on the periphery, there are residential gardens (Figure 7) and pocket parks. Even if the spatial resolution of the utilized images is very good, the 9 sqm pixels cannot optimally represent individual trees, especially those with small crowns, as in the case of many species encountered in the small urban green areas in the Mediterranean region. Even if the pixel is identified as green, the intrusion of the artificial areas surrounding the trees will lower the registered NDVI value [91]. On the other hand, in Bucharest the differences are less between the centre and the periphery in terms of small green areas, their surface and characteristics being less contrasting.

In both Bucharest and Athens, the highest values of NDVI and MSAVI2 were usually registered at medium distance from the main roads. This phenomenon might be related to the poor air quality in the proximity of main roads and the lack of maintenance works in the peripheral areas, which are located at a great distance from them.

Our results regarding the variations of NDVI and MSAVI2 in respect of built-up density in Athens are in line with those of Yang et al. [92], who found that in China, more concentrated building density generates a poorer quality of urban green areas in similar natural conditions. In Bucharest, this relationship is much less significant, with fewer differences between the classes and no clear tendency. This might be explained by the characteristics of the temperate deciduous vegetation, which is often higher than the buildings, especially in single-family residential areas, and therefore visible. Nawar et al. [24] argue that the decrease in the surface of green areas is directly related to the decrease in their quality. Our analysis did not focus on the evolution of the quality of individual green patches. Instead, it highlighted that small urban green areas are characterized by lower values of NDVI and MSAVI2 than large areas (associated mainly with parks and forests).

4.3. Influence of climatic and biogeographical characteristics

We tested the method for extracting the small urban green areas of two cities from different climatic and biogeographical areas, to ensure its higher potential of application. Considering the different climate zones of the analysed cities, we focused on creating training samples specifically for each city. Even though the acquired images were from the same period of time, the texture and the spectral response were different across the two cities. In the case of Bucharest, vegetation in small patches was easy to observe, while for Athens this was more difficult, due to the low water content of the vegetation [93]. In Athens, there are areas covered by low vegetation, which may become drier during certain periods, therefore, their spectral response may lead to different results; the drier the vegetation, the more likely it is that these areas are classified as "developed".

The identified surface of small green areas is related to the climatic conditions in the period prior to the analysed images. In Bucharest, for example, the smallest surfaces of the small green areas, registered in June 2018 and July 2020, are associated with the lowest rainfall [92] and the highest average temperature at the time of analysis (Table 5). The values of NDVI and MSAVI2, calculated at patch level, register higher differences in Bucharest than in Athens along the analysed timeseries. This may also be explained by the significant climatic variations [94] in Bucharest compared to those registered in Athens during the period before the images were acquired.

Table 5. Climatic conditions in Athens and Bucharest within the 30 day period before the analysed images [95].

City	Image code	Rainfall (mm)	Rainy days (no.)	Average temperature (°C)
Athens	A20180613	0	0	24.1
	A20190708	0	0	27.1
	A20200621	0	0	21.5
	A20200722	0	0	26.3
Bucharest	B20180610	31	9	21.2
	B20190613	157	14	20.1
	B20200626	109	14	19.8
	B20200715	83	9	23.7

The two indicators we selected for the analysis complement one another, especially in the case of the Mediterranean climate. In the case of Bucharest, the large surfaces with high values of NDVI reduce the contribution of MSAVI2. Virtually, all surfaces identified as small green areas on all images have the potential of developing dense vegetation. However, in Athens, MSAVI2 better highlights the areas where there is high potential for dense vegetation development and also identifies the areas with herbaceous vegetation, which cover larger surfaces in the Mediterranean city.

5. Conclusion

The novelty of our research relates, in the first place, to the resolution of utilized satellite images, which allows for the analyses of small urban green areas at city level. Past research only focused on large natural or urban green areas, or on small scale case studies. Our study is one of the first to analyse small green areas at urban level and provides a complex image of their distribution and quality. GEOBIA proved reliable in the analysis of small urban green areas and the use of timeseries improves the results. The method is easily replicable and an increased number of analyses on the subject would support the elaboration of a guideline to establish the suitable parameters for GEOBIA. The method rendered good results in both the temperate and mediterranean climatic regions, the main uncertainties being related to the individual trees and street alignments which require an even better spatial resolution and to the intense dynamics of these areas. An advantage of the presented method is the possibility of including in the assessments the private green spaces, which are difficult to analyse through field methods.

Planet images support the calculation of some vegetation indices, which can provide a general image of the state and quality of small urban green areas. Both NDVI and MSAVI2 register higher values in the temperate region due to the climatic and biogeographical characteristics supporting a greater vegetation density and water content. Testing the method in two different climatic regions proved its potential for generalization and revealed valuable insights in relation to the characteristics of small urban green areas. Future studies may target other climatic and biogeographical regions to ensure validation.

The proposed methodological framework can represent the basis for a large number of applications which require an accurate easy to implement method for extracting urban green areas. Such studies may relate to the assessment of cities sustainability, quality of life in urban areas, health and epidemiological studies.

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