Open-source automatic extraction of Urban Green Space: Application to assessing improvement in green space access

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Keywords: Google Earth Engine, Dynamic World, Object-based image analysis, Edge detection, Neighborhood analysis, Urban parks.

Abstract

Urban Green Space (UGS) is vital for improving the public health and sustainability of cities. Vector data on UGS such as open data from governments and OpenStreetMap are available for retrieval by interested users, but the availability of UGS data is still limited on global and temporal scales. This study develops the UGS Extractor, a web-based application for the automatic extraction of UGS given user inputs of Area of Interest and Date of Interest. To accommodate various types of green spaces, such as parks or lawns, the application additionally allows users to set parameters for the minimum size of each UGS and the Minimum Urban Neighbor Density, enabling customization of what qualifies as UGS. The UGS Extractor implements a methodological framework that applies object-based image processing, edge detection and extraction, and image neighborhood analysis on the near real-time 10m Dynamic World collection of Land Use/Land Cover images. The application's utility was demonstrated through two case studies. In the first, the UGS Extractor accurately mapped major parks when compared to open data sources in New Orleans, USA. In the second, the UGS Extractor demonstrated significant increases in the total area of UGS from 2015 to 2023 in Songdo, South Korea, which consequently improved green space accessibility. These results underscore the UGS Extractor's utility in extracting specific types of UGS and analyzing their temporal trends. This user-friendly application overall offers higher spatial resolution compared to publicly available satellite-based methods while facilitating temporal studies not possible with vector datasets.

1. Introduction

Urban Green Space (UGS) is essential in developing sustainable cities as it provides a multitude of socio-ecological benefits (Badiu et al., 2016; Rostami et al., 2015). First, UGS creates a cooling effect through the absorption of heat by evapotranspiration, thereby mitigating Urban Heat Islands (UHI) (Bao et al., 2016; Hardin and Jensen, 2007; Wang et al., 2022). This importance of UGS in cooling cities is highlighted in the InVEST Urban Cooling Model where identification of green areas is essential to compute a city's heat mitigation index (Zawadzka et al., 2021). UGS also improves the physical and mental health and wellness of nearby residents by filtering out air pollution, providing shade, promoting opportunities for physical exercise, and reducing stress (Gómez-Baggethun and Barton, 2013; Rostami et al., 2015; Wolch et al., 2014). Lastly, UGS provides habitats for various animal species, thereby increasing biodiversity in cities (Gómez-Baggethun and Barton, 2013). Overall, UGS is beneficial for cities by improving the quality of life at the individual level (Badiu et al., 2016; Rostami et al., 2015) as well as providing economic benefits at the city level (Li et al., 2015; Zhang et al., 2012). Given the importance of UGS in cities, it is vital for cities to have access to accurate and comprehensive spatial datasets of UGS.

To generate maps of UGS, various remote sensing methodologies have been developed (Farkas et al., 2023). Pristeri et al. (2021) classified UGS through thresholding of NDVI derived from high-resolution orthophotos and integration with a topographic database. Huang et al. (2021) mapped the coverage of UGS in different cities across the globe by utilizing repeated random forest classifications on Landsat-derived images in Google Earth Engine. Ju et al. (2022) produced 10 m resolution UGS maps across major Latin American cities by classifying Sentinel-2 images and applying support vector machines. Meanwhile, Lahoti et al. (2019) employed a georeferencing of Google Earth images and manual digitization of UGS to create thematic maps of public UGS.

Aside from remote sensing methods, several crowdsourced data are also available for retrieval by users. OpenStreetMap (OSM) provides open vector data on UGS which can be easily be utilized to compute park access and service areas (Spangler et al., 2023). In addition to being a free vector data of UGS, OSM has also been heavily used as an auxiliary data in image classification of Sentinel-2 images to produce fine-scale UGS maps (Chen et al., 2023, 2021; Ludwig et al., 2021; Weigand et al., 2023). Many cities and countries have also released detailed UGS datasets. However, the quality and quantity of OSM and open data are highly variable across countries and regions (Herfort et al., 2023).

Although various methods and open vector data are available to be utilized for the identification of UGS in an urban study area, three limitations still exist in the availability of UGS spatial datasets. First, the outputs from the studies implemented on a continental or global scale are in a raster format; hence, UGS is not differentiated as features that have properties such as names, area, or greenness. Second, the described methods can only be implemented by users with a spatial data science background.

To the best of the knowledge of the authors, there has not been any developed open tool that can extract UGS in any area indicated by a user. It is essential to provide a user-friendly tool for those interested in analyzing UGS, especially for residents in developing countries where data on UGS may be lacking. Third, although open vector data on UGS are available, these data are often static and lack information spanning different time periods. The lack of temporal data limits the analysis of changes in UGS, which may be vital for monitoring the highly dynamic nature of cities. Overall, the development of an open-source tool that can map UGS as features in any part of the world and for different time periods is needed.

To achieve this goal, this study presents the UGS Extractor, a flexible web-based application that can map UGS given user inputs of Area of Interest and Date of Interest. The application uses the near real-time 10 m Dynamic World collection of Land Use/Land Cover (LULC) images as the main source of data. These images are processed by following a methodological framework involving user inputs, object-based image processing, edge detection and extraction, and image neighborhood analysis. The application outputs a shapefile of the UGS which can be exported by users. The UGS Extractor application and the methodological framework developed in this study have achieved scientific contributions in multiple fields, including but not limited to urban planning, geography, and public health. Potential applications of this tool include UGS planning and siting, assessing the health benefits of UGS in developing countries, and evaluating inequalities in access to UGS. The user inputs allow for flexible UGS definitions, which may vary depending on discipline or user needs.

The paper is organized as follows: Section 2 presents the methodological framework for extracting UGS given four user inputs; Section 3 describes two case studies that test the capabilities of the UGS Extractor application; Section 4 presents the results and discusses its implications; and Section 5 concludes the study.

2. Methodological Framework

An application for the automatic extraction of UGS, hereafter called the UGS Extractor (Figure 1), was developed using Google Earth Engine (GEE). GEE is an online platform that can retrieve and process different types of geospatial data such as remotely sensed images (Gorelick et al., 2017). The quick cloud-based processing capabilities of GEE were utilized to implement the methodological framework for extracting UGS, which is mainly composed of five parts: user inputs, pre-processing, object-based image processing, edge detection and extraction, and image neighborhood analysis (Figure 2). The UGS Extractor can be accessed through this link: https://ee-geotools.projects.earthengine.app/view/theugsextractor.

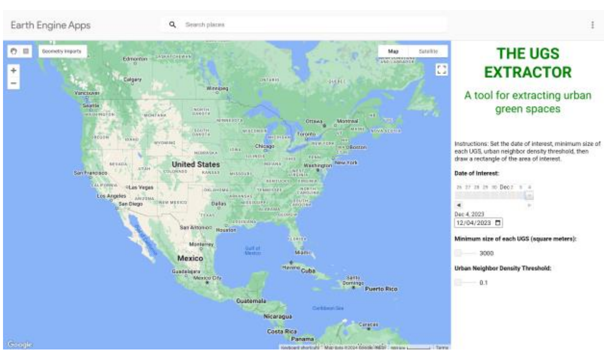

Figure 1. The web-based application for the UGS Extractor

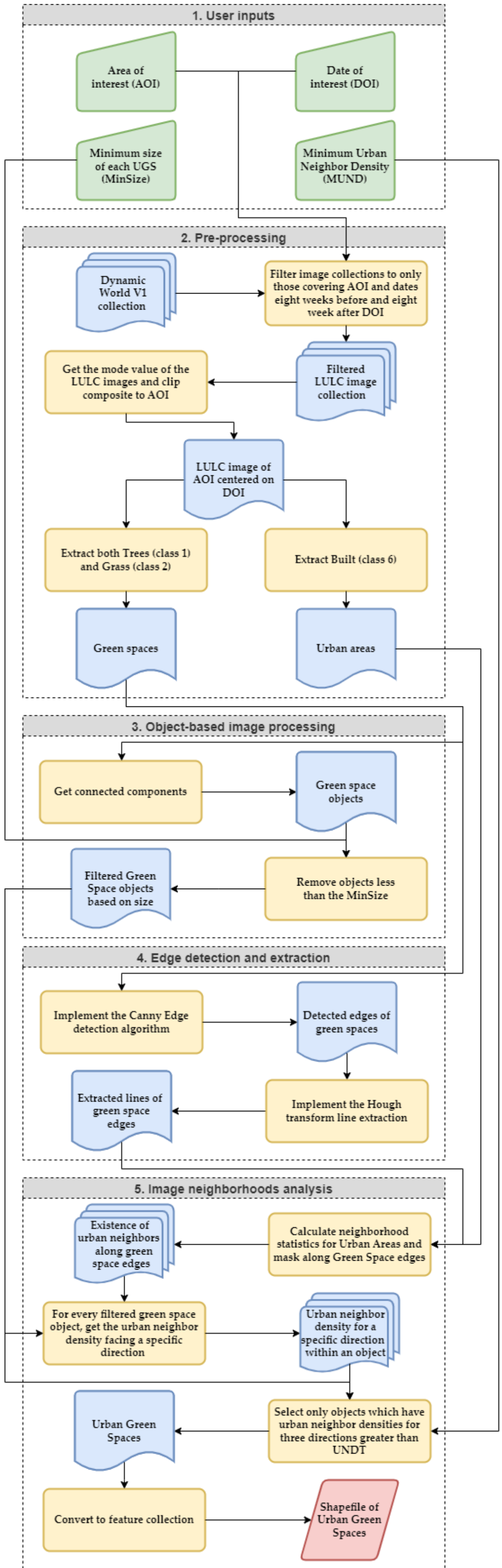

Figure 2. The methodological framework for the UGS Extractor

2.1 User Inputs

Upon opening the UGS extractor, users will be prompted to input the following parameters: Area of Interest (AOI), Date of Interest (DOI), Minimum size of each UGS (MinSize), and Minimum Urban Neighbor Density (MUND). The AOI is indicated by a rectangular polygon drawn by a user which signifies the extent of where UGS will be extracted. The DOI indicates a historical date of when the state of the UGS will be mapped. The MinSize indicates the area (in square meters) a green space feature should at least be to be classified as a UGS. Lastly, the MUND is a value indicating the minimum density of urban areas surrounding a green space to be classified as a UGS. How these inputs will be processed will be discussed in the following sub-sections.

2.2 Pre-processing

The Dynamic World collection of LULC images was used as the main source of data for the UGS extraction. Dynamic World is a collection of global near real-time LULC derived from Sentinel 2-imagery (Brown et al., 2022). It features consistent classifications of eight LULC types which are the following: water, trees, grass, flooded vegetation, crops, shrub and scrub, built area, bare ground, and snow and ice. Dynamic World was chosen for three reasons. First, it is a free LULC dataset that can provide global coverage at an acceptable accuracy. Second, it is near real-time, updating its LULC collection from 2015 up to the present every 2 to 5 days. This enables the temporal analysis of UGS. Last, it has a spatial resolution of 10 m which can capture the shape of a UGS feature.

Pre-processing was implemented to derive raster images of both urban areas and green spaces. First, the Dynamic World collection was spatially filtered to only include images covering the AOI. These images were then temporally filtered to only include images from eight weeks before the DOI to eight weeks after the DOI. As Dynamic World images are also cloud-masked, it is essential to include a four-month span of images to generate a complete LULC composite for a given DOI and AOI. From these filtered images, a LULC composite of the AOI was generated by getting the mode value of the images and clipping the mode image to the AOI. From the generated LULC composite, an image of Green Spaces was generated by extracting pixels of both Trees and Grass classifications (classes 1 and 2, respectively). Meanwhile, an image of the Urban Areas was generated by extracting pixels classified as ‘Built’ (class 6).

2.3 Object-based image processing

The extracted green spaces were converted to objects through an object-based method where connected pixels of the same classification are treated as one object (Blaschke, 2010; Hossain and Chen, 2019; Walter, 2004). These green spaces were then filtered down to only include objects that have areas greater than the input MinSize. This results in green space objects that are within the size set by the user.

2.4 Edge detection and extraction

The edges of green spaces were detected by implementing the Canny Edge algorithm which applies four different filters to identify edges (Canny, 1986). Lines were then extracted from the detected edge by applying the Hough transform (Duda and Hart, 1972). These steps output a classified image showing only the edges of green spaces.

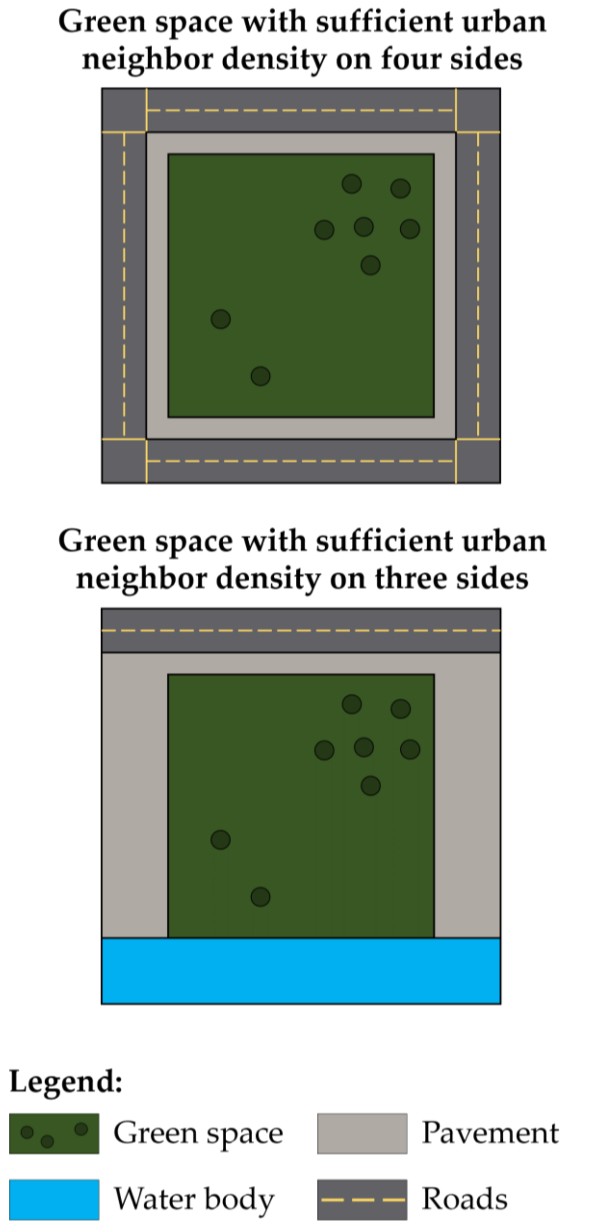

Figure 3. The types of green spaces that would be classified as a UGS: Green spaces with four or three sides of sufficient urban neighbor density.

2.5 Image neighborhood analysis

The last part of the UGS extraction framework is an image neighborhood analysis considering the urban density around the neighborhood of edges of the filtered green space objects.

Initially, the urban neighborhood was defined by considering the existence of an urban class pixel in a pixel neighborhood (along the four directions of north, east, south, and west). This was implemented in GEE through the neighborhoodtoBands function which creates four bands based on the four directions. For example, for the band indicating the North neighbor, a value of 1 is assigned to a pixel when an urban area exists in the north direction while a value of 0 is assigned if it is not the case. The same applies to the other three directions in the other three bands. This 4-band image was masked along the green space edges. The resulting image indicates the existence of urban neighborhoods (in four directions) along the green space edges.

The next step computes the density of urban neighbors along a specific direction by computing the mean value along the edges of every filtered green space object. This means that for every filtered green space object, four values were generated: density of urban neighbors facing the north, facing the east, facing the south, and facing the west.

Lastly, the filtered green space objects were once again filtered by only including objects that satisfy the following condition: at least three out of the four urban neighbor density values must be greater than the MUND (Figure 3). This rule was set to consider that Urban Green Spaces are green spaces surrounded by urban areas but there are cases where one side may not be surrounded by an urban area such as parks by a river (bounded by water on one side). Given this condition, as long as the urban density along three of the four sides satisfies the urban neighbor density condition, the green space will be considered a UGS. MUND was set as a user input as green space can be classified as a UGS depending on the nature of the city.

The resulting UGS objects are converted to a feature collection where every UGS has a unique label. For each UGS feature, two properties were added that indicate the percentages of tree cover and grass cover (both adding to a value of 1.0). This UGS feature collection can be exported as a JSON file along with the AOI rectangle which has a property indicating the area percentage of UGS within the AOI.

3. Case Studies

To test the capabilities of the UGS Extractor, two case studies were implemented. The first case study assessed the accuracy of the outputs from the UGS extractor by comparing extracted UGS to the open vector data of parks from the U.S. ParkServe Dataset (The Trust for Public Land, n.d.). The second case study explored the applicability of the UGS extractor in conducting temporal analyses of UGS by assessing the changes in green space accessibility in a newly planned city.

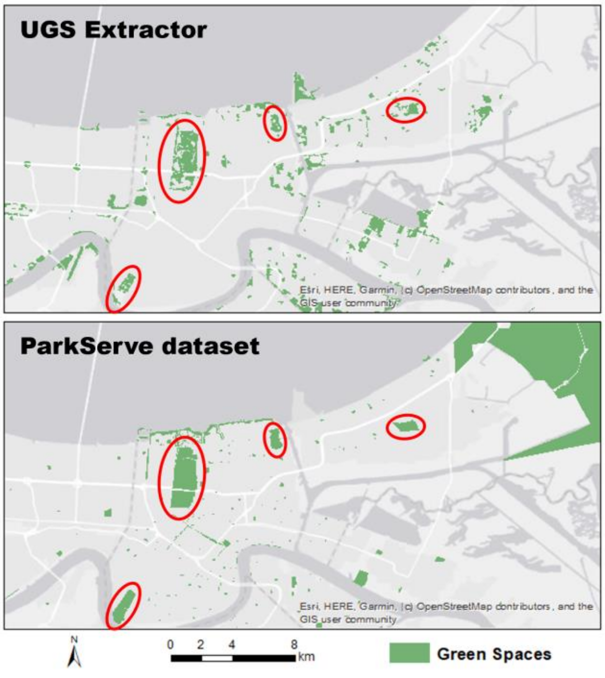

Figure 4. Comparison of green spaces retrieved from the UGS extractor and ParkServe data. UGS inside the red circles are major parks in New Orleans.

3.1 Comparison with open vector data

The UGS extractor was utilized to extract UGS in New Orleans, Louisiana, USA (Figure 4). New Orleans was chosen as the study area for the inspection of extracted UGS. The study area contains the Bayou Sauvage Urban National Wildlife Refuge, which is a protected marshland. It was also of interest how the UGS Extractor would classify blue carbon ecosystems in urban areas.

For the case study, the eastern side of New Orleans containing the protected marshland was selected as the AOI. May 15, 2023, was chosen as the DOI as this is the date indicated in the ParkServe dataset as the date of creation of the shapefiles. The minimum size of each UGS was set as 3,000 square meters (the minimum set value for this parameter) as small features can be seen in the ParkServe data. The MUND parameter was set as 0.1 (the minimum set value for this parameter) so that more UGS could be detected.

3.2 Assessing changes in green space access

The UGS extractor was utilized to assess changes in green space accessibility in Songdo International City, South Korea (Figure 5). Songdo is a new city developed on reclaimed land as part of the Incheon Free Economic Zone (Shwayri, 2013). Development of the city started in 2004 and the first phase of the city's development was completed in 2009 (Kim, 2010). As Songdo is envisioned to be a ubiquitous eco-city, vast development in green spaces is expected in this new urban area (Shwayri, 2013).

For assessing the changes in green space access, the central portion of Songdo was chosen as the study area. November 1 of the years 2015, 2019, and 2023 were chosen as the DOIs for observing the UGS in those years. MinSize was set as 3,000 square meters and the MUND was set as 0.1 to extract more UGS. After generating maps of the UGS for the given years, the total area of the UGS for every year was calculated by getting the sum of the area of every feature in a UGS shapefile. Green space access was then assessed by calculating the average distance within the study area to a UGS. The Euclidean distance tool in ArcGIS was used to generate a raster image showing the shortest distance from a UGS to a pixel within the bounding box of the study area. Zonal statistics were then executed to calculate the average distance to a UGS within the study area.

4. Results and Discussion

4.1 Comparison with open vector data

Visual inspection of the green spaces retrieved from the UGS extractor and the ParkServe dataset showed alignment for UGS of large sizes (Figure 4). It can be confirmed through visual inspection that data aligned for the four major parks in New Orleans (New Orleans City Park, Audubon Park, Pontchartrain Park, and Joe W. Brown Park). It can also be observed that the marshland in the northeastern part of the study area was not detected by the UGS Extractor. This difference can be attributed to the definition of UGS in the UGS Extractor. As it was built in the methodological framework that UGS are green spaces bounded by urban areas on at least three sides, the marshlands were excluded as they are primarily surrounded by water bodies. In this scenario, blue carbon ecosystems such as mangroves and marshlands will not be considered as UGS by the UGS Extractor.

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Differences in identified green spaces can also be observed when it comes to smaller areas. Small green spaces identified in the ParkServe dataset were not identified by the UGS Extractor. This can be attributed to two factors: first, the main source of data of the UGS Extractor is Dynamic World, which may not classify such small spaces as trees or grass classes if the spectral signatures exhibited by the areas don't exhibit enough greenness. Second, a limit in minimum size was also set in the UGS Extractor, hence smaller spaces may have been excluded. It can also be seen that the UGS Extractor was able to extract more UGS within the study area. This indicates that the UGS Extractor can detect UGS that are not considered parks. For example, it also included the green spaces between highway interchanges.

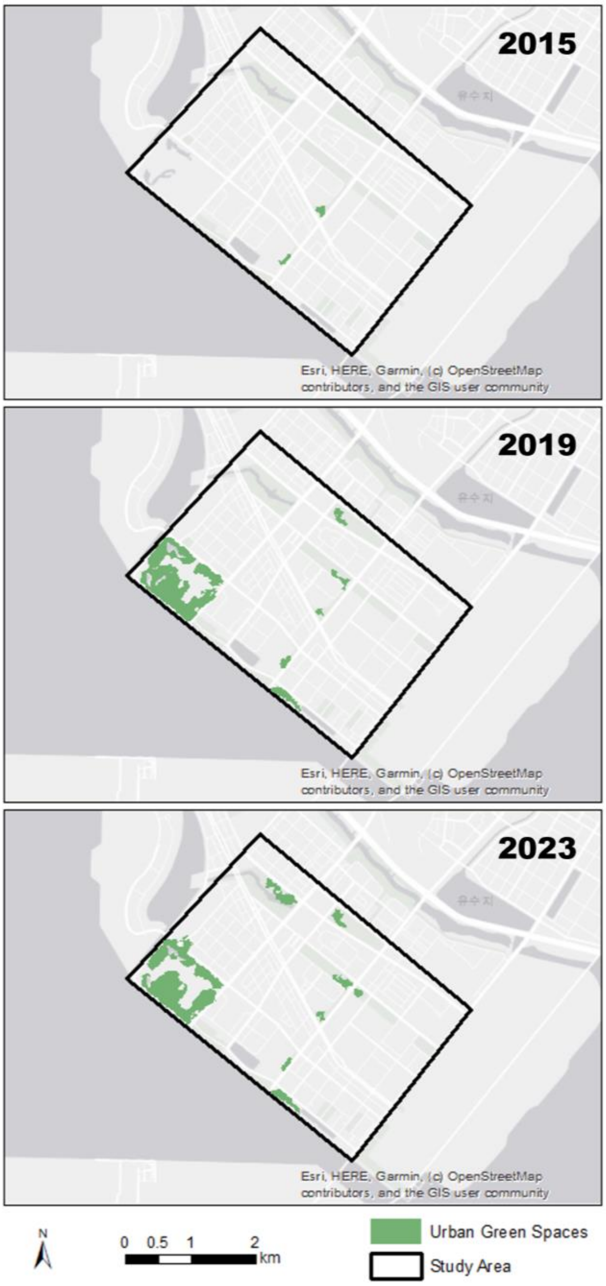

Figure 5. Maps of Urban Green Spaces in Songdo International City for the years 2015, 2019, and 2023

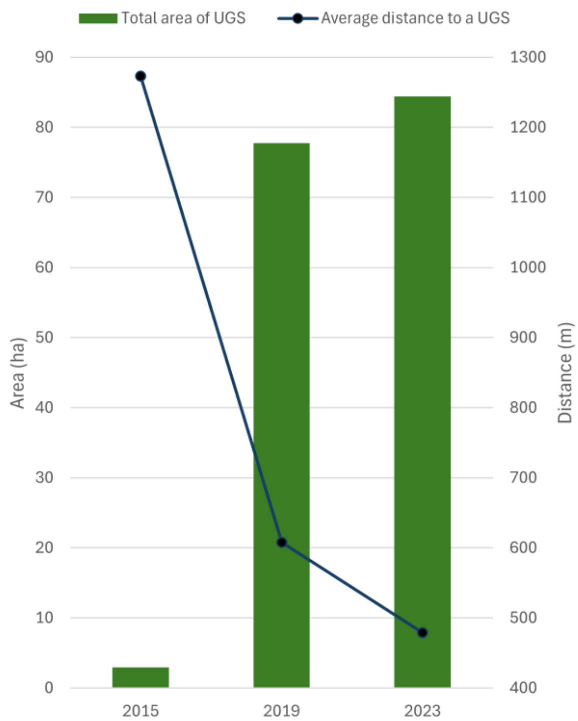

Figure 6. The trends in total area of UGS and average distance from a UGS for the years 2015, 2019, and 2023

Based on this comparison, the extracted UGS from the UGS Extractor may be different from currently available open vector data. The definition of UGS can cover different types of places which may not just be parks but also cemeteries, airports, interchanges, golf courses, or mansion lawns. Depending on the application, users can set what can be classified as a UGS by setting the minimum size of each UGS and the UNDT. The most important thing to note is that it only detects green spaces surrounded by urban areas and excludes forests, marshlands, and mangroves.

4.2 Assessing changes in green space access

Maps of UGS on the Songdo International City were generated for the years 2015, 2019, and 2023 (Figure 5). The generated maps showed that the total area of UGS increased every four years from 2015 to 2023 (Figure 6). The study area experienced a 75-ha increase in UGS for the first four years, from the UGS having an area of just 3 ha in 2015 to 78 ha in 2019. For the next four years, the UGS increased by 7 ha, where the final area in 2023 was 84 ha.

Consequently, because of the increase in cover of UGS, the analysis of the average distance to a UGS showed decreases from 2015 to 2023. The average distance decreased by 665 m in the first four years, from 1273 m in 2015 to 608 m in 2019. The distance then decreased by 129 m in the next four years, with the average distance in 2023 being 479 m. This distance analysis indicates that green space access in the central part of Songdo has dramatically improved from 2015 to 2023.

These results demonstrate the effectiveness of the UGS Extractor for conducting temporal analyses of UGS. This is particularly valuable for enhancing the availability of UGS data over time, as current open vector datasets of UGS typically represent the state of UGS at a single point in time. With the

UGS extractor, data on UGS for various periods can be retrieved, thus broadening the range of possible analyses that can be implemented with UGS. For instance, as demonstrated in this case study, it enables the assessment of changes in green space access over time. A limitation that was observed for this case study is that the UGS Extractor was not able to fully capture the shape of the parks. This may be attributed to the presence of roads or water bodies inside the parks, resulting to the Dynamic World images classifying these areas as Built or Water LULC types. These areas then appear as discrepancies between the extracted and actual shapes of the parks.

4.3 Advantages, limitations, and future directions of the UGS Extractor

As discussed in the previous sections, the UGS Extractor is especially useful for three applications. First, it addresses the limitations of open vector data that often focus solely on specific types of greenspaces, such as parks. The UGS Extractor provides users the flexibility to include other types of UGS by controlling the minimum size of each UGS and the minimum urban neighbor density. Second, unlike open vector data that are typically static, the UGS Extractor is capable of mapping UGS across different time periods. This facilitates dynamic temporal analyses of UGS, offering insights into how urban greenspaces evolve. Third, the application offers a solution for generating global UGS data, which is particularly beneficial for filling data and knowledge gaps in the planning and understanding of UGS in resource-constrained areas where local datasets may be lacking or non-existent.

The methodological framework implemented by the UGS Extractor also provides a novel approach for extracting UGS from an LULC image collection. Researchers working on a specific study area can apply this methodological framework to localized LULC data to extract more accurate shapefiles of the UGS.

As with any model tool, the UGS Extractor also has its limitations. First, extracted UGS does not strictly follow the actual shape of the UGS as the extracted UGS is dependent on the classified LULC from Dynamic World. At the same time, non-green space pixels can occur inside green spaces such as water or urban pixels, which can create holes in the extracted UGS. In the case that the shape of the UGS is essential, open vector files such as data from OpenStreetMap may be more suitable to use.

Although the UGS Extractor puts labels on every UGS feature (thus each UGS can be differentiated from the other), the actual names of each UGS still need to be identified one by one. In cases where the names of each UGS need to be identified, searching through online maps such as Google Earth and manually inputting the names in a UGS shapefile can be implemented.

Lastly, for temporal analysis, the mentioned two limitations may be compounded when dealing with the analysis of the changes for every individual UGS. In this case, each extracted UGS needs to be labeled with its proper name. To deal with discrepancies in shape, the intersection tool can be used to harmonize the shapes of UGS for two periods.

In future work, the time-series analysis capabilities of the UGS Extractor could be improved by making sure that the shape of a given UGS feature aligns for two selected periods. An algorithm can also be added where if two features align, then they will be assigned the same label. This way, encoders of the names of the UGS will have an easier time labeling two shapefiles. The holes in the extracted UGS can also be solved by adding an algorithm that masks out non-green space pixels inside the UGS. This algorithm may be more complex as it may seem as several exceptions may occur, such as roads traversing parks, which may end up not as a hole but as a cavity with an opening on one side of the UGS.

5. Conclusion

This study developed the UGS Extractor, a web-based and user-friendly application for the automatic extraction of UGS across the globe. The UGS Extractor implements a methodological framework composed of user inputs, pre-processing, object-based image processing, edge extraction, and image neighborhood analysis to provide users with a shapefile of UGS for an area of interest and date of interest. The application also accepts user inputs of a minimum size of each UGS and minimum urban neighbor density to enable users to choose what would classify as a UGS.

The UGS Extractor uniquely balances the ability to analyze UGS both spatially and temporally, offering a higher spatial resolution compared to most publicly available satellite-based methods while facilitating near real-time temporal studies not possible with vector datasets. The methodological framework developed in this study can also be further modified by other researchers to local LULC datasets of their study areas to provide more accurate representations of the UGS. In the future, improvements in the model are recommended such as automating the labeling of UGS features and improving the consistency of shapes of UGS between two time periods.

Acknowledgments

This research was supported by the Robert Wood Johnson Foundation Evidence for Action grant (#78386), the University of Arizona Health Sciences Career Development Award, and the National Science Foundation under Grant Number 2314709. Research reported in this publication was also supported by the National Institute on Environmental Health Sciences of the National Institutes of Health under the Southwest Center on Resilience for Climate Change (SCORCH) (P20ES036112) and the Southwest Environmental Health Sciences Center (P30ES006694). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. This material is based upon work supported by the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research’s Urban Integrated Field Laboratories research activity, under Award Number(s) DE-SC0023520. The funders did not have any role in the paper design, data collection, data analysis, interpretation, or writing of the paper.

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Appendix

The UGS Extractor application can be accessed here: https://ee-geotools.projects.earthengine.app/view/theugsextractor. Meanwhile, the source code of the app can be accessed here: https://code.earthengine.google.com/88c5bc43183fe42877194b640fc675f5.