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The integration of UAV, deep learning, and GIS in the assessment of a new neighborhood concept

Xin Hong *[1]

[1] *Koç University, Research Center for Anatolian Civilizations, Türkiye, xhong21@ku.edu.tr*

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Abstract

Built environments of a neighborhood are significant for promoting physical activities and preventing diseases. In quantitative research for built environments at the neighborhood scale, the operational unit neighborhoods should be clearly predefined. Most of the time, census geography is the surrogate neighborhood unit in health research. However, neighborhood boundaries based on census geography can hardly respect the social and spatial dimensions of the residents of a neighborhood. A recently proposed concept, sidewalk-homogenous neighborhoods, attempts to move beyond census geography and operate as a measurable neighborhood unit that captures the economic and behavioral components of residents for community health research. This paper evaluated this newly proposed neighborhood concept by assessing built environments among different residential communities using the integration of unmanned aerial vehicle (UAV) images, deep learning, and Geographic Information Systems (GIS). The applicability of the neighborhood concept was tested in four residential areas at different economic levels in Northeast Ohio of the United States. The study addresses that the sidewalk-homogenous neighborhoods concept can help identify the spatial disparity of built environments between neighborhoods at different economic levels. The study also reveals the inequality in UAV research opportunities between economically advantaged and disadvantaged neighborhoods.

1. Introduction

A neighborhood in the ordinary language can be approximated by the dictionary definition: "a district or portion of a town, city, or country, esp. considered in reference to the character or circumstances of its inhabitants" [1]. Even though neighborhood has been used extensively in academic literature to denote small spatial units, a unanimous consensus on the definition of this concept is absent. There is more than one operational definition of neighborhood in the literature. When a spatial definition of neighborhood is required in quantitative analysis of neighborhood effects, the boundaries of neighborhoods sometimes rely on geographic boundaries measured by Census Bureau or other administrative agencies. In the United States, Census tracts and blocks, ZIP code areas, poverty areas, health districts, spheres of social relationships, boundaries drawn by residential perceptions, and small clusters of housing units are usually the operationalized scales for neighborhoods [2]. Clapp and Wang [3] argued that census geography is so appealing as a surrogate neighborhood because it is so simple as to require little elaboration of a neighborhood. Another reason could be that census geography provides easy and cost-effective methods for aggregating individuals for neighborhood-level measurements. Census geography does offer a reasonable boundary delineation to some neighborhood research. For example, census tracts are referred to, by White [4], as "statistical neighborhoods" since census tracts follow visible geographic boundaries and economics and demographics within the same unit are relatively homogenous [5]. How neighborhoods are defined and delineated greatly affects the statistical results of analyses. In addition, the concept of neighborhood is multi-dimensional that includes social and spatial dimensions, while the ability of census geography to capture both dimensions is questionable. Therefore, researchers may need to move beyond census geography and develop a neighborhood concept that maximizes sociological reality and statistical measurability for targeted research. In the context of health-related built environment research, there is apparently a need for an operational definition of neighborhoods that best fits the research question and appropriately relates to the contextual and compositional aspects of neighborhoods.

Many findings in the literature have revealed the correlation between increased walkability in built environments and better health. A place that is "walkable" means that the living place is facilitated with built environments of non-motorized transportation. It encourages people to practice active forms of transportation, such as walking and biking [6]. However, in many cases, the quality and distribution of built environments between neighborhoods at different economic levels are not even or equal. The identification of the deprivations of built environments at the neighborhood level could help better mitigate health inequities.

With the technological advancement of deep learning in classifying high volumes of fine spatial resolution images and the cost-effective application of unmanned aerial vehicles [7-11] (UAVs) (commonly called drones), the detection of built environments at the street level with the coupling of deep learning and UAV images is feasible. In response to the current absence of a clear, operational definition of the neighborhood concept for public health research, this study offered an examination of a recently proposed neighborhood concept, sidewalk-homogenous neighborhoods, which was originally proposed by Hong [12]. This study assessed the applicability of the concept of sidewalk-homogenous neighborhoods in describing health-related built environments across neighborhoods at different economic levels. The main method used in the examination was integrating UAV images, deep learning, and Geographic Information Systems (GIS) for identifying the spatial patterns of built environment distributions at the street level.

2. Material and Method

This section begins by introducing the newly proposed operational unit sidewalk-homogenous neighborhoods. It then goes on to the characteristics of the four selected sidewalk-homogenous neighborhoods as the test areas and the UAV data collection process. An overview of the classification of the built environments using deep learning and GIS is also presented.

2.1. Sidewalk-homogenous neighborhoods as a new neighborhood concept

The concept of sidewalk-homogenous neighborhoods was originally proposed in Hong's [12] doctoral dissertation research and later published with a focus on the workflow of classifying built environments [13]. The purpose of the proposed neighborhood concept is to have a practical and reasonable spatial unit for revealing the spatial distributions of neighborhood environments between neighborhoods with different economic levels. Corresponding to such purpose, the sidewalk-homogenous neighborhoods are demarcated by real estate values and the intersections of Local and Collector Roadways [14]. Two criteria should be followed in practicing the delineation: 1) The real estate prices within the neighborhood are at the same level, and 2) all the roadways within the neighborhood are Local (residential) Roadways, which have the slowest traffic speed in the roadway system. The first criterion suggests that the economic profiles of residents in a neighborhood are similar. It offers the maneuverability to detect the differences between neighborhoods by economic levels. The second criterion ensures slow traffic speeds within a neighborhood, where all the roadways are less than 25 or 30 miles per hour (around less than 40 or 48 km per hour). Automobile traffic adjacent to sidewalks can greatly influence residents' usage of sidewalks. Local Roads may be more favorable to pedestrians and bicyclists than Collector Roads, as residents are more likely to limit their sidewalk usage zone within local roadways in their living environment, which have less traffic volume [15].

2.2. Characteristics of the test areas and data collection

According to the criteria defined in the previous section, four sidewalk-homogenous neighborhoods in Northeast Ohio, United States were selected to test the applicability of the newly developed neighborhood concept (Figure 1). They are residential areas located in Kent, Brimfield Township, and Akron of Ohio of the United States. In the interest of simplicity, the neighborhoods are named (according to the name of the main street) North Cherry, Sandy Lake, Summit Mall, and River Bend. The boundaries of each neighborhood were demarcated based on the real estate price in the year 2018 and the intersection between Local and Collector Roadways. These four neighborhoods are at different economic levels, as represented by different ranges of real estate values. Their house price ranges and the areas of the neighborhoods are listed in Table 1. The real estate values in the order from highest to lowest are as follows: River Bend (~ $300K and ~$ 900K), Summit Mall (~$220K to ~$500K), Sandy Lake (~$170K to ~$300K), and North Cherry (~70K to ~150K) [16-18].

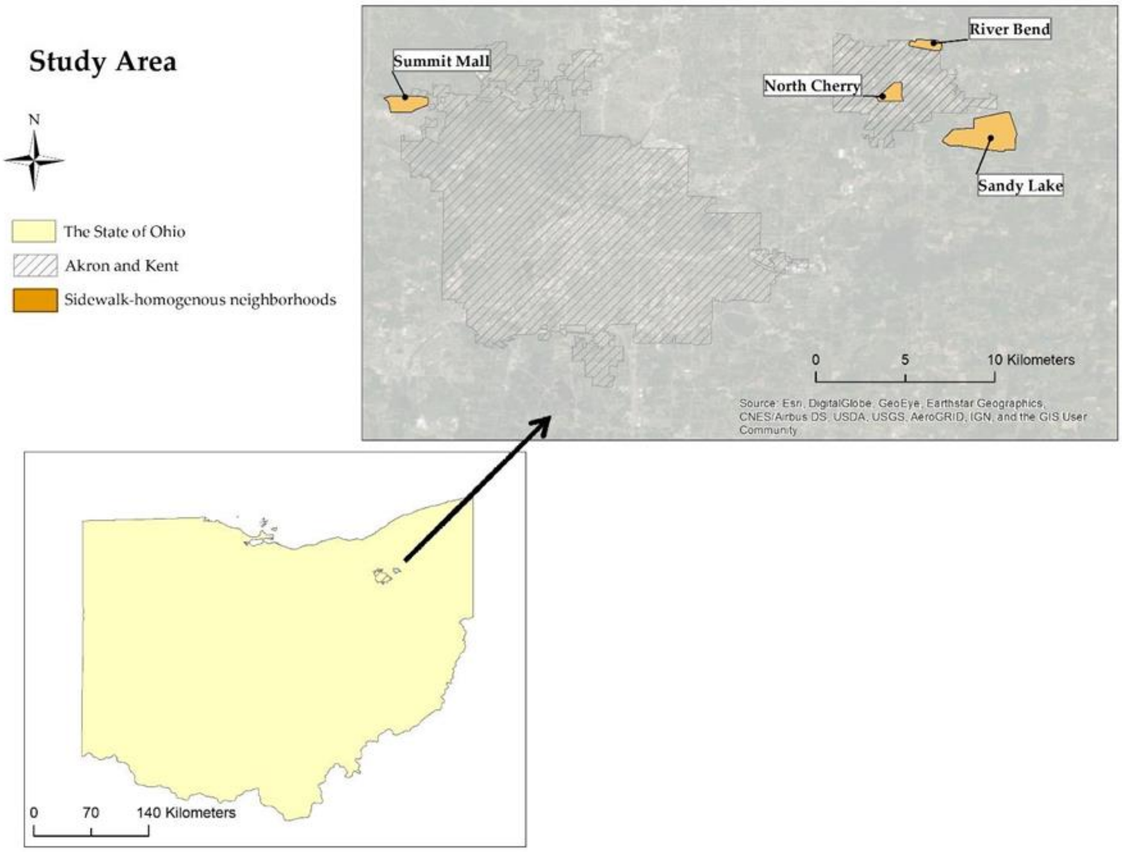

Figure 1. The location of the four selected sidewalk-homogenous neighborhoods in Northeast Ohio, United States [14]

Table 1. House prices and the area of neighborhoods

Neighborhood	House price (Thousand US $)	Area (sq km)
North Cherry	70 – 150	0.8
Sandy Lake	170 - 300	4.48
Summit Mall	220 - 500	1.13
River Bend	300 - 900	0.61

Through field visits to study sites, the in-situ observations suggest that estate values are associated with street amenities and housing densities. River Bend and Summit Mall, which have higher estate values, are facilitated with a greater presence of sidewalks, and most of the sidewalks are covered by trees and surrounded by lawns (Figure 2a), while the lower economic level North Cherry has a sparser presence of sidewalks and lawns (Figure 2b). Building density is another difference. Through visual comparisons from the bird-view images, we may discern the economic disparity is reflected in the building density (Figure 3). The neighborhood of lower economic level (North Cherry) appears to have higher building density as compared to the other three wealthier neighborhoods. The difference is more discernable between those with a higher economic gap: the building density between the poorest North Cherry and the wealthiest River Bend is more different than the middle classes Sandy Lake and Summit Mall. All these highlighted characteristics and variations in built environments between the selected neighborhoods suggest that they are suitable for testing the applicability of the concept of the sidewalk-homogenous neighborhood.

(a) (b)

Figure 2. Field observation of built environment differences between the higher and lower economic level neighborhoods (a) An example of built environments in River Bend (b) An example of built environments in North Cherry

Figure 3. Google Earth images of a part of the neighborhoods, showing greater details of the housing density. All images were set at the same spatial scale (1:10,000) for comparison

The model DJI® Mavic 2 Pro with an ultra-high spatial resolution sensor was deployed for data collection in this study. The major specifications of the UAV are listed in Table 2. The field survey was carried out in the 2019 summer between July and August, which was the growing period for vegetation. The flights were performed in the Waypoints autonomous navigation mode, which meant that the drone was set to fly automatically following a predefined route and capturing configurations. The waypoints mode was set up to fly along every street in the test areas with a flight speed of 10.1 kph and an altitude of 40 m above ground level (AGL). The gimbal was tilted to the nadir facing. The video quality was set to ultra-high definition (4k) 3840×2160 resolution and 30 frames were captured per second. The GPS information was recorded for every image frame and stored as .SRT format. Dates under completely clear sky conditions at between 10 a.m. and 2 p.m. local time were selected as the acquisition time. The UAV flight paths are shown in Figure 4, and the total distance of all the routes was about 57.7 km. While flying the UAV to videotape the street scenes during the field survey, the sidewalk density of every street was also manually coded into one of the pre-defined categories according to the presence of sidewalks [13]: (a) high, (b) moderate, (c) enhanced, (d) slight, and (e) absent.

Table 2. The Major specifications of DJI Mavic 2 Pro

Characteristics	Description
Type	Quadcopter
Dimensions	Unfolded: 322×242×84 mm (length×width×height)
Weight	907 g
Max flight time (no wind)	31 minutes (at a consistent 25 kph)
Sensor	Hasselblad L1D-20c camera: 1-inch CMOS RGB sensor
Video resolution	4K: 3840×2160 24/25/30p
Video format	MP4 / MOV (MPEG-4 AVC/H.264, HEVC/H.265)

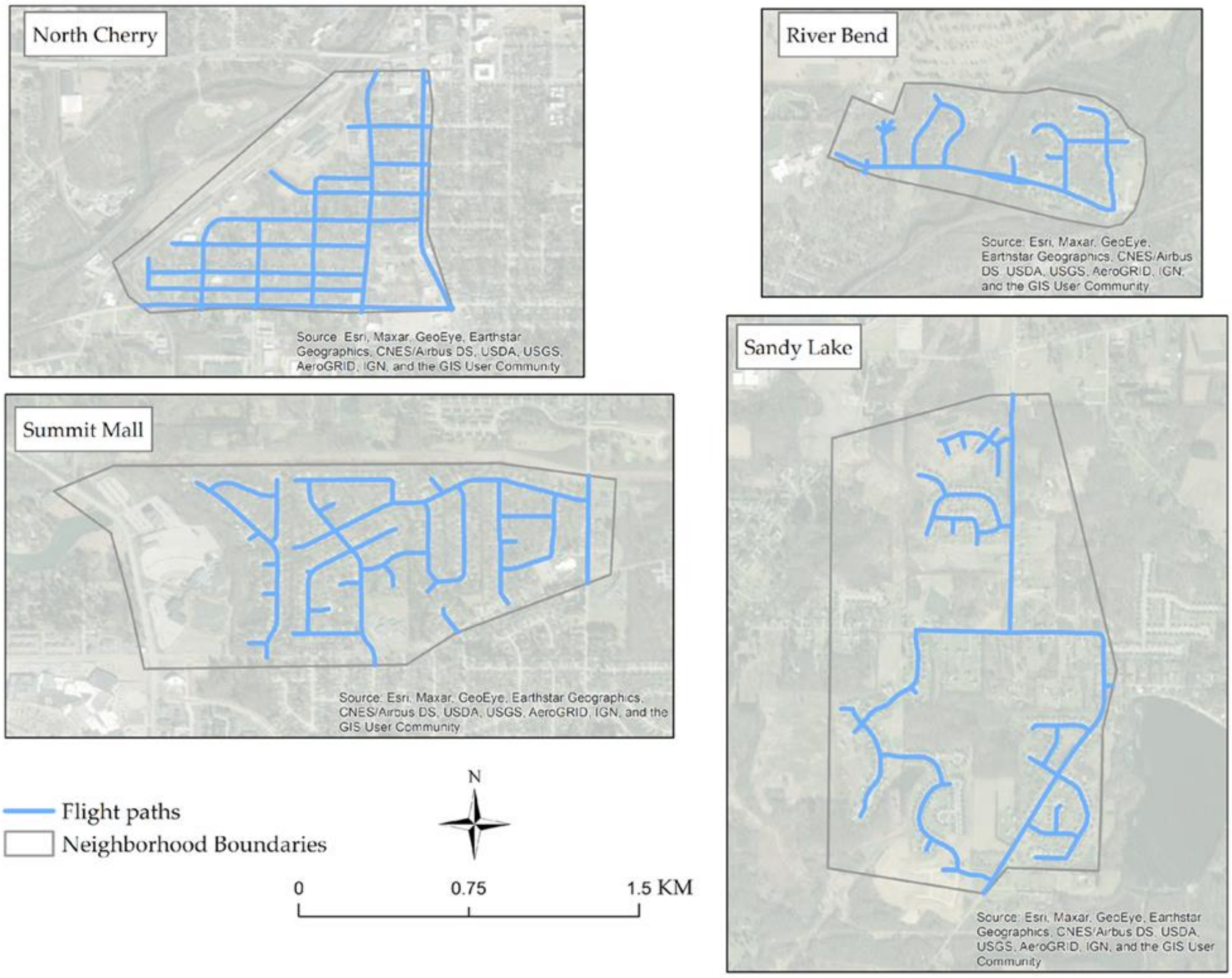

Figure 4. The flight paths of the UAV in data collection

2.3. Detecting built environments using deep learning and GIS

Deep learning and GIS were the main methods for detecting the densities of greenery and sidewalks at the street level. The image frames of every 20 seconds of the captured videos were converted to image files, and a total of 570 images were converted. The greenery pixels of the images were classified by the deep learning architecture U-net [19], and the greenery ratio was derived. The coordinate information of the 570 images was converted to a point vector as a shapefile format with greenery ratio and sidewalk category (logged during field surveys) as the attributes. After that, the Inverse Distance Weighted (IDW) interpolation was used to map the densities of greenery and sidewalks. Details on the workflow of image classification and built environment mapping has been explained in [13].

3. Results and Discussion

3.1. Evaluation of the sidewalk homogenous neighborhoods in characterizing-built environments

Sidewalk and greenery densities at the street level were examined to explore what built environment characteristics and patterns can be revealed as the spatial unit is bounded by the sidewalk homogenous neighborhoods.

The first aspect to explore was the presence of greenery and sidewalk by the spatial unit of sidewalk homogenous neighborhoods. Table 3 summarizes the percentage of each sidewalk density category and the percentage of average greenery by the sidewalk density category. In general, neighborhoods at higher economic levels are facilitated with a greater presence of sidewalks and greenery, and the streets with more sidewalks usually have more greenery cover. River Bend, as the most economically advantageous neighborhood, has sidewalks in all street segments, that is, has no streets in the Absent sidewalk category. Around 73 % of the street are facilitated with High sidewalks (two-sided sidewalks), and about 60% of the High sidewalks are accompanied by greenspace. Similarly, second to River Bend in terms of economic level, Summit Mall also has nearly 72 % of the streets on High sidewalks, and nearly 63 % of the High sidewalks are surrounded by greenery. Opposite patterns of the spatial combination of sidewalks and greenery are found in the counterpart neighborhoods. North Cherry, as the most economically disadvantageous neighborhood, has most of the streets facilitated with Enhanced (60.4 %) and High (26.17 %) sidewalks, but most of the greenery is combined with the lower sidewalk categories Slight and Absent. While only around 2 % of the streets are in the Absent sidewalk category, almost 80 % of the Absent sidewalks are accompanied by greenery. Also, no streets of North Cherry are in the higher sidewalk category Moderate.

Table 3. Presence of sidewalks and average greenness in sidewalk categories (%) [13]

	North Cherry	Sandy Lake	Summit Mall	River Bend
Approximate house price (Thousand US $)	70 – 150	170 - 300	220 - 500	300 - 900
High	26.17	31.38	71.70	72.97
Greenery in high	46.69	49.55	62.65	59.10
Moderate	0.00	17.02	7.55	14.86
Greenery in moderate	0.00	53.99	55.51	56.33
Enhanced	60.40	13.83	15.09	12.16
Greenery in enhanced	58.23	49.34	56.89	72.56
Slight	11.41	5.85	0.00	0.00
Greenery in slight	66.13	72.11	0.00	0.00
Absent	2.01	31.91	5.66	0.00
Greenery in absent	79.36	67.08	61.61	0.00
Total Greenery	56.54	57.19	61.18	60.33

High: denoting two-sided sidewalks the whole way; Moderate: denoting a street segment with two-sided and one-sided sidewalks; Enhanced: denoting three variations in a street segment: two sides, one side, and no sidewalks; Slight: denoting a segment with one side and no sidewalks; Absent: denoting no sidewalks in the entire segment

3.2 Intra-neighborhood discontinuity of built environments in low-income neighborhoods

Sidewalks and greenery can be characterized by neighborhoods with descriptive statistics as shown in Table 3, their spatial arrangements can also be visualized in maps (Figures 5 and 6). We may observe that there is a notable discontinuity of sidewalk density in low-income neighborhoods. The neighborhood at the lowest economic level, North Cherry, has a distinct change from the High sidewalk class in the east to the Enhanced sidewalk class in the west without a transitioning sidewalk class in between. A similar pattern can be found in the low-income Sandy Lake, where the east is mainly facilitated by the Absent sidewalk category, while immediately connecting with the High and Moderate sidewalk categories to the west. In contrast, there is a more evenly spread of better sidewalks than the merely overall high quantity of sidewalks in the high-income River Bend. The distribution of the High sidewalk category in River Bend is even across space without sharp discontinuity. In terms of the spatial arrangement of greenery density, we may also observe that an intra-neighborhood discontinuity in low-income North Cherry. Most street segments in the east of North Cheery have low coverage of greenery, while the other three neighborhoods with comparably higher income levels present more even and higher greenery coverage within their neighborhood boundaries.

3.2. The effects of airspace regulations on UAV data collection

Besides the aforementioned existing gap of built environments between the high- and low-income neighborhoods, the airspace regulations on UAVs may indirectly widen the gap. From the field survey experience, this study found that drones are not permitted to fly with the autonomous flight mode within a certain distance over areas that are classified as either restricted, authorization, or warning zones by the Federal Aviation Administration (FAA). In the original plan of the study, two more neighborhoods at the lower economic levels were planned as the study sites. However, they are located in the warning zone where the autonomous flight mode is not prohibited. Only manual flight mode is allowed. However, the manual flight can hardly ensure that all the scenes are captured with consistent configurations. For instance, constant flying AGL altitude and flying speed along all the routes are almost impossible. In addition, more labor costs and safety concerns are extra issues brought in by the manual flight mode.

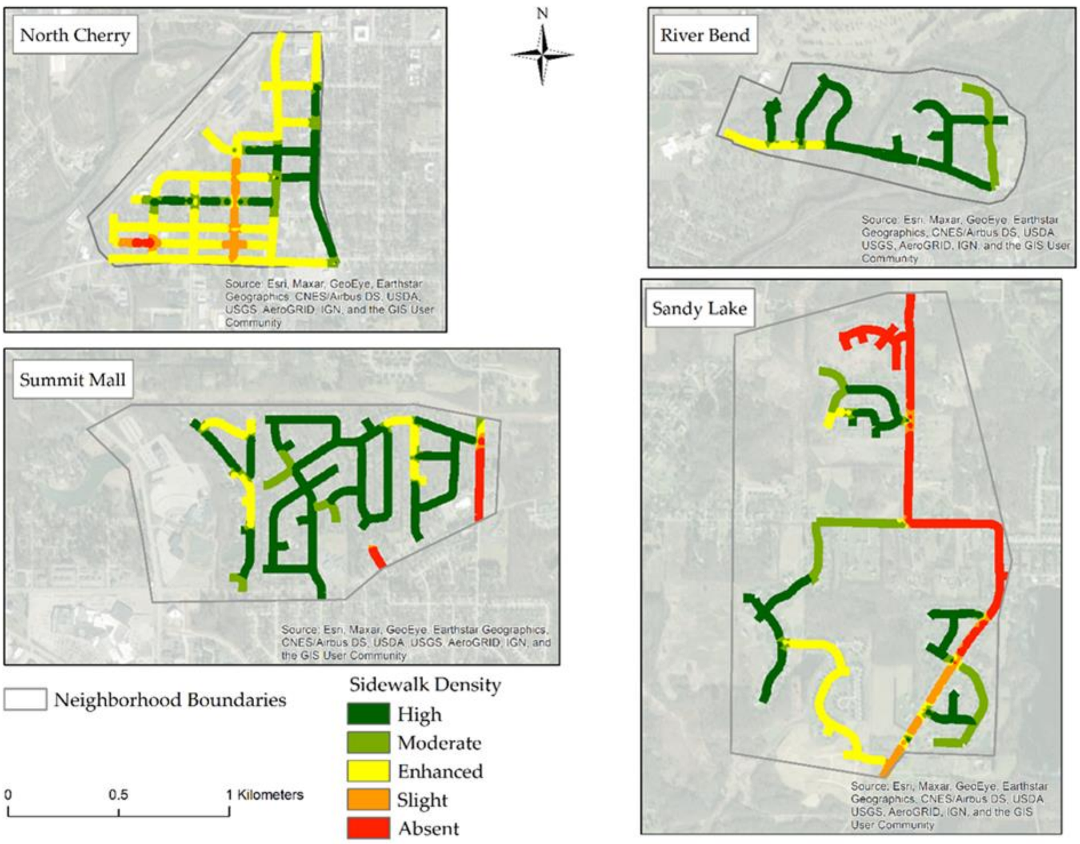

Figure 5. The spatial distribution of sidewalks. (a) high, denoting two-sided sidewalks the whole way; (b) denoting a street segment with two-sided and one-sided sidewalks; c) enhanced, denoting three variations in a street segment: two sides, one side, and no sidewalks; (d) slight, denoting a segment with one side and no sidewalks; and (e) absent, denoting no sidewalks in the entire segment [8]

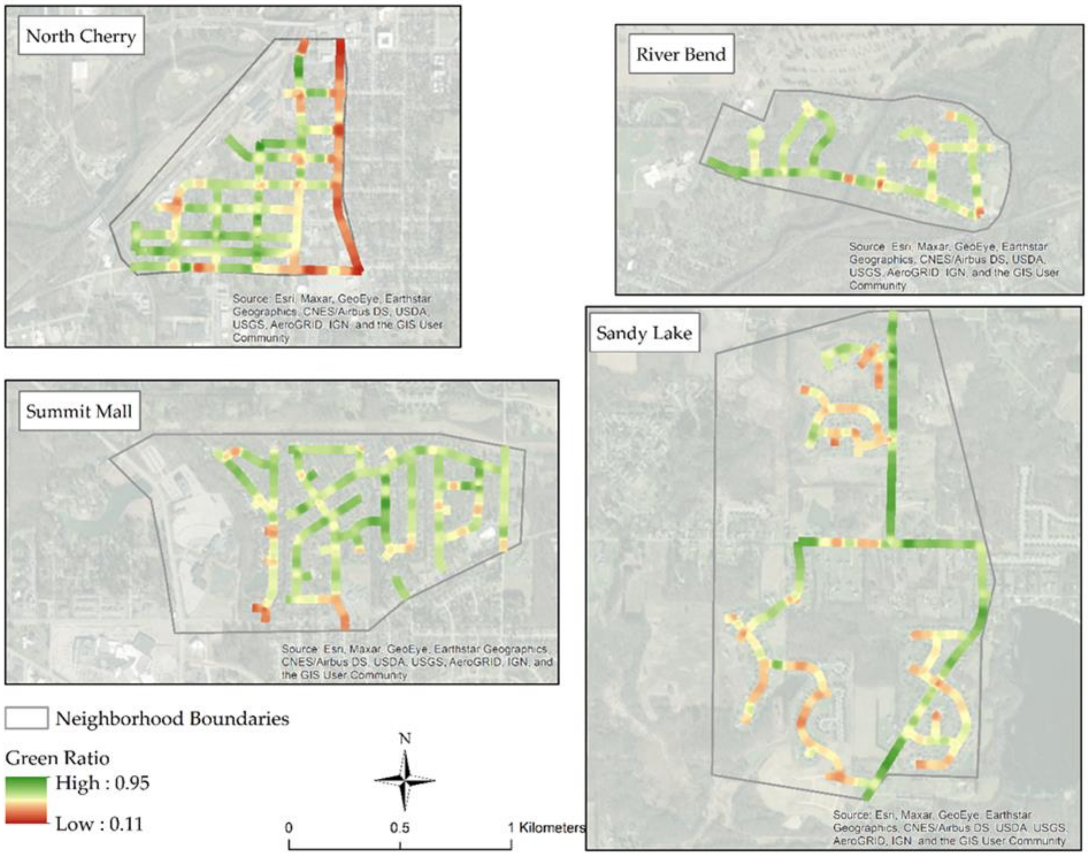

Figure 6. Spatial distribution of greenery [13]

Figure 7 displays restricted/ authorization/ warning zones around the study sites (the Greater Akron region in Northeast Ohio, United States). Not surprisingly, many marginalized neighborhoods in this region are within the warning zones of airspace (see the yellow zones in Figure 7) as the house prices are more affordable for low-income residents. These warning zones are the airspace from the ground of either an airport or a prison up to a certain distance. It turns out that on one hand, many marginalized neighborhoods are around an airport or a prison where UAVs can hardly fly over for research purposes; on the other hand, economically advantaged neighborhoods tend to be in the areas where UAVs are free to fly over. The inequality in UAV research opportunities, at least, between the high- and low-income neighborhoods may undoubtedly deepen and widen the gap in built environment quality between the rich and the poor.

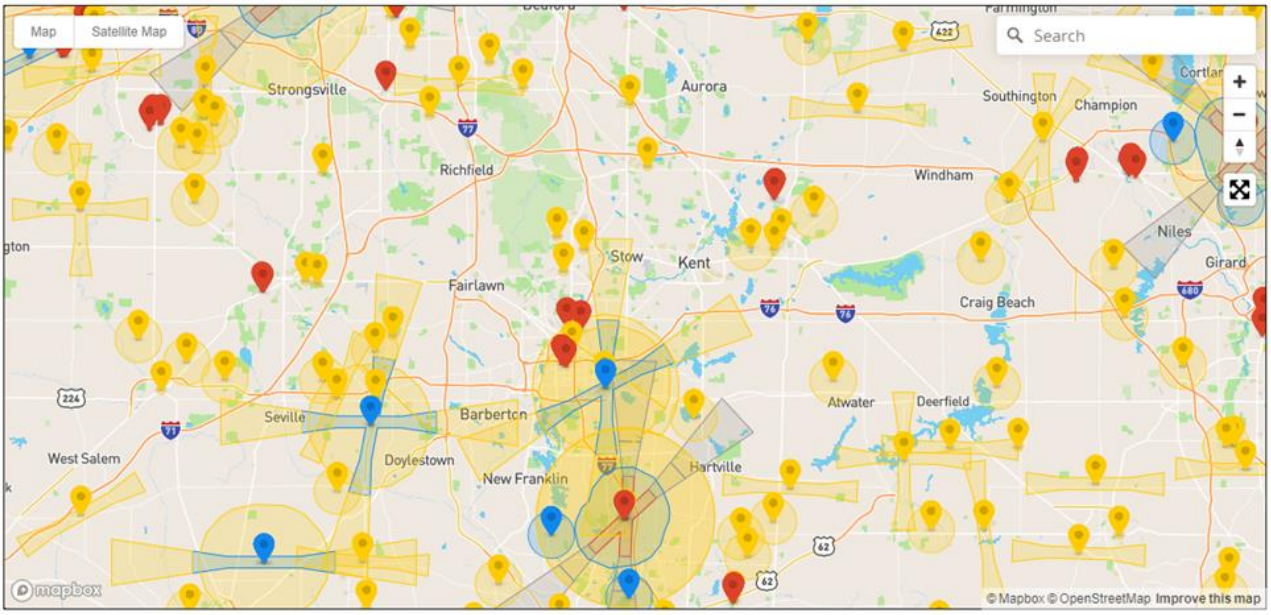

Figure 7. The restricted/authorization/warning zones in the Greater Akron region. Locators (in red, blue, or yellow) are the facilities (e.g., airports, prisons) that their airspace from the ground up to a certain distance are the restricted, authorization, or warning zones [20]

4. Conclusion

This paper evaluated the applicability of the concept of sidewalk-homogenous neighborhoods, as an operational unit, in the detection of spatial distributions of built environments at the neighborhood scale. The measurability of the concept was tested in four residential neighborhoods at different economic levels in Northeast Ohio, the United States. Sidewalk and greenery densities, as the representative health-related built environment attributes, were extracted and mapped from UAV imagery using deep learning and GIS. The results address the disparity of health-related built environments, the presence of sidewalks and greenery at least, between high- and low-income neighborhoods. The survey experience also reveals the inequality in UAV research opportunity between the rich and the poor neighborhoods.

This study demonstrates that the concept of sidewalk-homogenous neighborhood has moved beyond the traditional census geography surrogates as the neighborhood operational unit in quantitative health research. However, some limitations should be addressed. Since the sidewalk-homogenous neighborhoods is a newly proposed operational neighborhood unit and was only tested in four sites in this study, it should be tested in more study sites and/or regions that have very dissimilar landscapes or physical environments than the ones in this study. For example, the desert regions in the Southwest United States and the water canals of Venice, Italy where the facility of sidewalks and green space may require a different perspective with different variables (e.g., temperature effects or water levels; [21-22].

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Conflicts of interest

The authors declare no conflicts of interest.

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