Evaluation of urban green space per capita with new remote sensing and geographic information system techniques and the importance of urban green space during the COVID-19 pandemic

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Abstract A recently conducted study by the Centers for Disease Control and Prevention encouraged access to urban green space for the public over the prevalence of COVID-19 in that exposure to urban green space can positively affect the physical and mental health, including the reduction rate of heart disease, obesity, stress, stroke, and depression. COVID-19 has foregrounded the inadequacy of green space in populated cities. It has also highlighted the extant inequities so as to unequal access to urban green space both quantitatively and qualitatively. In this regard, it seems that one of the problems related to Malatya is the uncoordinated distribution of green space in different parts of the city. Therefore, knowing the quantity and quality of these spaces in each region can play an effective role in urban planning. The aim of the present study has been to evaluate urban green space per capita and to investigate its distribution based on the population of the districts of Battalgazi county in Malatya city through developing an integrated methodology (remote sensing and geographic information system). Accordingly, in Google Earth Engine by images of Sentinel-1 and PlanetScope satellites, it was calculated different indexes (NDVI, EVI, PSSR, GNDVI, and NDWI). The data set was prepared and then by combining different data, classification was performed according to support vector machine algorithm. From the landscaping maps obtained, the map was selected with the highest accuracy (overall accuracy: 94.43; and kappa coefficient: 90.5). Finally, by the obtained last map, the distribution of urban green space per capita and their functions in Battalgazi county and its districts were evaluated. The results of the study showed that the existing urban green spaces in the Battalgazi/Malatya were not distributed evenly on the basis of the districts. The per capita of urban green space is twenty-four regions which is more than 9m² and in twenty-three ones is less than 9m². The recommendation of this study was that Türkiye city planners and landscape designers should replan and redesign the quality and equal distribution of urban green spaces, especially during and following COVID-19 pandemic. Additionally, drawing on the Google Earth Engine cloud system, which has revolutionized GIS and remote sensing, is recommended to be used in land use land cover modeling. It is straightforward to access information and analyze them quickly in Google Earth Engine. The published codes in this study makes it possible to conduct further relevant studies.

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Introduction

The number of people living in cities is growing, and, globally, over 50% of the population is living in urban areas without any sign of this trend being reduced. Urban life usually not only provides access to health care, good sanitation, nutrition, and education, but also is connected to undesirable health effects (Engemann et al., 2019). In spite of this fact, the high concentration of people and activities in cities makes them weak against different types of stress or natural and man-made catastrophes. Given this, during the past decades, a great deal of research has been conducted regarding the impacts of different disasters on cities, especially the necessary planning, recovery, and adaptation measures that should be taken to overcome these disasters (Sharifi & Khavarian-Garmsir, 2020).

Urban green spaces (UGSs) are of great importance for both ecological balance and the individuals’ health. They are also influential in decreasing negative impacts of urbanization and enhancing physical activities of people (Khalil, 2014; Liu et al., 2021). In light of the pervasiveness and effects of depression, stress, and anxiety for over 30 years, experts have taken the connection with green space, a critical constituent of many environments. Plenty of studies have shown positive associations between green space and reductions in stress (Lafortezza et al., 2009; Nielsen & Hansen, 2007; Thompson et al., 2012; Van den Berg et al., 2010) and in the risk of psychosocial and psychological stress–related diseases (Adevi & Lieberg, 2012; Francis et al., 2012; Kuo & Sullivan, 2001). Studies indicate that green space is pertinent to reductions in depression (Berman et al., 2012; Beyer et al., 2014; Maas et al., 2009; McCaffrey, 2007), anxiety (Beyer et al., 2014; Maas et al., 2009; Mackay & Neill, 2010), and anger and aggression (Bodin & Hartig, 2003; Kuo & Sullivan, 2001; Ulrich, 1979). Additionally, green space is related to positive physiological health (Akpinar et al., 2016; Herzog & Strevey, 2008; Park et al., 2008; Zhang et al., 2015).

UGS can directly and indirectly enhance the quality of life, as it might also provide safety from an increasingly stressful daily lifestyle, encourage social cohesion, stimulate physical activity, improve health, and even promote a person’s health and mental conditions (Ugolini et al., 2020). In addition, UGSs are taken as the green lung of cities and usually perform important functions, such as absorbing pollutants and rainwater and mitigating urban heat. They also bring about remarkable socioeconomic benefits, such as communication, rest and restitution, and increasing property values (Khalil, 2014; Liu et al., 2021). From an ecological perspective, UGS might also provide habitable space for plants and animals as a basis to maintain and preserve basic ecological features and procedures (Daniels et al., 2018). So, UGS is considered to be a key element in improving quality of life and creating an suitable framework for sustainable cities (Badiu et al., 2016; Daniels et al., 2018; Uchiyama & Kohsaka, 2020).

The recent prevalence of the coronavirus disease 2019 (COVID-19) has affected people’s health not only physiologically but also mentally, as reported by recent studies and statistics (Liu et al., 2021). It has caused unprecedented changes to mobility, economic activity, and the associated environmental footprint (Venter et al., 2020). A recently conducted article by the Centers for Disease Control and Prevention highlighted the importance of access to UGS for the public over the outbreak of COVID-19 in that having exposure to UGS can positively affect the physical and mental health conditions, involving reduced level of obesity, heart disease, stroke, depression, and stress (Liu et al., 2021).

COVID-19 caused some restrictions throughout the world that, in turn, the use of fresh air, parks, and other green spaces doubled in importance. In fact, it caused people to increase their awareness of the importance of urban green space. During COVID-19, different countries followed different policies and strategies. In Sweden, strict rules were not used. Instead, soft rules that considered social distance were applied. This, in turn, caused people to go to urban nature more than before and their tendency to walk in greener and more distant regions increased. Further, urban green space for sport activities, which are forbidden in building environment, are used, especially for those who are stressed due to COVID-19. Britain was one of the countries that, at the beginning of lockdown, recommended people to observe social distancing and not cut their relationship with nature and parks to be able to cope with isolation stress. One restriction that was imposed during lockdown was social distancing and...

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lack of presence of employees in sectors where the rate of COVID-19 was high. This, in turn, caused the staff responsible for urban nature protection and maintenance to be unable to do their duties well and interact appropriately with the nature (Douglas et al., 2020; Uchiyama & Kohsaka, 2020; Xie et al., 2020).

UGS is typically taken as the most common quantitative index to estimate urban green infrastructure (Badiu et al., 2016). To do this, the type of use and ownership is taken into account in that type of ownership might affect the access rate of the public. UGS has varying categories such as parks, street trees, school public institutes’ green areas, gardens, residential gardens, fields, cemeteries, sports fields, green space of industrial and commercial areas, and urban jungles (Badiu et al., 2016).

The ideal UGS has been determined by the World Health Organization (WHO) to be 50 m² and its minimum to be 9 m². It is also different in different countries of Europe. In some countries such as Belgium, Germany, and Australia, UGS is almost 200 m² whereas in other countries including Spain and Macedonia, and southern cities of Italy, it is roughly 4 m² (Badiu et al., 2016).

UGS per person in Türkiye is varies between 1 and 9 m² (Doğu et al., 2002). COVID-19 has foregrounded the inadequacy of green space for crowded cities such as Malatya city. It has also highlighted the extant inequities related to unequal access to UGS quantitatively and qualitatively.

Data obtained from remote sensing satellites helps to have a consistent observation of the earth. These data play a key role in research studies related to agriculture (Weiss et al., 2020), weather (Kafy et al., 2021), and also urban planning and environmental management (Deliry et al., 2021). Given the outbreak of COVID-19 in the past year, these data have been used in examining the effect of the disease on urban development (Hegazy & Kaloop, 2015), water quality examination (Yunus et al., 2020), and air quality (Liu et al., 2021; Zhou et al., 2021a, b). These data are also used in studies pertinent to the land cover and also land application. Categorizing the satellite images can help to calculate the area of each class separately (Aghlmand & Kaplan, 2021). Satellites belonging to families of Landsat, Sentinel, and different indexes have provided a considerable amount of required data (Aghlmand et al., 2021; Cai et al., 2019; Carrasco et al., 2019; Steinhausen et al., 2018).

The aim of the study was to evaluate UGS per capita and to investigate their distribution based on the population of the districts of Battalgazi county in Malatya city. In line with this, in Google Earth Engine, and satellite images of PlanetScope and Sentinel-1, indexes of the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), pigment specific simple ratio (PSSR), green normalized difference vegetation index (GNDVI), and normalized difference water index (NDWI) were calculated. After that, classification was done by combining different data via support vector machine (SVM) algorithm method. The most accurate map was then selected from the obtained land cover maps. The selected map was used to extract the areas with vegetation, and it was analyzed and examined with the area population.

**Material and method**

**Description of the research area**

The City of Malatya is one of the cities of Eastern Anatolia Region in Türkiye (35° 54’ to 39° 03’ N, 38° 45’ to 39° 08’ E), with rich ecological, natural, historical, and cultural resources. It is under the heavy pressure of rural to urban migration. Green areas and quality of environment are decreasing. Malatya City is a sub-region of the upper Euphrates on the southwestern edge of the depression zone covering the provinces of Adıyaman, Elazığ, Bingöl, Muş, and Van. Having a surface area of 12,313 km², this province is neighbor with Kahramanmaraş in the west, Elazığ and Diyarbakir in the east, Adıyaman in the south, and Sivas and Erzincan in the north (Atik et al., 2013). Malatya City has four counties one of which is the central county (Fig. 1). Battalgazi is the most crowded county and is closest to the city center and located in the Malatya lowland (Tuna et al., 2020). This area was chosen as the research area because of its dense settlements.

**Methodology**

The aim of the study was to evaluate UGS per capita and to investigate their distribution based on the population of the districts of Battalgazi county in Malatya city by using remote sensing techniques, artificial intelligence methods in the cloud platform of Google Earth Engine (GEE), and geographic information system (GIS) (Fig. 2). The following steps were followed to calculate the UGS per capita and to analyze
the distribution of urban green spaces in Battalgazi/Malatya:

Data gathering—consulting and reviewing related literature, connection with Battalgazi Municipality to gain districts, urban green spaces in some districts, population statistical data, and on-site analysis with photography for functional research of some urban green spaces.

Dataset creation—accordingly, in GEE by images of PSScene4Band and Sentinel-1 satellites, it was calculated NDVI, EVI, PSSR, GNDVI, and NDWI. Then the dataset was prepared.

Data processing—by combining different data, classification was performed according to SVM algorithm on the GEE platform. From the landscaping maps obtained, the map was selected with the highest accuracy.

Interpretation of the results—extracting diagrams and cartographic material via GEE, ArcMap 10.7.1.
Google Earth Engine

GEE has revolutionized the analysis of remote sensing data (Wang et al., 2020a, b, c). GEE is a cloud-based platform that can provide access to very large geospatial datasets and the ability to planetary-scale geospatial analysis (Gorelick et al., 2017). The best image processing algorithms can be used in GEE, and all operations were performed in parallel and simultaneously (Becker et al., 2021; Praticò et al., 2021; Qu et al., 2021; Wang et al., 2020a, b, c).

In the present study, GEE has been used and all steps of image processing, indexing, and classification have been performed in it. GEE is a cloud platform that can be used for free. In the cloud platform, any analysis is done in a very short time. In this platform, without the need to download satellite images, they can be analyzed. Also, if there are no images in the GEE database, it can be uploaded as a Tiff file. In the present study, PSScene4Band satellite images were uploaded as Tiff in GEE.

PSScene4Band

One of the most important parameters in selecting images is resolution. Resolution in Landsat 8 satellite images is 30 m (with the 15-m pan-sharpening band) (Adepoju & Adelabu, 2020). Additionally, Sentinel-2 satellite has a 10-, 20-, and 60-m band and the resolution of Sentinel-1 images is 10 m (Ghasemi et al., 2021; Steinhausen et al., 2018). In recent years, Planet Score satellite has taken images with 3-m resolution. These images are obtained daily and have been able to offer good temporal and spatial resolution compared with other satellites (Planet Team, 2018). The PlanetScope was operated by Planet Labs, Inc. (Planet Team, 2018). The PlanetScope comprises 130 CubeSats gauging 10×10×30 cm. The PlanetScope satellites have four spectral bands: blue (455–515 nm), green (500–590 nm), red (590–670 nm), and NIR (780–860 nm) (Sadeh et al., 2021). Imaging of the study area is implemented daily and one image is available for each day. Download the image from Planet Labs, Inc. for this research. In this research, the image 20200707_072919_63_2277_3B_AnalyticMS_DN_udm has been used. Orbit Type was LEO-SSO satellite and Orbit Direction DESCENDING. The image is downloaded in geoTiff format and uploaded to GEE.

Sentinel-1

Sentinel-1 satellite data has been used in various studies in classification (Carrasco et al., 2019; Ienco et al., 2019; Sayedain et al., 2020; Sica et al., 2019). The results show that the addition of these SAR data increases the classification accuracy (Kpienbaareh et al., 2021; Lu et al., 2018; Navarro et al., 2019; Tavares et al., 2019). Sentinel-1 data is available on GEE (GEE, 2021). In the
present study, two images related to the dates 13/07/2020 and 07/07/2020 have been used. Orbit direction is ascending in the first image and descending in the second image. Both images have VV and VH bands. In the present study, the VV band was used from both images. Figure 3 shows Orbit Direction of the Sentinel-1.

Determination of UGS with different indexes

In various researches, the calculation of indexes and their use in classification has increased the accuracy of classification (Aghlmand et al., 2021; Becker et al., 2021; Chung et al., 2021; Dammalage & Jayasinghe, 2019; Venkatappa et al., 2019). In this study, with the aim of increasing the accuracy of classification of plant indices, NDVI, EVI, PSSR, GNDVI, and NDWI were calculated and placed in the database. Information about each index is listed in Table 1.

Table 1  Index information and formulas used in the study

| Indexes         | Formula                                                                 |
|-----------------|------------------------------------------------------------------------|
| NDVI (Hu et al., 2016) | \( \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \)          |
| EVI (Matsushita et al., 2007) | \( G \times \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \) \times \frac{\text{GREEN} - \text{NIR}}{\text{GREEN} + \text{NIR}} \times \frac{\text{BLUE} + \text{L}}{\text{RED} - \text{C}} \times \frac{\text{C} + \text{RED}}{\text{C} + \text{BLUE}} + \frac{\text{L}}{\text{GREEN} - \text{NIR}} \) |
| NDWI (Li et al., 2013)   | \( \frac{\text{NIR} - \text{GREEN}}{\text{NIR} + \text{GREEN}} \)          |
| PSSR (Frampton et al., 2013) | \( \frac{\text{NIR}}{\text{RED}} \)                                      |
| GNDVI (Frampton et al., 2013) | \( \frac{\text{NIR} - \text{GREEN}}{\text{NIR} + \text{GREEN}} \)          |

There are many different classification algorithms available on the GEE platform. The SVM algorithm is one of them. The SVM algorithm is known as one of the successful algorithms (Poursanidis et al., 2015), and in the last 10 years many studies have used the SVM algorithm in nonparametric controlled classification studies (Foody & Mathur, 2004; Li et al., 2020a, b; Pal & Mather, 2005). In the case of limited data, the SVM method gives much better results than other traditional methods such as maximum likelihood (Mantero et al., 2005; Mountrakis et al., 2011). SVM performs the classification process using hyperplanes that best separate classes (Park et al., 2018). In this study, Support Vector Machines Library (Lib-SVM) algorithm (Chang, 2011) was used.

In this method, training points belonging to different classes are selected first. In this study, 5 different classification areas were determined. These are Build-up, Vegetation, Road, Bareland, and Water. The number of sample areas was determined with formula 1 (Jensen, 1996) given below. This formula is applied by determining points for each class.

In order to select the points and record their characteristics, the background image of GEE along with the image of PSScene4Band were used. Also, the correct choice of features was confirmed by field visit. Later, 70% of the points were randomly selected for training and 30% for testing (Table 2).
Table 2  Classification information and numbers of points

| No. | Class name   | Training Points | Test Points | Color |
|-----|--------------|-----------------|-------------|-------|
| 1   | Build-up     | 210             | 90          |       |
| 2   | Vegetation   | 210             | 90          |       |
| 3   | Road         | 315             | 135         |       |
| 4   | Bare land    | 210             | 90          |       |
| 5   | Water        | 210             | 90          |       |

Table 3  Overall accuracy and kappa coefficient calculated for different combinations

| No. | Combination                                      | Bands | Overall accuracy | Kappa coefficient |
|-----|--------------------------------------------------|-------|------------------|-------------------|
| 1   | PSS4                                             | 4     | 90.84            | 85.72             |
| 2   | PSS4 + NDVI + NDWI                              | 6     | 91.58            | 86.47             |
| 3   | PSS4 + NDVI + NDWI + GNDVI + PSSR + EVI         | 9     | 91.98            | 86.95             |
| 4   | PSS4 + S1VVA + S1VVD                            | 6     | 92.33            | 89.08             |
| 5   | PSS4 + NDVI + GNDVI + PSSR + EVI + NDWI + S1V  | 11    | 94.43            | 90.5              |

Fig. 4  Classification result by combining data PSS4 + NDVI + GNDVI + PSSR + EVI + NDWI + S1VVD + S1VVA in the Battalgazi county
where \( p \) is the expected percent accuracy of the entire map, \( q = 100 - p \), \( E \) is the allowable error, and \( Z = 2 \) from the standard normal deviate.

All the steps of classification and its accuracy were done in GEE. Different data combinations were used in the classification. Table 3 shows the overall accuracy and kappa coefficient for different combinations of data. Initially, the classification was performed with only 4 bands of PSS4 satellite and the overall accuracy and kappa were 90.84 and 85.72, respectively.

Then two indices NDVI and NDWI were added to the layers. By adding these two layers, overall accuracy and kappa increased to 91.58 and 86.47, respectively. In order to better classify, other indices such as GNDVI, PSSR, and EVI were also calculated. In this way, the amount of overall accuracy and kappa coefficient increased to 91.98 and 86.95. The overall accuracy and kappa coefficient in the combination of VV band in ascending and descending images of Sentinel-1 with PSS4 bands have increased (92.33 and 89.08). By combining the 4 bands of PSS4 satellite; the indexes of NDVI, GNDVI, PSSR, EVI, and NDWI; and 2 images related to the VV band of Sentinel-1 in the mode of ascending and descending, overall accuracy and kappa coefficient increase.

Figure 4 is the result of this classification, which is output as Geotiff from GEE, and other analyses have been performed on it in ArcMap 10.7.1 software. In order to evaluate only the green areas in the map obtained from the classification (Fig. 4) results, a map with two classes (one was the green spaces class and the other was a combination of all other classes) was

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**Fig. 5** UGS in districts of Battalgazi county

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obtained by combining the other classes except green areas into one class using the ArcMap 10.7.1 (Fig. 5).

In ArcMap, the number of pixels of the green areas crossed out by the area of the pixel, and the green area of each district is extracted. In order to calculate the distribution of UGS per capita in Battalgazi county and its districts, the total green area of each district was divided by the number of populations of that district. The 2019 population numbers of the districts were obtained from the Battalgazi municipality. UGS per capita was compared to the standard of WHO (it has set a minimum target of 9 m²). Thus, the green area situation of each district is explained (Fig. 6).

In order to examine the distribution and determine the characteristics of UGS according to their functions, especially in the district with high UGS per capita, analyses were done on site.

**Result**

The aim of the study was to evaluate UGS per capita and to investigate their distribution based on the population of the districts of Battalgazi county in Malatya city by developing an integrated methodology (RS and GIS). Accordingly, in GEE by images of PlanetScope and Sentinel-1 satellites, it was calculated NDVI, EVI, PSSR, GNDVI, and NDWI. Then, the data set was prepared. Then, by combining different data, classification was performed according to the SVM method. From the landscaping maps obtained, the map was selected with the highest accuracy. Finally, by the last map obtained, it was evaluated the distribution of UGS per capita and their functions in Battalgazi county and its districts.

Processing satellite images in desktop software is very time-consuming. GEE is a free cloud platform and is a revolution in remote sensing science. This platform has a strong database and almost all satellite images are ready and without the need for pre-processing. It is also possible to upload images to it. Therefore, in the present study, this platform was used.

High-resolution satellite imagery is difficult to classify due to its high detail, so different indexes with image bands should be used. Also, in this study, the use of Sentinel-1 satellite images eliminated errors related to the shadow of tall buildings and increased the accuracy of the classification.

According to the results obtained, Battalgazi, as the most crowded county of Malatya city, has a total of 3,571,581 m² USG and according to the total population (219,014), it was 16.30 m² per capita. WHO has set a minimum target of 9 m² of UGS per capita.
and thus the obtained value is above the minimum value of WHO. But the important aim of this research has been to test the even distribution of existing USG in districts. Therefore, the value of the UGS per capita for each district has been calculated.

According to the data of the relevant municipality, there are 47 districts in the Battalgazi county. The UGS values were calculated for per district and according to Fig. 6, differences were detected in the obtained UGS per capita. In total, in 24 districts, the UGS per capita was well above or equal and in 23 districts well below the WHO minimum value (Table 4). Considering the distribution of UGS at the level of the districts, it is clearly seen that there is an unbalanced distribution.

In urban areas, UGS are typically depicted as structural components of urban green infrastructure that are completely or partly covered by vegetation (Diluiso et al., 2021; Zhou et al., 2021a, b). Varying typologies of urban green spaces have been utilized in literature and policy, providing detailed and flexible taxonomy plans, also showing the heterogeneity in the extent and type of urban green areas throughout Türkiye. UGS in the case study of this paper (Malatya city) includes private green areas, green areas affiliated to government institutions, agricultural areas (especially apricot fields), parks and recreation areas, children’s playgrounds, green riverbanks, cultivated land, and water body and courses.

Some districts have high UGS values, but these large green spaces are either state or privately owned, so they are not open to the public and not everyone benefits. According to the data obtained from the results, some districts with high UGS values were examined and the reason for the high values and the details of the relevant green areas in terms of functionality were explained. On-site analysis and investigation were conducted to explain the properties and functional functions of the determined areas.

Both of the two large green areas (designated location 2 with 28,688 m² in Fig. 7) seen in the Çamurlu district are orchards that are special. In addition, the reason for the high amount of the UGS value in this district compared to other districts is being far from the city center and the population number was low, so there was high UGS per capita (156.2 m²) in Çamurlu district. It is seen that there are afforested semi-rural areas (designated locations 6 and 7 with 51,871 m² in Fig. 7) and private agricultural area (designated location 8 with 12,319 m²) in Çoşnuk district, so the UGS per capita was determined too high (14.5 m²).

The largest green area in the Firat district is state owned and closed to the public as a regulatory zone (designated location 10 with 53,154 m²). The largest green area in the Zafer district is Hürriyet Park and recreation area (designated locations 13 and 14 with 246,637 m²). The largest green area in the Kernek district is army station and has a regular function (state owned) (designated location 11 with 39,806 m²). The largest green areas in the Saray and Farhadiye district are parks and recreation areas (respectively Emekliler Park designated location 15 with 8799 m² and Vilaey Park designated location 12 with 5880 m²). Large green areas (designated location 1 with 111,342 m²) seen in the Beydağı district are orchards that are private areas. A large green area (designated location 16 with 4889 m²) seen in the Ataköy district is children’s

| Table 4 The UGS values in the Battalgazi |
|-----------------------------------------|
| The districts that are above 9 m²       | The districts that are below 9 m² |
| Districts | UGS (m²) | Districts | UGS (m²) |
| Hidayet   | 267.5    | Zafer     | 8.7      |
| Beydağı   | 262.5    | Ferhadiye | 8.7      |
| Çamurlu   | 156.2    | Hamidiye  | 8.6      |
| Battalgazi| 90.7     | Saray     | 8.5      |
| Yıldıztepe| 74.8     | Ataköy    | 5.6      |
| Taştepe   | 38       | İzzeiye   | 5.4      |
| Beylerbaşi| 30.2     | Cevherizade| 5.1     |
| Şehitfevzi| 30       | Nuriye    | 5.0      |
| Yamaç     | 28.8     | Sancaktar | 5.0      |
| Göztepe   | 19.8     | Paşaköşkü| 4.5      |
| Seçikçül   | 15       | B. Mustafa Paşa| 4.5 |
| Çoşnük    | 14.5     | İsmetiye  | 4.3      |
| Çirkınlar | 14.3     | Niyazi    | 4.0      |
| Üçbağlar  | 13.8     | B. Hüseyinbey| 3.9 |
| Tandoğan  | 13       | İstiklal  | 3.0      |
| Yenihamam | 12.5     | Kırçuval  | 2.8      |
| Sarıçoglu | 11       | Haci Abdı | 2.5      |
| Firat     | 10.8     | Aslanbey  | 2.5      |
| Kernek    | 10       | Akpınar   | 2.2      |
| Başharık  | 9.5      | Kavaklıbağ| 2.0      |
| Hasan Varol| 6.4     | K. Mustafa Paşa| 2.0 |
| İskender  | 9.2      | Şifa      | 1.9      |
| Şıkşık    | 9        | Dabakkane | 1.6      |
| K. Hüseyinbey | 9  |

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The largest green area in the Firat district is state owned and closed to the public as a regulatory zone (designated location 10 with 53,154 m²). The largest green area in the Zafer district is Hürriyet Park and recreation area (designated locations 13 and 14 with 246,637 m²). The largest green area in the Kernek district is army station and has a regular function (state owned) (designated location 11 with 39,806 m²). The largest green areas in the Saray and Farhadiye district are parks and recreation areas (respectively Emekliler Park designated location 15 with 8799 m² and Vilaey Park designated location 12 with 5880 m²). Large green areas (designated location 1 with 111,342 m²) seen in the Beydağı district are orchards that are private areas. A large green area (designated location 16 with 4889 m²) seen in the Ataköy district is children’s
play garden and park. In Battalgazi district, the number of population and settlement areas were low as it covered semi-rural areas. Most of the green areas here have been identified as agricultural areas (designated locations 3, 4, and 5). Finally, in Uçbağlar district, a large green area with 25,563 m², it was determined to belong to Battalgazi Municipality (designated location 9).
In this study, which examined the green areas of the districts in Battalgazi county, it was shown that most of these areas belong to the state and are not open to the public, although the rate of UGS per capita mostly is high. Some of the green areas with large areas are also private agricultural and cultivated land and are not possible to use for physical activity and recreation.

Looking at the functions of the green areas in Malatya city, it is seen that they generally do not have many functions. Obviously, as the area covered by green areas shrinks, it has been observed that the functions in these areas decrease and even fall to a single function such as resting only. In the parks with different functions, there are generally a small children’s playground, sports equipment area, walking area, and jogging track area.

**Discussion and conclusions**

According to the results obtained, Battalgazi, as the most populated county of Malatya city, has a total of 3,571,581 m² USG; and according to the total population (219,014), it was 16.30 m² per capita. WHO has set a minimum target of 9 m² of UGS per capita (Badiu et al., 2016); thus, the obtained value is above the minimum value of WHO. However, the important aim of this research was to test the even distribution of existing USG in districts. Given this, the value of the UGS per capita for each district was calculated. According to the data of the relevant municipality, there are 47 districts in the Battalgazi county. The UGS values were calculated for per district and according to Table 4, differences were detected in the obtained UGS per capita. In total, in 24 districts, the UGS per capita was well above or equal and in 23 districts well below the WHO minimum value. Considering the distribution of UGS at the level of the districts, it is clearly seen that there is an unbalanced distribution. In addition, most of UGSs belong to the state and are not open to the public, or these spaces are also private agricultural and cultivated lands and are not possible to use for physical activity and recreation.

One thing that is very important about green space is its location. “The park should be in a place where life is in full swing, where culture and commercial and residential activities are,” said Jane Jacobs, a critic of contemporary urban planning (Laurence, 2016). Several urban areas have such valuable focal points of life that they are suitable for creating local parks or public squares. Accordingly, the location of green space should follow principles such as “centrality, hierarchy, and access”: Centrality of green space means that green space should be located in the center of the neighborhood, district, or urban area as much as possible (Chen & Chang, 2015; Laurence, 2016; Li & Liu, 2016; Song et al., 2018). Also, green spaces at different scales, including neighborhood parks, regional parks, and the like, should be adapted to their respective physical structure (La Rosa et al., 2018), for example, a regional park within the area should be proposed. One of the other criteria that should be considered in locating green space is the criterion of “accessibility” (Gu et al., 2020; Jian et al., 2020; Rahman & Zhang, 2018), in the sense that urban parks should have access to the communication network from four directions in order for more crowds to use it and increase the possibility of social monitoring and park security. In this way, it is possible to visually exploit the beautiful effects of the park for passers-by from four directions (Laurence, 2016).

The existence of inequality in the distribution of green space in different neighborhoods of a city is not a new phenomenon in any city in the world (Sharifi et al., 2021). This inequality and imbalance in cities are a natural thing and it is impossible to eliminate it if it is not exaggerated; but it can be done as little as possible.

Research has shown that there is still unequal access to green spaces in different countries, such as the USA and China. In general, wealthy neighborhoods have better quality and access. The size, accessibility, and quality of urban green space may affect its use (Chang et al., 2019; Nilsson, 2018; Xu et al., 2019). But it is important to keep in mind that the mere existence of green space does not guarantee its use; access to green space depends not only on geographical proximity or accessibility (i.e., the presence of green space at a reasonable distance from the house) but also on the quality of green space (i.e., the existence and quality of facilities) (Zhang et al., 2017).

Given the increasing rate of urbanization and in light of the fact that over half of the population dwells in cities, UGS is a vital factor in cities’ sustainability as well as urban transformation. Considerable inclinations and movements in urbanism, including ecological urbanism, landscape urbanism, ecological landscape urbanism, and ecosystem urbanism, highlight the point that prioritizing nature and ecological considerations is likely to improve
the quality of life in communities—and that UGS is a key factor to achieve this. UGS can enhance the quality of life directly and indirectly (Ugolini et al., 2020).

Numerous experts have confirmed the positive impacts of UGS. It is commonly believed that urban green spaces (such as parks) can provide a set of ecosystem services, which, in turn, aid the public to overcome different diseases and promote the quality of their life as well as their health conditions. To be more specific, stress is likely to negatively affect the psycho-physiological health, and spending leisure times in green spaces such as parks can help to minimize or remove these negative states. According to Sturm and Cohen, there is a positive relationship between UGS and mental health, and the residents who are within 400-m walking distance from UGS were reported to have better perceived mental health. Going to green environments can considerably promote mental health and decrease anxiety. Additionally, those who regularly visit a UGS have better health conditions compared with those who do not, because UGS can provide opportunities and conditions for varying outdoor activities for different groups of people. The results of a survey in developing countries revealed that regular UGS visits can decrease health problems and enhance life satisfaction. All these findings and comments highlight the e-effectiveness of UGS in promoting physical and mental health. Furthermore, UGSs also provide social environments for people and, consequently, promote social interaction. Vegetation in UGS is a critical factor in green spaces. Trees and grass can comfort people and encourage them to spend their time in the open air. Attending UGS can also develop friendship among residents in the society. Both children and teenagers tend to play and communicate with others in UGS, which, in turn, is key to growth of children (Xie et al., 2020).

Thus, having access to UGS is a vital factor in public health while inequities in terms of access to UGS are likely to bring about serious health-related problems. In addition to public health merits, UGS has also been reported to be influential in providing economic, ecological, environmental, and recreational advantages (Bozdağ, 2020).

It is stated that COVID-19 has affected 174,061,995 people in the world as of 10 June 2021 (WHO, 2021). In Türkiye, the number of people affected by COVID-19 as of this date is expressed as 5,313,098 (TMH, 2021). The impact of pandemic diseases on individual and community life is multifaceted. The COVID-19 pandemic is a process that needs to be addressed with its social, economic, political, and spiritual consequences. This process threatens the lives as well as assets of people and can cause traumatic distress in people. It is known that the COVID-19 pandemic particularly causes psychological problems. It is stated that the ability to overcome this crisis process in a healthy way depends largely on conducting research on the psychological effects of the pandemic (Bozdağ, 2020).

The psychological reactions of people during the pandemic process significantly affect the spread of the disease and the emotional distress and social dysfunctions that may be experienced in the next stage. According to the research conducted by Wang et al. (2020a, b, c) in China, the pandemic process causes moderate and severe psychological effects in humans. Due to the pandemic, people experience psychological problems such as depression, anxiety, and stress. In Li et al. (2020a, b), the COVID-19 pandemic causes a decrease in people’s positive emotions and an increase in their negative emotions. After a pandemic, which is a stressful process, people may experience anxiety. Stressful situations need to be managed effectively in order to prevent anxiety which can turn into more severe anxiety and panic. It is important to understand how people react to the pandemic threat and how they cope with this process (Bozdağ, 2020).

The importance of urban green space close to living places and accessible green area has increased especially during the pandemic process. Studies show that people’s desire to go to open green areas increases during the pandemic process. The biggest reason for this was to get rid of mental and physical troubles and to stay away from being preoccupied with the possibility of death.

Urban green space is a relatively large space, consisting of vegetation with a quasi-forest structure, and has a relatively specific environmental or ecological efficiency and is appropriate to the environmental situation prevailing in the city (Haq, 2011). The existence of urban green space is a necessity to achieve sustainable development both in terms of environment and improving the quality of life. On the other hand, the pollution of urban space and its continuous intensification in recent years has multiplied this necessity (Shi & Woolley, 2014). Achieving social justice as the most important goal in sustainable development has led to the distribution of green space within the city and how urban residents have access to these spaces as an undeniable principle (Tsou et al., 2005). Therefore,
green space in terms of quantity and quality should be proportional to the population and size of the city and the needs of society according to the ecological situation and the future development of the city to have a suitable environmental and ecological role as green space (Chen et al., 2021; Richardson & Mitchell, 2010).

Accessibility, which is typically gauged as the proximity (linear distance or walking distance) of urban green spaces to societies, is pertinent to varying health merits. The World Health Organization recommends that green spaces with the minimum size of 1 ha and the maximum distance of 300 m to people’s residence need to be used as threshold values for accessibility. This recommendation is, in fact, a reference benchmark in constructing green spaces for health benefits. Other properties of urban green spaces, including vegetation composition (e.g., species richness or biodiversity), have also been related to human health, especially mental health. Numerous have revealed that high levels of species richness or biodiversity in Sheffield and Berlin have led to increased psychological benefits (Huang et al., 2017).

In addition, urban open green space systems in Türkiye are closely related to spatial planning and design processes, and consequently to the Zoning Law. However, when the current laws and regulations are examined, it is seen that there are many problems and deficiencies in the conceptual framework, typologies, standards, project design, and professional and institutional authorities and responsibilities (Hepcan, 2013; Onder et al., 2011). The deficiencies in the definition of green areas in the national legislation and the systematic inclusion of green area types and functions in zoning plans make an integrated planning system impossible. Moreover, the view that the spatial distribution and form of open green areas in our cities is irregular and dispersed is an accepted approach (Bilgili & Gökyer, 2012).

There are very important deficiencies in the legislation such as which inventory data will be used in the decisions regarding green areas in the planning and design process, from which institution and how they will be obtained, which analysis techniques will be used for the data, what the green area types and site selection criteria will be, and what the capacity and standards will be. For this reason, a detailed definition should be introduced in the legislation for green area analysis (Atila et al., 2020; Pouya et al., 2020).

In this study, which examined the green areas of the districts in Battalgazi county, it was shown that most of these areas belong to the state and are not open to the public, although the rate of UGS per capita mostly is high. Some of the green areas with large regions are also private agricultural and cultivated land and are not possible to use for physical activity and recreation. Looking at the functions of the green areas in Malatya city, it is seen that they generally do not have many functions. Obviously, as the area covered by green spaces shrinks, it has been observed that the functionality in these areas decrease and even fall to a single function such as resting only. In the parks with different functions, there are generally small children’s playground, sports equipment area, walking area, and jogging track area. The recommendation of this study was that Türkiye city planners and landscape designers should replan and redesign the quality and equal distribution of urban green spaces, especially during and following the COVID-19 pandemic.

Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare no competing interests.

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