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Delineating urban park catchment areas using mobile phone data: A case study of Tokyo

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Abstract
Urban parks can offer both physical and psychological health benefits to urban dwellers and provide social, economic, and environmental benefits to society. Earlier research on the usage of urban parks relied on fixed distance or walking time to delineate urban park catchment areas. However, actual catchment areas can be affected by many factors other than park surface areas, such as social capital cultivation, cultural adaptation, climate and seasonal variation, and park function and facilities provided. This study advanced this method by using mobile phone data to delineate urban park catchment area. The study area is the 23 special wards of Tokyo or *tokubetsu-ku*, the core of the capital of Japan. The location data of over 1 million anonymous mobile phone users was collected in 2011. The results show that: (1) the park catchment areas vary significantly by park surface areas: people use smaller parks nearby but also travel further to larger parks; (2) even for the parks in the same size category, there are notable differences in the spatial pattern of visitors, which cannot be simply summarized with average distance or catchment radius; and (3) almost all the parks, regardless of its size and function, had the highest user density right around the vicinity, exemplified by the density-distance function closely follow a decay trend line within 1-2 km radius of the park. As such, this study used the density threshold and density-distance function to measure park catchment. We concluded that the application of mobile phone location data can improve our understanding of an urban park catchment area, provide useful information and methods to analyze the usage of urban parks, and can aid in the planning and policy-making of urban parks.

Keywords: Urban park catchment area; Geocoded Mobile Data; Urban big data; Urban green systems; Tokyo

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1. Introduction

Urban parks provide both physical and psychological health benefits to each individual urban dweller and provide social, economic, and environmental benefits to society (Chiesura, 2004; Bedimo-Rung et al, 2005; Xu et al., 2019). These benefits include encouraging physical activities, increasing property value, enhancing ecological biodiversity, and cultivating social capital and interaction (Pickett et al., 2016; Xiao et al, 2019). On the other hand, planning urban parks without spatial integration can also introduce negative impacts such as spatial access inequity (Chang and Liao, 2011), public service disparity (Wolch et al., 2014), and gentrification (Zhai et al, 2018). A deeper understanding of the catchment area of urban parks – the area from which a park attracts a population that uses its services - is essential to the allocation of public amenities such as parks and can ultimately influence the healthy development of urban areas (Ratti et al., 2006; Rios and Munoz, 2017; Zhai et al, 2018).

Since early 21st century, the emergence of urban big data has provided considerable opportunity to examine urban mobility and the use of public amenities at a lower cost, larger scale, and higher efficiency (Evans-Cowley and Kitchen, 2011; Cao et al, 2015; Rios and Munoz, 2017; Riggs and Gordon, 2018; Xiao et al., 2019). For example, social media data, crowdsourcing data, traffic and vehicular data have been extensively used to analyze urban space and activities (Evans-Cowley and Kitchen, 2011; Cao et al, 2015; Zhai et al, 2019). Among the different types of urban big data, mobile application data can be used to support a variety of planning activities and research objectives. For example, Riggs and Gordon (2018) provide a taxonomy to define how the application of mobile phone data can change planning and local policy making. Xiao et al (2019) explored the disparities in park access through mobile phone data. However, using mobile phone data to understand the usage of urban parks remains understudied.

This study uses mobile application data to delineate urban park catchment areas in the 23 special wards of Tokyo or *tokubetsu-ku*, the core of the capital of Japan. The location data of over 1 million anonymous mobile phone users was collected from January 1 to December 31, 2011. The mobile phone users' residential location and distance to the urban parks they visited was identified and tracked using the data. We propose to answer the following questions: (1) What are the spatial patterns of urban park catchment area (UPCA)[1] using the geocoded mobile data (GMD)? (2) Can the density gradient of UPCA reveal systematic variations by park area? (3) What innovative spatial parameters can improve our understanding of UPCA?

The rest of the paper is organized as follows: The literature review section briefly introduces the conventional methods and the mobile phone data application of measuring urban park catchment area. The methodology section presents the application of mobile signaling data in park catchment area delineation before analyzing the results. The concluding section discusses urban park planning policy interventions using mobile phone data and the challenges and opportunities of such an application for delineating UPCA.

2. Literature review

2.1. Conventional approaches for park catchment area estimation and park planning

[1] Catchment area and service area, in this paper, are used interchangeably.

Earlier research relied on distance or walking time from residential location as the most important precondition for use of green spaces to delineate UPCA (Grahn and Stigsdotter, 2003; van Herzele and Wiedemann, 2003; Wolch et al., 2014). For example, according to most researchers, neighborhood parks should be situated within a five-minute walk, corresponding to a maximum 400m radius from a user's residence, if they are to be perceived as accessible (Perry, 1929; Xiao et al, 2019). Other studies have proposed planning and design guidelines for urban parks that ought to adhere to a hierarchical system of standards, where each class of parks has a different walkable catchment area, partly determined by its size (Gobster, 2002; van Herzele and Wiedemann, 2003; Giles-Corti et al., 2005; Ahas et al., 2010; Dai, 2011; Wolch et al., 2014; Reyes et al., 2014).

In Belgium, for instance, standard of local park authorities recommended a 5 ha minimum surface area and a catchment radius of 800 m for a neighborhood quarter park and 10 ha and a 1,600 m for a district park (Herzele and Wiedemann, 2003). The U.S. community parks of 6 ha or more should have a catchment radius of 400-800 m and city parks cover a one-hour driving radius (Lancaster, 1983). A community park is considered to serve 1,000 people per 1-2 acres up to 5,000 and a city park to serve 1,000 people per 5-6 acres (National Recreation and Park Association, 1995). In some more densely populated cities in Asia, there are similar distance-based regulations on catchment areas. For example, the Bangladesh regulation calls for local and neighborhood parks services for frequent visits within a walking distance of 400 m (Jafrin and Beza, 2018). In China, the parks guideline recommends that the service radius of district parks and neighborhood parks should be between 300-500 m and 500-1000 m, respectively (Zhai et al, 2018).

Requirements and recommendations for park environment and facilities are often provided in conjunction with the assumed park catchment size. Marcus and Francis (2003) offered an expansive list of user groups, activity types, and design recommendations for general neighborhood parks. For smaller mini parks and pocket parks, it assumed most of the park users come from within four residential blocks. Hence, the recommendation for those park types emphasized understanding the population characteristics of nearby residential blocks and prioritizing the user groups with lower mobility. Woolley (2003) presented three categories for the open space classification, domestic, neighborhood, and civic open spaces, based on where the users would mostly come from and stated design goals and recommendations accordingly.

2.2. Urban park planning theory and park catchment area estimation in Japan

The guidelines for open space catchment area in Japan is largely based on the concept of the Neighborhood Unit Planning (Ishida, 1987; Ishikawa, 2001; Committee for the Publication of Urban Parks in Japan, 2005). Since 1972, the City Park Enhancement Five-Year Plans, systematically applied the Neighborhood Unit Planning approach for the planning of playgrounds, neighborhood parks, and district parks, see **Figure 1** (Committee for the Publication of Urban Parks in Japan, 2005)**.** These plans aimed to provide four playgrounds and one neighborhood park for every neighborhood unit, or *kinrin jyuku*, and one district park for every four neighborhood units (Ishida, 1987; Ishikawa, 2001). As one neighborhood unit corresponds to an area of 800 m by 800 m, the approximate radius of the catchment area served

by a neighborhood park is 400 to 500m. In the case of district parks, the catchment area radius would be 800 m to 1000 m (Ishida, 1987; Ishikawa, 2001).

The park catchment area estimations and guidelines explained in the paragraphs above are mostly based on normative criteria: neighborhood parks should be located within a five-minute walking distance, for example. These guidelines also implicitly assume that people will use the parks that they have closest access to. However, empirical evidence on actual park visit behaviors and how far park visitors come from rarely exists, especially for neighborhood parks. We can list up many other probable factors that may influence the park visit distance, such as job location, transportation, physical environment of parks, beyond the simple distance between a park and residential location. Due to the scarcity of related studies, we are yet to know how different the assumed park catchment area and the actual park visit behavior are. Newly available data that are able to show individual daily travels using georeferenced digital records open up the possibility of understanding the actual park catchment area.

2.3. Usages of georeferenced location data and their application to the park catchment area measurement

Georeferenced data from various sources have been used to estimate human mobility and the use of public facilities, including those related to parks (Evans-Cowley and Kitchen, 2011; Cao et al, 2015; Rios and Munoz, 2017; Riggs and Gordon, 2018; Xiao et al., 2019). These real time geocoded location data include sensor data, Internet of Things (IoT), and Point of Interests (POIs) data (Fan et al, 2017; Rios and Munoz, 2017; Riggs and Gordon, 2018). For example, Levin et al (2015) used data from the Flickr photo-sharing website as a proxy to identify which areas people use for recreation.

Also important are the data available from cell phones. Call Detailed Records (CDR) has increasingly been recognized as a potential data source for new urban applications (Steenbruggen et al, 2014). Using mobile base stations to identify the location of phone users, CDR data have been applied to understand use patterns of urban facilities in complex environments. (Ratti et al, 2006; Xu et al, 2015). Florez et al (2017) also argued that CDR data from mobile phones are novel resources for travel demand models.

These geocoded location data are not without weaknesses including the spatial mismatch between activities and records, inaccurate interpretation of location from the recording posts, and bias toward particular types of application users. (Xu et al, 2015; Fan et al, 2017). Especially, the CDR data, which rely on mobile base stations, are more prone to this precision issue as they are the records of nearest or accessed base stations instead of the records of actual phone locations (Xiao et al., 2019). In contrast, the Global Positioning System (GPS) records of mobile phones are the records of the actual phone locations and thus greatly reduce the inaccuracy issue.

2.4. Measuring urban park catchment area with mobile data application

In the use of mobile phone location data, it was not necessary to rely on the mobile base station. Unlike Euclidean distance-based and network-distance based measures, this study introduced a density-based approach to measure the UPCA. Density decay or a density gradient is a conventional approach which has been used in urban economics (Louail et al, 2014). As

mentioned earlier, the actual usage of urban parks depends on many factors other than proximity to the park such as safety, neighborhood social capital, function and facilities provided, size and shape, terrain, and vegetation, among other things. (Madge, 1997; Pickett et al., 2016; Xiao et al, 2019). Under the assumption that people may use parks based on numerous criteria (not just the parks that they have closest access to), multiple service areas can be applicable to measure UPCA (Sorensen, 2002; Shin, 2004; Xiao et al., 2019). The benefit of using multiple service areas is to reflect the frequency of park usage in addition to the physical proximity to parks. Thus, we propose that multiple service radii should be used to understand park usage in contrast to the conventional use of a single radius. In order to do so, we need to come up with density gradient to capture the thresholds of the multiple service radii. Understanding the actual service radius (radii) of UPCAs is critical for professionals involved in urban park planning, such as policy makers, landscape designers, community advocates, and environmentalist, to have a better grasp of the value of urban parks and come to agreement for decision making.

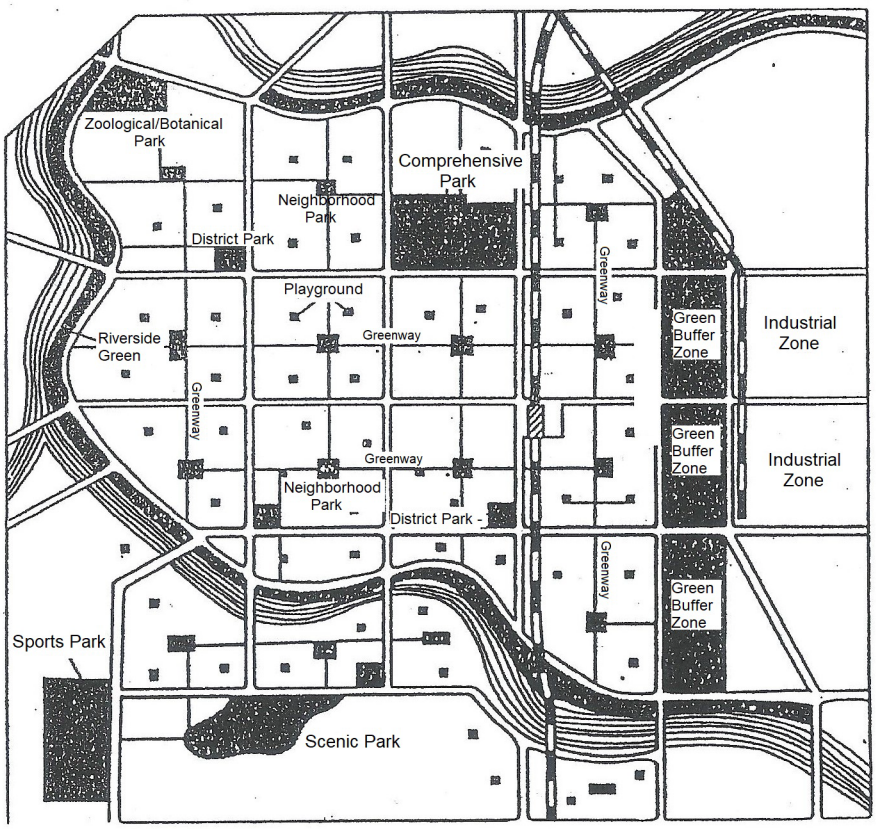


Figure 1. A model park plan of the first Five-year Plans for City Park Enhancement based on Neighborhood Unit Planning principle. Source: Committee for the Publication of "Urban Parks in Japan" 2005, page 69.

3. Data and Analytic Methods

3.1 Data collection

For a comprehensive understanding of park visitors in terms of both park size and seasonal changes, we estimated and analyzed visitors of 30 urban parks, varying in size, in the central Tokyo. The data collecting period includes four different months in 2011, representing each season. The following sections explain the estimation process of park visitors and their residential locations, and the sampling of parks and months.

Estimating park visitors and their residential locations

We used the dataset called Konzatsu-Tokei ® Data from one of the predominant mobile phone operators in Japan, with over 50 million subscribers. Konzatsu-Tokei ® Data refers to people flows data aggregating individual location data sent from mobile phones under users' consent, through applications such as "docomomap navi" service (map navi, local guide etc.) provided by NTT DoCoMo, INC. Those data are processed collectively and statistically in order to conceal the private information. The original location dataset is GPS data (latitude, longitude) sent in about every minimum period of 5 minutes and does not include the information to specify individual. (Akiyama, Horanont, & Shibasaki, 2013). Covering all areas of Japan, the dataset includes all 365 days of the year 2011, from January 1 to December 31, and approximately 1.5 million cell phone IDs. This GPS point count is not the same as the total number of visitors of a park although it is expected to be proportional to the actual volume of the visitors.

To specify visitors of the sample parks, we introduced a two-step process. First, the park boundary polygons and GPS points that were overlapping spatially were identified. Points within the boundary of each sample park were assumed to be park visitors. Second, only the GPS points that stayed longer than five minutes in a park were defined as a 'visitor'. The accuracy error is in general at a minimal level (within 15-30 meters in optimal conditions, that is to say without obstructions of high-rise buildings) for those open air records. In the urban environment, the error margin can be higher. We applied the five-minute criterion to exclude those who were simply passing through the parks since those located closer to a transportation hub or crowded streets are more likely to have a higher number of 'passers-through'. This criterion was chosen as a proxy to differentiate the purposes of travel / visit.

We estimated the residential locations of the park visitors defined as above by tracing back his/her daily movement. If the cell phone location of a visitor showed repeated stays at or around the same point overnight throughout a year, the point is assumed as the residential location of the visitor. The residential location detection criteria included (1) user is at residential location between 8pm to 7am and (2) at least four days a week for more than half of the year. This estimation enabled us to execute the following analyses on park visitor distribution.

3.2 Analytic Methods

Sampling time periods and parks

As mentioned earlier, we picked four different months to sample all four seasons. More precisely, we picked four weeks (28 days) for each season. The sampled weeks roughly overlap with March, June, September, and December, see **Table 1a.**

For the sampling of parks, we used the stratified random sampling based on the size of parks. Japan's Urban Park Law classifies urban parks into several categories and suggest recommended size for each category. We chose five categories, roughly corresponding to the legal

classification and excluded the category for pocket parks, the smallest ones, see **Table 1b.** For each of the five size categories, we selected six parks randomly. In sum, our park sample comprises a total of 30 parks and our analysis is based on visitors of the 30 parks during 16 weeks in 2011, see **Figure 2**.

Table 1a. Sampled periods

Season	**Spring**	**Summer**	**Autumn**	**Winter**
Period	**March 28 days** (2011/03/05, SAT - 2011/04/01, FRI)	**June 28 days** (2011/06/04, SAT - 2011/07/01, FRI)	**September 28 days** (2011/09/03, SAT - 2011/09/30, FRI)	**December 28 days** (2011/12/03, SAT - 2011/12/30, FRI)

Table 1b. Summary of the parks sampled

Category	**Size Range**	**Corresponding Administrative Category**	**Total Number of Parks in the Size Range***	**Sample Park List**	
				Park ID	**Park Name (Location – Ku)**
A	**0.5 – 1 ha**	City Block Park	217	A1 (95)	Kamezuga (Minato)
				A2 (112)	Kitakashiwagi (Shinjuku)
				A3 (269)	Magomenishi (Ota)
				A4 (278)	Tamagawa Daishibashi (Ota)
				A5 (371)	Momozonogawa (Suginami)
				A6 (392)	Yabatagawaminami (Toshima)
B	**1 -3 ha**	Neighborhood Park	186	B1 (70)	Shin Tsukishima (Chuo)
				B2 (109)	Ochiai (Shijuku)
				B3 (159)	Yokoamicho (Sumida)
				B4 (160)	Mukojima Hyakkaen (Sumida)
				B5 (252)	Nakameguro (Meguro)
				B6 (268)	Higashichofu (Ota)
C	**3 – 10 ha**	District Park	103	C1 (71)	Ishikawajima (Chuo)
				C2 (137)	Rokugien (Bunkyo)
				C3 (147)	Kinshi (Sumida)
				C4 (242)	Komaba (Meguro)
				C5 (304)	Setagaya (Setagaya)
				C6 (310)	Tamagawa Tamagawa (Setagaya)
D	**10 – 50 ha**	Comprehensive Park	51	D1 (63)	Kokyo Higashigyoen (Chiyoda)
				D2 (102)	Shiba (Minato)
				D3 (241)	Shiokaze (Shinagawa)
				D4 (271)	Heiwano Mori (Ota)
				D5 (343)	Kinuta (Setagaya)
				D6 (385)	Wadabori (Suginami)
E	**50 ha -**	National Park	10	E1 (120)	Shinjuku Gyoen (Shinjuku)
				E2 (353)	Yoyogi (Shibuya)
				E3 (435)	Arakawa Todabashi (Itabashi)
				E4 (606)	Koiwa (Edogawa)
				E5 (651)	Kasai Linkai (Edogawa)
				E6 (666)	Hikarigaoka (Nerima)

*as of 2014, excluding 'Marine Park'.

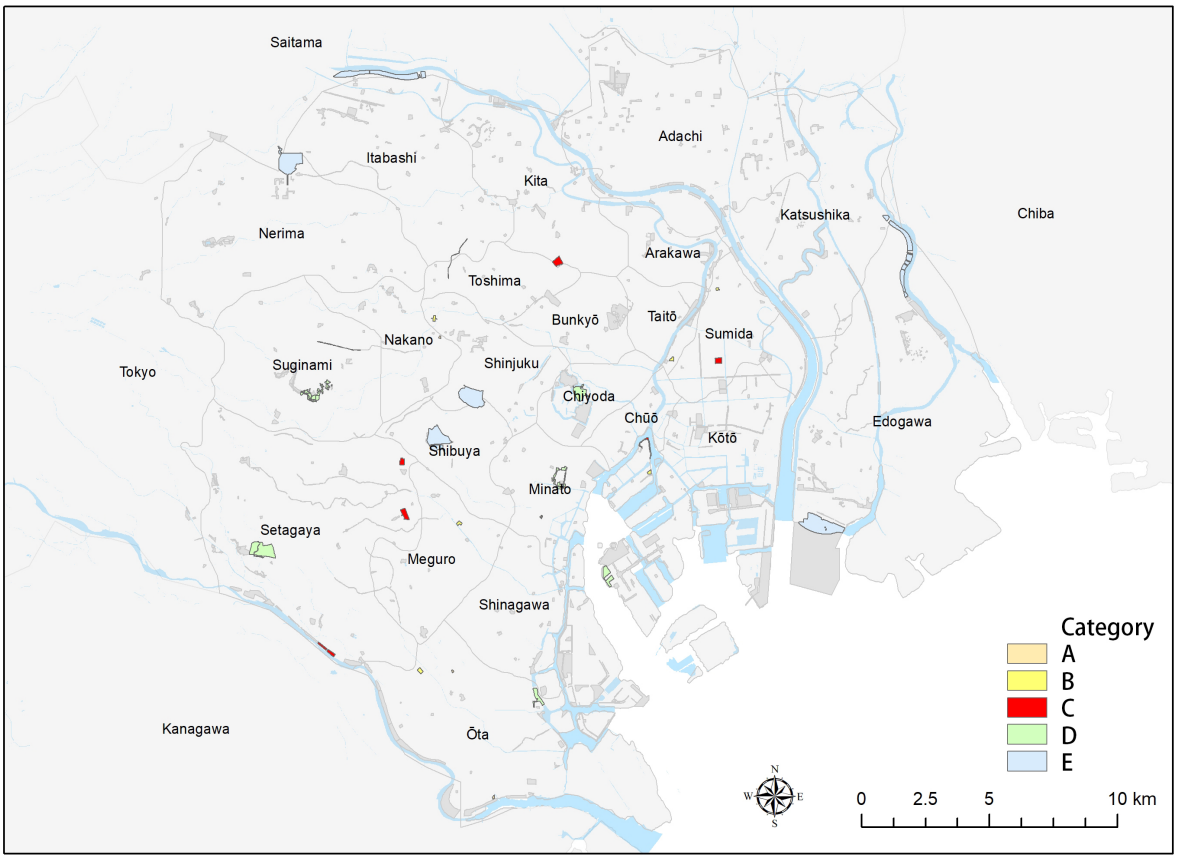


Figure 2. Location of parks.

Basic statistics, mapping, and density-based analysis

To summarize the distance traveled for the park visits, the average, standard deviation, median, and several percentile cut-offs were calculated based on the closest distance between the estimated residential locations and the boundary of the parks using ArcGIS. We applied density-distance mapping, density curve gradient, and density-distance decay function to measure UPCA. (a) Density-distance maps were generated in ArcGIS, as the results of the spatial interpolation of kernel density. Density distance gradients were used instead of distance-based buffers to define urban park catchment areas. As such, the thresholds are the density or the frequency of park visitors recorded in the sampling group. The results were exported to tables and categorized by density thresholds to generate (b) Density curve gradient: A density curve gradient was applied to identify the UPCA, using density cut-off thresholds (DTs). We categorized park catchment areas using DTs of 0.001, 0.01, 0.1, 1, 10, and 100 users per km^2. We tried multiple search radiuses: When use radius higher than 5 km, the locational variation starts to disappear. We then fixed the search radius as 5 km. In addition, 5 km is also roughly the maximum distance to cover the shortest diameter of any of the 23 wards in Tokyo. We created 6 density groups, group 1 being the highest (over 100 park users) and group 6 being the lowest (less than 0.001 park users) per km^2. In order to captured the density variation of locations, we measured (c) Density-distance decay function and "bandwidth": The concept of a "bandwidth" was used to measure density variation of locations that have the same distance to the center,

which in this case, were the selected urban parks. The higher the bandwidth, the greater the variation. Together, the three analyses provide a comprehensive measure of UPCA.

4. Results

4. 1. Basic statistics

Table 2 summarizes the results of the travel distance to sampled city block parks in Category A. The study found that: (a) In general, the average travel distance to a city block park is much longer than the median, suggesting that there were visitors originating from places further away and hence increasing the average travel distance. (b) In five of the six cases, the median travel distances fell within a rather reasonable range, from approximately 80m to 1.2km. At least half of the visits originated from areas close to the city block parks. (c) Park A4, which had an exceptionally high median travel distance, is a park adjacent to a large riverside park. One explanation could be that there were many visitors originating from places further away to use the large riverside open space regularly, such as sports club members. (d) There were also a significant proportion of park visitors originating from places further away. They could be workers, students, or other non-residents whose daytime jobs or schools are around the parks. (e) Comparing the summary statistics including all repeat visitors and those excluding repeat visitors, we find that the frequent visitors (repeats) originate from areas nearby the parks. This shows that those repeat visitors are actual park users rather than those passing through to work. The results of categories B, C, D and E are shown in **Appendix 1**. Considering the protection of private information, comprehensive processing of the GPS data in this paper were performed in ZENRIN Datacom Co., Ltd (ZDC) received the request of NTT DoCoMo and we were provided only aggregated results.

Table 2. Summary of park travel distance (in meters).

	No. of Obs*	**Average**	**SD**	**Median**	**10%**	**25%**	**75%**	**90%**
				Including repeats				
A1(95)	75	9,153	15,837	463	4	4	10,772	32,690
A2(112)	83	4,869	10,183	681	68	87	1,786	18,472
A3(269)	62	4,014	7,950	***1,160***	9	244	1,160	11,558
A4(278)	175	14,869	16,782	***10,032***	16	237	25,480	48,697
A5(371)	275	6,355	10,703	239	10	36	10,101	20,886
A6(392)	344	34,397	140,565	84	5	16	8,333	24,450
Category A	**1,014**	**17,280**	**83,434**	**716**	**10**	**34**	**10,338**	**27,129**
				Excluding repeats				
A1(95)	26	13,111	20,533	4,239	40	463	15,906	33,392
A2(112)	34	9,887	13,366	1,875	82	325	16,377	33,877
A3(269) Magomenishi (Ota)	18	4,925	7,907	998	20	188	4,308	20,300
A4(278) Tamagawa Daishibashi (Ota)	56	13,527	16,362	2,608	84	390	26,968	39,232
A5(371)	156	8,546	12,250	3,550	20	92	12,794	24,917
A6(392)	157	46,661	165,159	2,632	18	53	12,331	29,994
Category A	**447**	**22,779**	**99,894**	**2,458**	**21**	**105**	**14,255**	**29,994**

Source: Konzatsu-Tokei ®, © ZDC.
* The number of visitors are based on the sampling data sets. The multiplier is 100+ based on the total population. That is to say, for the smallest park categories, the visitors are in the range of 6,200 to 34,400 including multiple repeat visits. The numbers are much higher for other categories.

4.2. Park catchment areas based on the density cut-off thresholds

The boundaries of the UPCAs were derived using six DTs. The spatial patterns of UPCAs were observed across the five park size categories by area. The UPCAs are shown in **Figure 3** (for Category A) and **Appendix 2** (for Categories B, C, D, and E). We address (1) the area and radius of the UPCA across different DTs; (2) the spatial patterns and shapes of the UPCA; and (3) whether or not the UPCA is centered around the park.

For city block parks (Category A 0.5-1 ha), as shown in **Figure 3**, we observed circle shaped UPCA at the highest DT at 10-100 park visitors per km^2, for all parks. The shapes of the catchments areas do not differ much from the conventional Euclidian distance derived catchment. The radiuses of the circles are measured at 2.51km, 3.02km, 2.38km, 2.95km, 4.03km, and 4.12km, respectively, which is larger than most of the regulations (such as a 500m-service radius) for a neighborhood park. At the 1-10 DT, UPCAs for Parks A1, A2, and A3 are concentric circles of the 10-100 DT UPCAs. However, for parks A4, A5, and A6, the UPCAs of the 1-10 DT are irregular shapes surrounding the 10-100 density threshold UPCA. In addition, some of the UPCAs have two centers. For example, park A4 has a second catchment at the 1-10 threshold, appearing in the Arakawa-Sumita-Katsushika area, which is located diagonally across the city.

The resultant catchment areas for neighborhood parks (Category B 1-3 ha) are shown in **Appendix 2**. At the highest DT, the area of the UPCAs varied from 10.86km^2 the smallest (B1) to 143.0 7km^2 (B3) the largest. Both circular-shaped (B1, B4, and B6) and irregular-shaped (B2, B3, and B5) UPCAs were observed. Four of the parks' UPCAs were centered and two were off-centered (B3 and B5). Park B3 had irregularly-shaped UPCAs across all DTs. Park B1 has the highest DT at 1-10 with a radius of 1.86km. Park B4 has two circular-shaped catchment areas at the 10-100 DT. The larger one had a 3.75km radius centered around the park and the smaller one had a 1.35km radius located 15km due west of the park. Park B6 has a circular-shaped catchment with a radius of 3.81km at the 1-10 DT centered around the park.

For the district parks (Category C 3-10 ha), the UPCAs ranged from 1.33 km^2 (C2) to 207.00 km^2 (C1) (see **Appendix 2**) at the 10-100 DT. The circular shape catchment area was observed only in park C5. The radius of the catchment area circle was 3.11km, centered around the park. Park C1 had no UPCA at the 1-10 and 10-100 DT. At the 0.1-1 DT, Park C1 had a circular catchment area. The results show that the frequency of park visitors to this park is lower than other parks in this category. For this particular example, the study may not have enough data to reveal the true catchment area of this park. Park C2 had a UPCA with a 650-meter radius at the 10-100 DT, centered around the perimeter of the park. At the 1-10 DT, the UPCA was irregular in shape. Park C4 had multiple centers at the 0.1-1DT. Park C6 also has a circular catchment area at the 1-10 density level with a radius of 1.92 km. The catchment area was not centered around the park. At the 0.1-1 DT, there were multiple catchment areas.

The comprehensive parks in Category D (10-50 ha) are shown in **Appendix 2**. The size of the UPCAs at the highest respective DT ranged from 9.61 km^2 (D1) to 715.96 km^2 (D3). At the 10-100 DT, we observed that four of the six parks had circular UPCAs: D2, D4, D5, and D6. Except for park D4, the UPCAs were all centered around the park. Park D2 had a circular catchment area at the 10-100 DT with a 1.76 km radius. There was a significant increase in the UPCAs from 10-100 DT to 1-10 DT. This indicates that a further breakdown of the 1-10 DT can reveal more useful information of the UPCA. Park D4 had a circular catchment area at the 10-100 DT with a 2.81km radius. The UPCA was off-centered 1.62 km from the center of the park. The park also has three separate catchments at the 1-10 DT, one around the park, one to the west, and the third one to the northeast. The shape of the UPCA at the 0.1-1 DT became irregular. Park D5 had a catchment roughly centered around the park at the 10-100 DT with a 3.75km radius. The catchment areas at the 1-10 DT included two parts: one with a corrugated perimeter around the park and the other was 13.72km away from the center of the park. Park D6 had a catchment area centered around the park at the 10-100 DT with a 3.56 km radius. At the 1-10 DT, the catchment was roughly centered around the park. However, the 0.1-1 DT catchment was irregularly shaped with spokes radiating in different directions.

The parks in Category E (>50 ha) are shown in **Appendix 2**. The size of the UPCA at the 10-100 DT varied from 2.83 km^2 (e435) to 122.66 km^2 (e353). None of the parks had a circular catchment area at the 10-100 DT. However, three parks exhibited oval-shaped catchment areas: E1, E2, and E4. In addition, two parks, E5 and E6, showed slightly deformed, circular service areas. At the 10-100 DT, park E3 had a UPCA located 2km due south and with two catchment areas. The larger one surrounded the park and the smaller one was 10 km away due south. Both were oval shapes. At lower DTs, the shapes of UPCAs becomes irregular.

The important parameters (DT and its radius, shape, and location) used to delineating UPCA are highly relevant to park planning: DT illustrates the density distribution of park users at multiple levels. A higher DT shows more intensive usage of parks, which provides important facts for maintenance and providing park user facilities. The radii of DTs can be used to compare with existing park planning regulation. Shape and location of a UPCA are not only affected by park size but also related to land use planning of the surrounding areas and transportation accessibility. Next section further investigates the UPCA using density curve gradient.

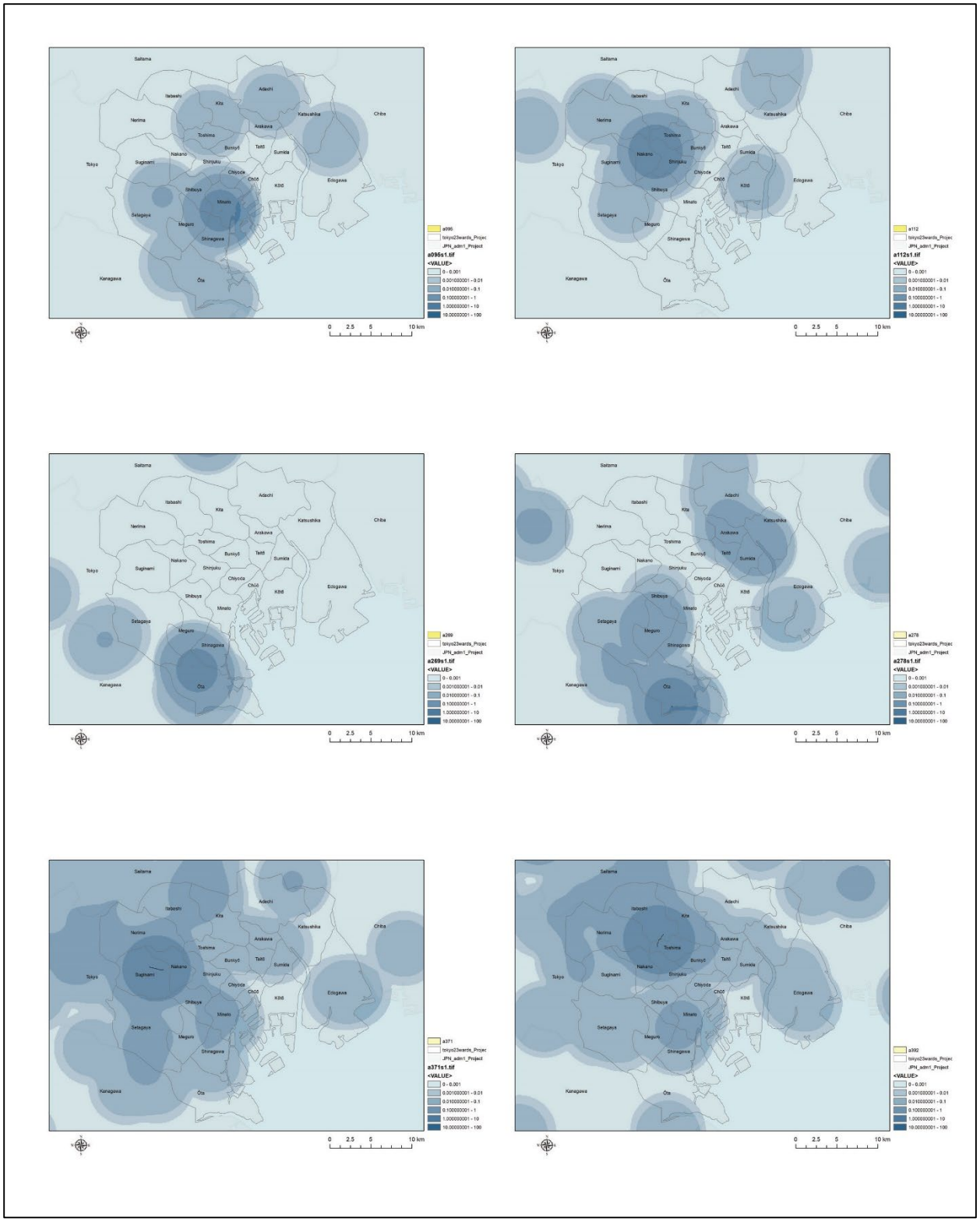


Figure 3. UPCA – Category A (0.5-1 ha).
Source: Konzatsu-Tokei ®, © ZDC.

4.3. Catchment area density curve gradient

Using the conventional Euclidean distance and network distance catchment areas as baselines, the area density curve was expected to increase from high to low DT. The distance-based catchment is a function of $A = \pi r^2$ (*A* is area and *r* is radius) and the network-based catchment is a function of buffer $A = \alpha sd^2$, (*d* is travel distance and *s* is speed). In both cases, it is a non-linear power function. However, what we observed using the DT method is a polynomial function. For the polynomial curve, two values are relevant in the UPCA derivation: the *maximum value* and the *point of inflection*. The point of inflection is where the distribution curve changes direction. In this study, the point of inflection indicates the DT at which most of the park user activities are captured. Moreover, if the maximum points are coinciding with the inflection points, the implication is that the DT that the inflection point is in should be subdivided and/or study areas should be extended. The inflection points can be observed in the catchment area density curve in **Figure 4**.

The number of land parcels by DTs is summarized in **Table 3**. In category A, the largest number of land parcels for all parks were in the smallest DT (<0.001). The 0.01-0.1 DT is the point of inflection, presented in bolded letters, where the distribution curve changes from being concave to convex. In the neighborhood parks (Category B), park B3 has both a maximum point and inflection point in the 0.1-1 DT while park B4 has both points in the 0.01-1 DT. In the district parks (Category C), three parks had both maximum and inflection points in the 0.1-1 DT and two parks, C4 and C6, had inflection points in the 0.01-1 DT and maximum points in the <0.001 DT. In the comprehensive parks (Category D) and national parks (Category E), all parks except D1 had their maximum and inflection points in the 1-10 and 0.1-1 DT. If the maximum point occurred in the smallest DT (<0.001), then we assume most of the catchment area information were included: all parks in category A, four parks in category B, two parks in category C, and one park in category D. In this situation, the DTs equal or higher than the inflection point were the most applicable areas of the UPCA analysis.

Table 3. Number of land parcels in each UPCA density threshold.

City Scale Park	DT 10-100	1-10	0.1-1	0.01-0.1	0.001-0.01	< 0.001
A1	-	2,009	4,855	**27,789**	10,653	109,336
A2	-	3,431	3,827	**25,629**	11,932	109,823
A3	-	2,111	5,487	**12,255**	5,859	128,930
A4	-	3,169	18,650	**28,823**	12,221	91,779
A5	-	5,280	25,312	**54,870**	14,002	55,178
A6	-	5,775	19,627	**53,917**	14,349	57,142
B1	-	1,843	20,587	**58,143**	15,896	58,173
B2	-	3,537	18,728	**46,286**	13,822	72,269
B3	-	11,838	**61,602**	44,574	8,352	28,276
B4	-	4,265	32,234	**62,146**	9,720	46,277
B5	-	4,861	19,686	**38,183**	10,411	81,501
B6	-	6,314	22,626	**41,353**	10,703	69,814
C1	-	-	20,290	**90,950**	20,802	22,600

City Scale Park	DT 10-100	1-10	0.1-1	0.01-0.1	0.001-0.01	< 0.001
C2	33	15,915	**83,709**	23,828	5,887	25,270
C3	6,350	47,252	**74,726**	6,117	1,843	18,354
C4	-	-	23,168	**55,332**	14,195	61,947
C5	3,990	24,725	**62,357**	32,620	6,417	24,533
C6	0	1,531	12,990	**21,367**	7,770	107,152
D1	-	1,040	**27,976**	14,578	4,190	103,026
D2	1,247	**68,849**	56,118	5,828	2,657	16,111
D3	-	58,281	**67,402**	5,313	2,418	17,396
D4	2,061	12,291	**58,667**	38,370	7,612	31,809
D5	4,801	18,482	**70,799**	25,790	5,288	25,650
D6	4,019	7,888	**53,713**	36,070	8,556	40,564
E1	2,550	**61,903**	59,616	4,788	1,873	20,080
E2	13,859	**99,306**	14,733	3,840	1,890	17,182
E3	101	17,178	**50,713**	40,106	7,630	35,082
E4	1,816	16,036	**64,703**	35,665	5,608	26,982
E5	8,734	**103,639**	17,910	2,953	1,375	16,199
E6	9,196	25,308	**75,768**	19,725	3,033	17,780

Source: Konzatsu-Tokei ®, © ZDC.

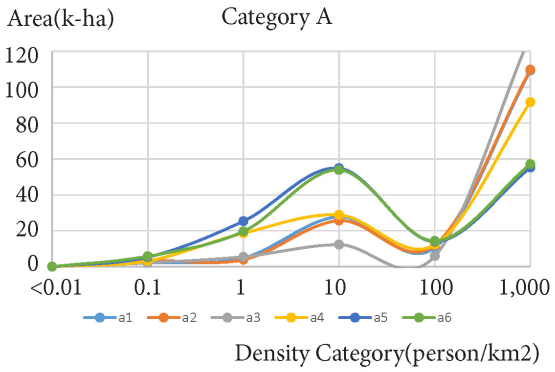
4.4. Distance-Density decay function analysis

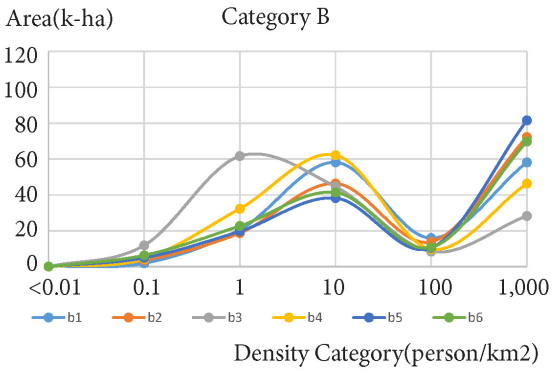
The study observed that the catchment areas of the parks were positively associated with their areas and revealed the applicable DT of the catchment areas. However, it is also important to find out the activity patterns of park users and how they were spatially distributed in relevant to the location of parks. Using the multi-scale catchment areas delineated earlier, the distance-density relationship was analyzed using scatter plot charts, as shown in **Figure 5** (for Category A) and **Appendix 3** (for Categories B, C, D, and E).

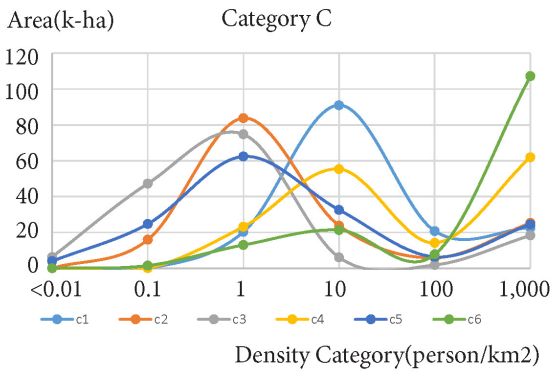
If the distance-density decay function holds, it means the further away from the park, the less visitors come to the park. The other important variable in the distance-density function of UPCA is bandwidth. As mentioned earlier, bandwidth captured the variation in density locations. With the exception of park A2, most city block parks (Category A) showed an inverse relationship between distance and density within a 100 m radius. In the case of park A2, there were too few observations to draw a conclusion. Within 1 km, all parks complied with the distance-density decay rule. Between 1 km and 5 km, distance-density decay function was only observed in parks A5 and A6. Between 5 km and 10 km, the decay function was also observed in parks A5 and A6, however, the rate of decay was higher. After 10 km, no decay function was observed. The bandwidth is shown in **Appendix 4**.

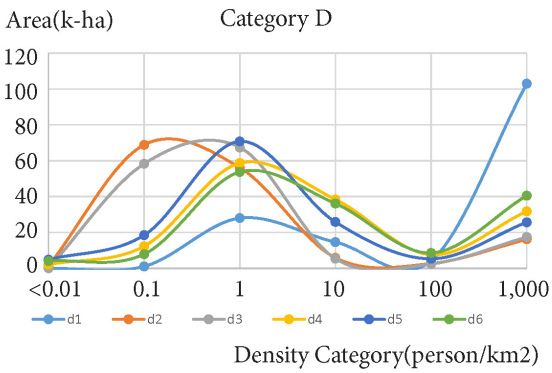
In the neighborhood parks (Category B), parks B3, B4, and B6 exhibited the density-distance decay function within a 100 m radius from the perimeter of the parks. Between 1km and 5km and between 5 km and 10 km, all the neighborhood parks, with the exception of park B1, exhibited the decay function. From the analysis, park B3 deserves closer investigation because the variation of density distribution at the same distance was large. This broader bandwidth implies higher variation of density location. In the district parks (Category C), C2 and C3 had

broader bandwidths of density distributions for all distances observed. Parks C1 and C4 followed the density distance decay function until a radius of 5 km, then the bandwidth of density began to increase. In the comprehensive parks (Category D), all but D1 showed broader bandwidths of density. Park D1 did not have sufficient points that were valid (not that there are few visitors, on the contrary, there are more than 1,000 visit observed). In the national parks in Category E, all exhibited higher bandwidths of density distribution. For larger parks, not only should the study extend beyond the city scale, the higher density threshold (10-100) should also be subdivided to observe more nuanced variations.









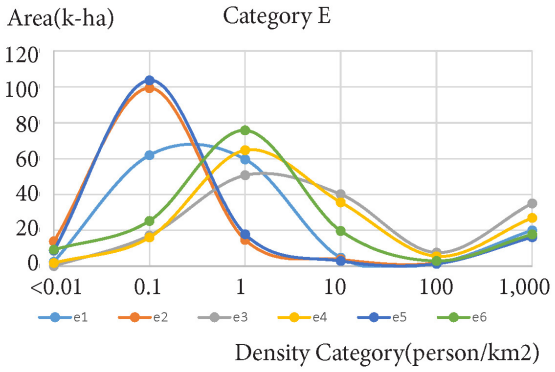


Figure 4. UPCA density-area curves by surface area categories: normalized into six density thresholds. Each line represents a park. The x-axis is density of park visitors. The y-axis is area measured in hectares, representing the theoretical catchment area. Source: Konzatsu-Tokei ®, © ZDC.

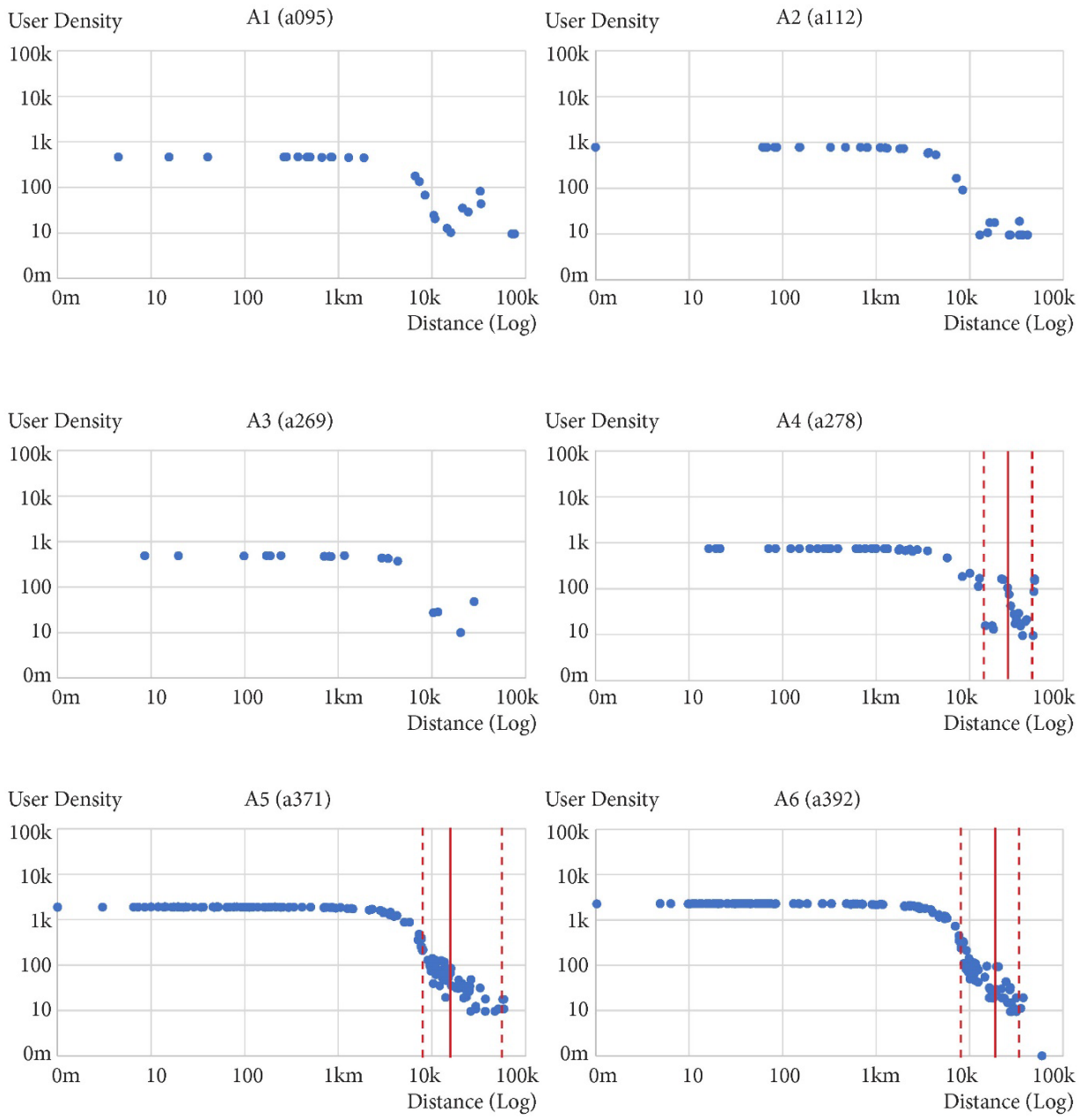


Figure 5. Park user density – distance function. Source: Konzatsu-Tokei ®, © ZDC.

5. Discussion

5.1. Delineating the UPCA using the density thresholds

One of the contributions of this paper was to delineate a UPCA based on actual park user activity. The data required was GPS-enabled mobile phone location data. The Euclidean distance derived UPCAs were based on locations of the facilities, which rarely change; the network distance derived UPCAs were based on the infrastructure network, which change overtime with financial investment cycles and varies due to services provided; the mobile phone location derived UPCA were delineated based on actual park user activity, which is inherently dynamic because of their travel patterns.

For smaller city block parks in category A, the average UPCA radius derived was 3.17 km, which is larger than defined by most of the existing planning regulations. For example, a 500 m service radius for a neighborhood park. If the density threshold was increased, from 10 to 50 visitors per km^2, for example, the resultant radius would be smaller. A DT corresponding to a 500 m-radius catchment circle could be derived. However, the results showed that even for the smallest park category, a higher percentage of visitors were from outside of the 500 m radius. The appropriate DTs used to derive the UPCAs, as mentioned earlier, should follow the maximum and inflection points of the density area curves. Depending on the number of DTs applied, the resultant UPCA would have multiple instead of singular centers.

5.2. Interpreting UPCA use spatial parameters

In both the city block and neighborhood parks (Categories A and B), the highest DT catchments encircled the corresponding parks. The explanation is that for smaller parks between 0.5 and 3 hectares, the proximity to parks is strong correlated with the usage of parks. For district and comprehensive parks (Categories C and D), there was considerable variation in the area and shape of the UPCA. This suggests that after the park size reached over 3 hectares, the usage of parks depends on many other factors (such as location, accessibility, function, and facilities provided) other than proximity. For example, park C6 exhibited similar catchment areas as the city block parks in category A, with concentric circles around the park. This anomaly suggests that park size is not the determinant factors. For parks C2, C3, and C5, the highest density threshold reached 10-100 DT and at the 1-10 DT, they exhibited irregular shapes instead of circles. Park D1 shows similar patterns of UPCA as those in city block parks. This shows even comprehensive parks can have a catchment area attracts only people from close by. On the other hand, park D2 has the largest number of land parcels in the 1-10 DT. It suggested that the delineated UPCA cannot effectively differentiate across park user activities.

The shape of the catchment area did not necessarily become more irregular as the area increased. For example, there were more circular UPCA in the comprehensive parks than the district parks. In addition, the shape of the park can affect the shape and area of the parks. For example, parks E3 and E4 are linear because they are riverside waterfront parks. The nature of the park may contain systematic patterns reflected in the catchment areas.

5.3. Relating UPCA to land use and infrastructure

Area of DT, shape, and location are three important parameters defining an UPCA. While conventional park planning mainly relies on park surface area and facilities provided, the

combination of area of DT, shape, and location of UPCAs can provide additional information to understand park usage. In general, the UPCA is positively correlated with the park areas. We can identify anomaly when this is not the case. For example, when a large park has a relatively small catchment area. Moreover, the shape of the UPCA can indicate travel mode and activities of park usage. For example, an irregular shaped UPCA could be affected by transit lines that people used to visit park. Another example is that some of the UPCAs' geometric centers do not match the location of the park. This can occur in riverfront parks where the main activity is the gathering of sports club members who travel (drive) from far distance. While most of the UPCA with the highest DT are circular, oval-shaped UPCAs began to emerge in the district parks (Category C). For example, park C3, at the 10-100 DT was an oval shape with cross diameters of 4.25 km and 4.9 km respectively. Furthermore, the center of the oval-shaped UPCA was over 500 m away from the park. We suggest that the shape of the UPCA can be a function of external characteristics such as land use and infrastructure of the broader city beyond the study areas. We also suggest that the provision of facilities, vegetation, and amenities in the parks and the proximity to other parks can be important determinants of the UPCA. In this paper, we didn't investigate these conditions.

5.4. Limitations

While the application of mobile phone data improved our understanding of the UPCA, the limitations that can be addressed in future studies include: First, more investigations into the facilities provided in and around the parks, such as land use and park function. Second, the conclusion can be strengthened if more parks were included. We can extend study to duration of stay by park visitors; group or individual activities; and daily, weekly, and seasonal variations. Third, the office staff who visit parks near their companies but far away from residential location were not excluded. In this study, we want to include all visits, not just "directly from residential location to park" type. We didn't include people who visited parks near their secondary residential locations as well as moving, traveling, and intro-company job relocations/transfers (*Tenkin*) during the study period in our analysis as they only represent a small percent of the samples. Last, the selection of radius is arbitrary: as the search radius become smaller, density, shape, and size of the catchment areas can also change. All of the above-mentioned can affect the actual catchment area, together with social capital cultivation, cultural adaptation, weather variations.

6. Conclusions

In this paper, the UPCA was delineated using GMD in the Tokyo metropolitan area. Deriving the UPCA is important as it can affect current park planning practice in the following ways: (1) Demonstrate individual travel distances to parks; and (2) Account for diversity in park visitors of different park surface areas. Through the use of density-distance mapping, density curve gradient, and density-distance analysis, this study found that (a) The UPCAs were positively correlated with the park areas, albeit with variations within each park category; (b) Almost all the parks, regardless of its size and function, had the highest user density right around the vicinity. This is exemplified by the density distance function closely follow a decay trend line within 1-2

km radius of the park. However, across all the parks, beyond the 5-10 km radius, the density-distance decay function was not observed.

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Appendix 1. Basic statistics on travel distance.

	No. of Obs	Average	SD	Median	10%	25%	75%	90%
Including duplicates								
B1(70)	125	11,847	12,710	8,403	676	1,922	17,360	29,811
B2(109)	151	8,080	11,069	2,370	347	814	10,761	24,521
B3(159)	554	13,204	11,874	9,106	1,146	4,958	19,090	30,458
B4(160)	264	15,623	17,224	10,857	4	587	24,181	44,149
B5(252)	228	9,801	10,755	3,455	418	1,150	20,790	23,597
B6(268)	305	4,880	8,592	1,417	7	358	4,093	13,283
Category B	**1,627**	**10,979**	**12,755**	**6,291**	**204**	**1,289**	**16,346**	**27,479**
Excluding duplicates								
B1(70)	71	15,738	14,533	12,484	1,464	3,387	21,377	37,936
B2(109)	84	9,661	11,020	6,255	353	1,090	14,044	26,483
B3(159)	221	14,608	14,017	10,163	659	3,587	22,490	35,426
B4(160) Mukojima Hyakkaen (Sumida)	121	14,984	16,800	9,105	432	1,860	20,637	37,169
B5(252)	54	10,814	13,526	5,341	724	1,370	17,522	27,842
B6(268)	117	7,146	11,108	2,481	316	754	6,199	23,055
Category B	**668**	**12,561**	**14,101**	**7,754**	**456**	**1,814**	**18,128**	**31,722**

	No. of Obs	Average	SD	Median	10%	25%	75%	90%
Including duplicates								
C1(71)	128	14,279	14,334	10,607	61	94	31,932	33,404
C2(137)	1,103	12,479	12,133	8,448	368	3,085	17,928	30,779
C3(147)	3,762	12,554	15,663	6,900	342	1,640	17,082	32,686
C4(242)	99	13,881	13,605	8,399	228	3,251	18,926	40,146
C5(304)	1,663	7,767	11,295	3,066	218	729	10,637	18,762
C6(310)	86	12,541	13,842	3,223	320	1,068	27,620	33,165
Category C	**6,841**	**11,430**	**14,242**	**6,511**	**258**	**1,210**	**16,155**	**30,779**
Excluding duplicates								
C1(71)	52	11,785	12,901	6,140	65	381	19,834	32,242

	No. of Obs	Average	SD	Median	10%	25%	75%	90%
Ishikawajima (Chuo)								
C2(137)	392	13,701	12,467	10,844	718	3,570	18,876	31,577
C3(147) Kinshi (Sumida)	1,867	11,453	13,041	6,638	812	2,114	16,590	29,628
C4(242) Komaba (Meguro)	53	10,986	11,464	7,655	541	2,057	15,686	26,865
C5(304)	497	10,882	14,498	5,194	517	1,179	14,565	30,201
C6(310)	27	10,086	11,957	3,380	264	1,068	21,433	29,611
Category C	**2,888**	**11,645**	**13,206**	**6,895**	**699**	**1,993**	**16,960**	**30,244**

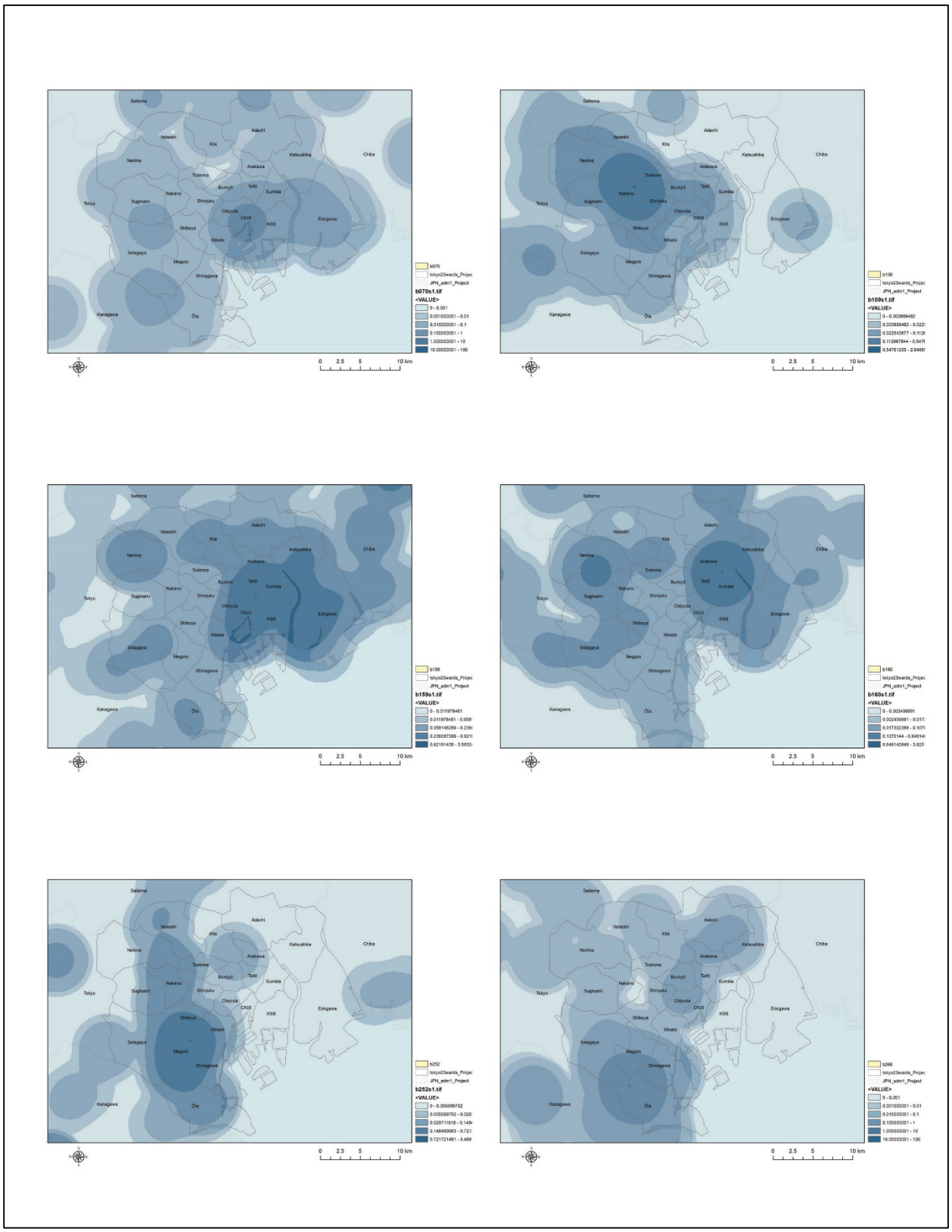
	No. of Obs	Average	SD	Median	10%	25%	75%	90%
Including duplicates								
D1(63)	1,068	353,017	306,386	345,046	16,457	51,731	516,782	887,836
D2(102)	2,892	17,274	13,746	14,233	1,657	7,568	24,611	35,692
D3(241)	1,996	20,247	12,592	17,911	5,965	10,767	28,342	36,911
D4(271)	1,138	10,508	11,944	4,132	212	1,638	17,906	29,214
D5(343)	2,003	6,318	8,917	2,566	82	576	8,023	19,677
D6(385)	1,121	4,720	9,641	1,228	13	273	4,703	13,648
Category D	**10,218**	**48,669**	**144,134**	**11,457**	**349**	**2,596**	**25,265**	**47,267**
Excluding duplicates								
D1(63) Kokyo Higashigyoen (Chiyoda)	502	255,507	272,665	122,095	15,999	36,408	401,453	749,825
D2(102)	1,868	18,764	14,480	14,993	3,411	8,222	27,261	37,263
D3(241) Shiokaze (Shinagawa)	768	20,451	13,336	17,407	5,783	10,664	28,642	38,906
D4(271)	371	10,695	12,256	4,620	413	1,784	17,669	29,356

	No. of Obs	Average	SD	Median	10%	25%	75%	90%
D5(343)	598	9,210	10,390	5,095	659	1,654	13,549	23,086
D6(385)	377	7,426	11,166	2,872	342	949	9,465	20,360
Category D	**4,484**	**42,662**	**119,152**	**14,149**	**1,411**	**5,641**	**28,831**	**47,974**

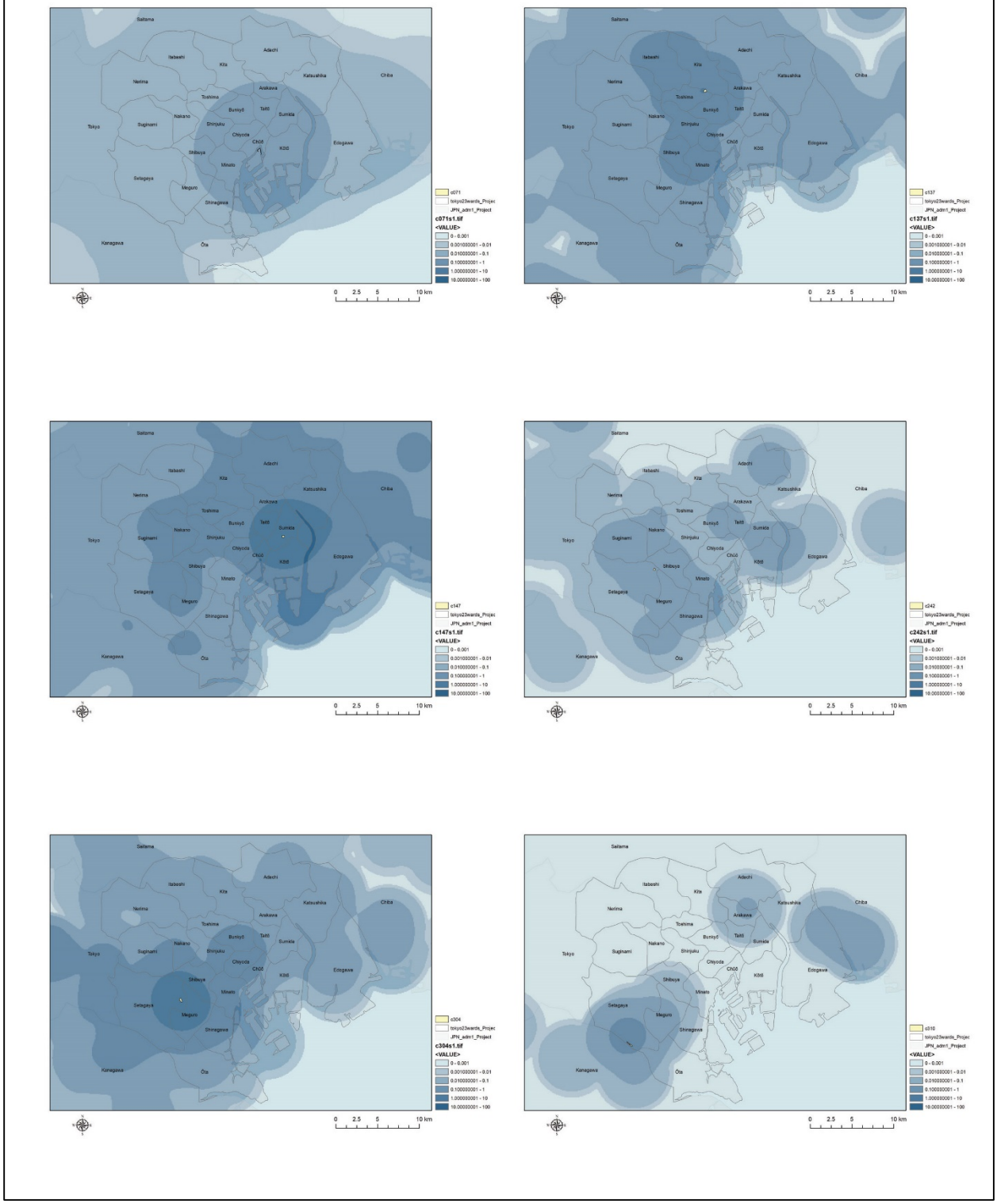
	No. of Obs	Average	SD	Median	10%	25%	75%	90%
Including duplicates								
E1(120)	3,448	51,235	149,190	15,224	2,538	6,947	30,718	48,326
E2(353)	10,316	46,399	126,746	13,574	2,149	5,982	28,494	67,326
E3(435)	968	33,630	123,266	5,313	1,714	2,373	13,265	28,053
E4(606)	1,071	18,692	73,110	3,653	693	1,358	8,674	25,923
E5(651)	9,786	46,991	109,013	20,643	4,682	11,622	36,925	77,335
E6(666)	5,439	23,840	109,833	1,879	169	608	7,341	23,845
Category E	**31,028**	**41,814**	**120,149**	**13,368**	**915**	**4,006**	**27,520**	**56,679**
Excluding duplicates								
E1(120) Shinjuku Gyoen (Shinjuku)	1,224	56,361	164,886	14,388	2,631	6,495	28,669	66,480
E2(353)	4,129	55,772	140,612	15,401	2,900	7,213	31,592	95,186
E3(435)	328	33,784	114,109	7,187	1,710	2,901	17,110	35,396
E4(606)	337	28,537	98,526	6,114	901	2,613	18,807	31,658
E5(651)	3,556	52,389	121,291	21,092	4,663	11,672	37,740	84,271
E6(666)	1,585	30,426	124,026	3,388	403	1,126	11,910	28,357
Category E	**11,159**	**49,689**	**133,918**	**15,122**	**1,828**	**5,738**	**30,059**	**76,308**

Source: Konzatsu-Tokei ®, © ZDC.

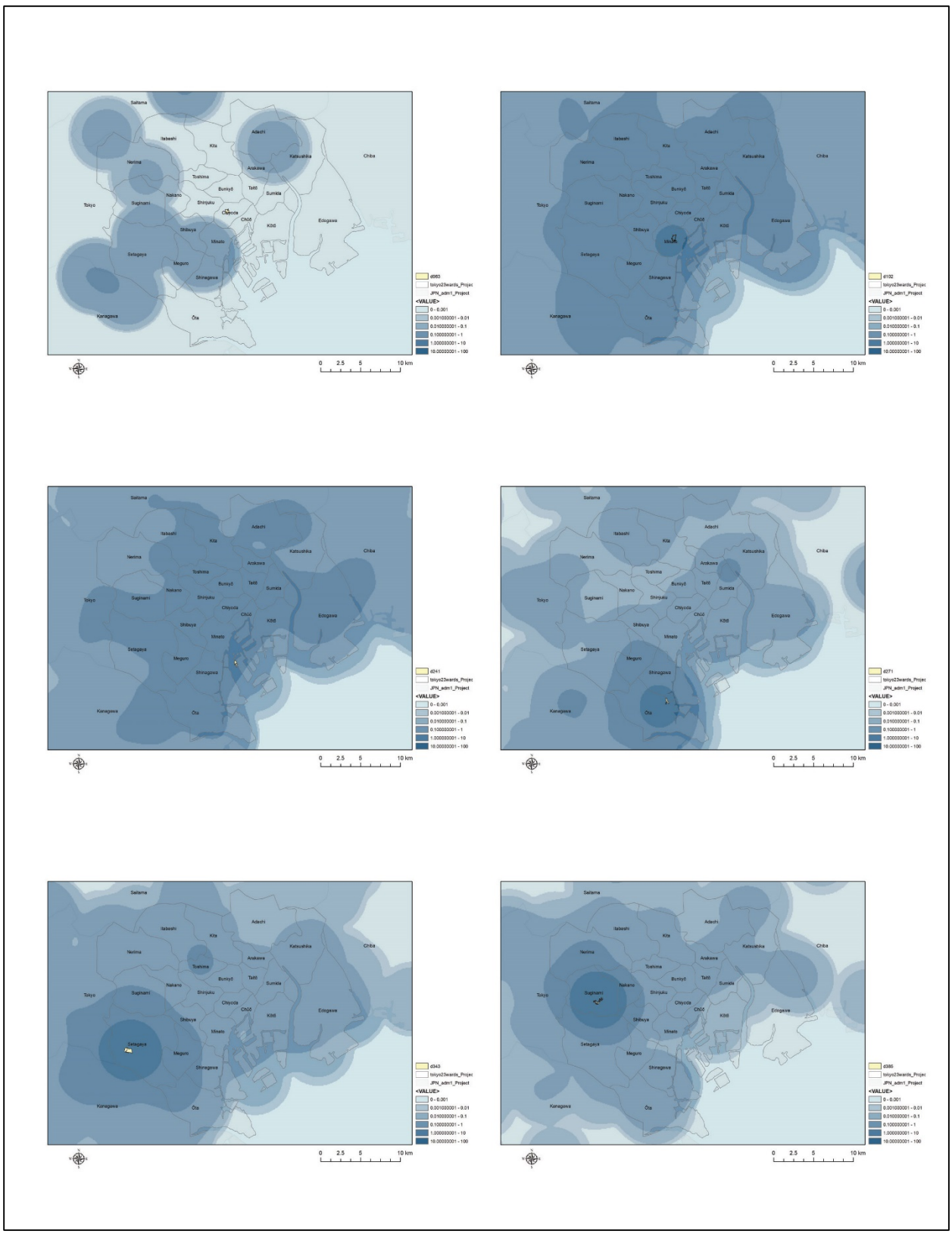
Appendix 2. UPCA–Categories B, C, D, and E.



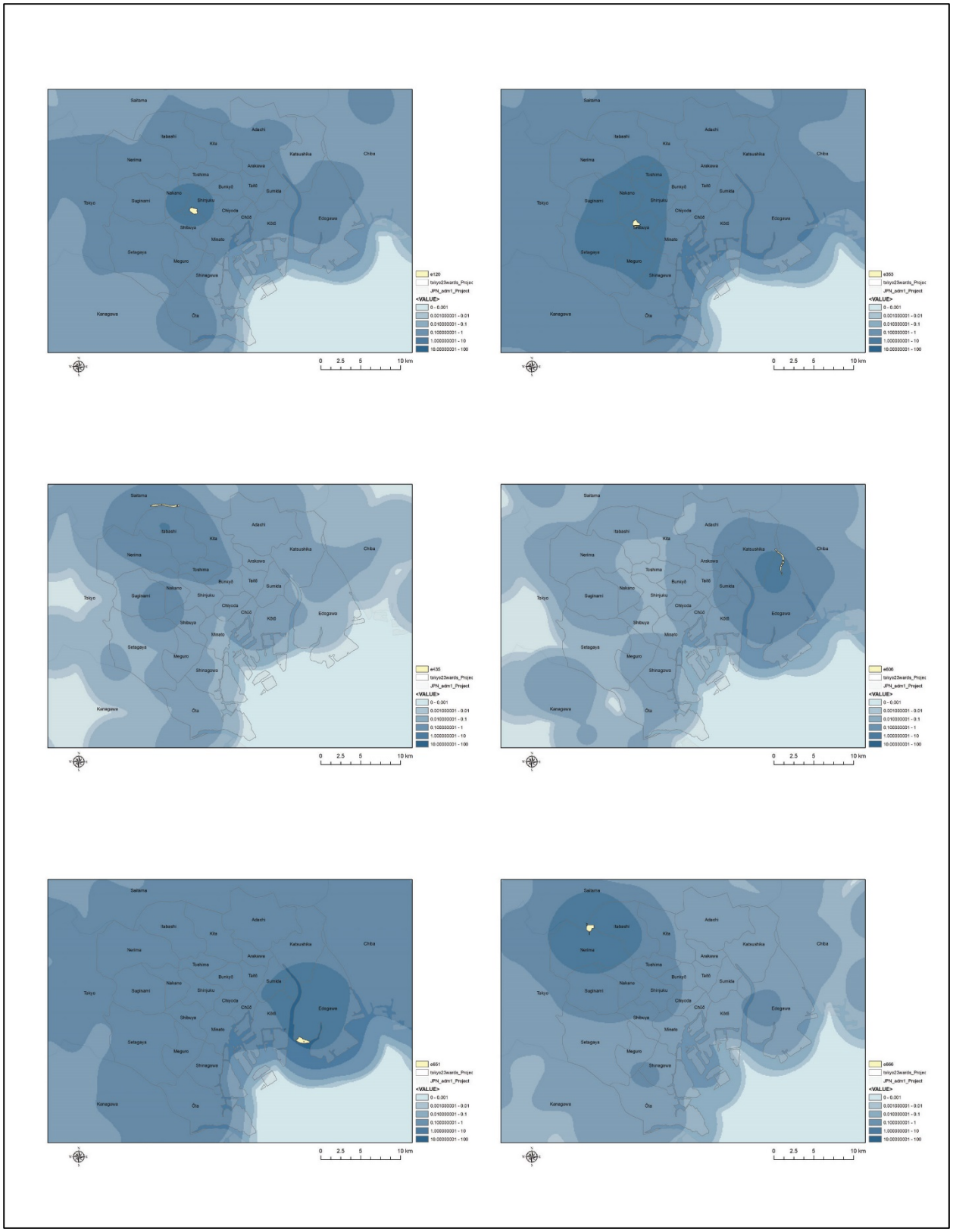
UPCA– Category B (1-3 ha).



UPCA– Category C (3-10 ha).

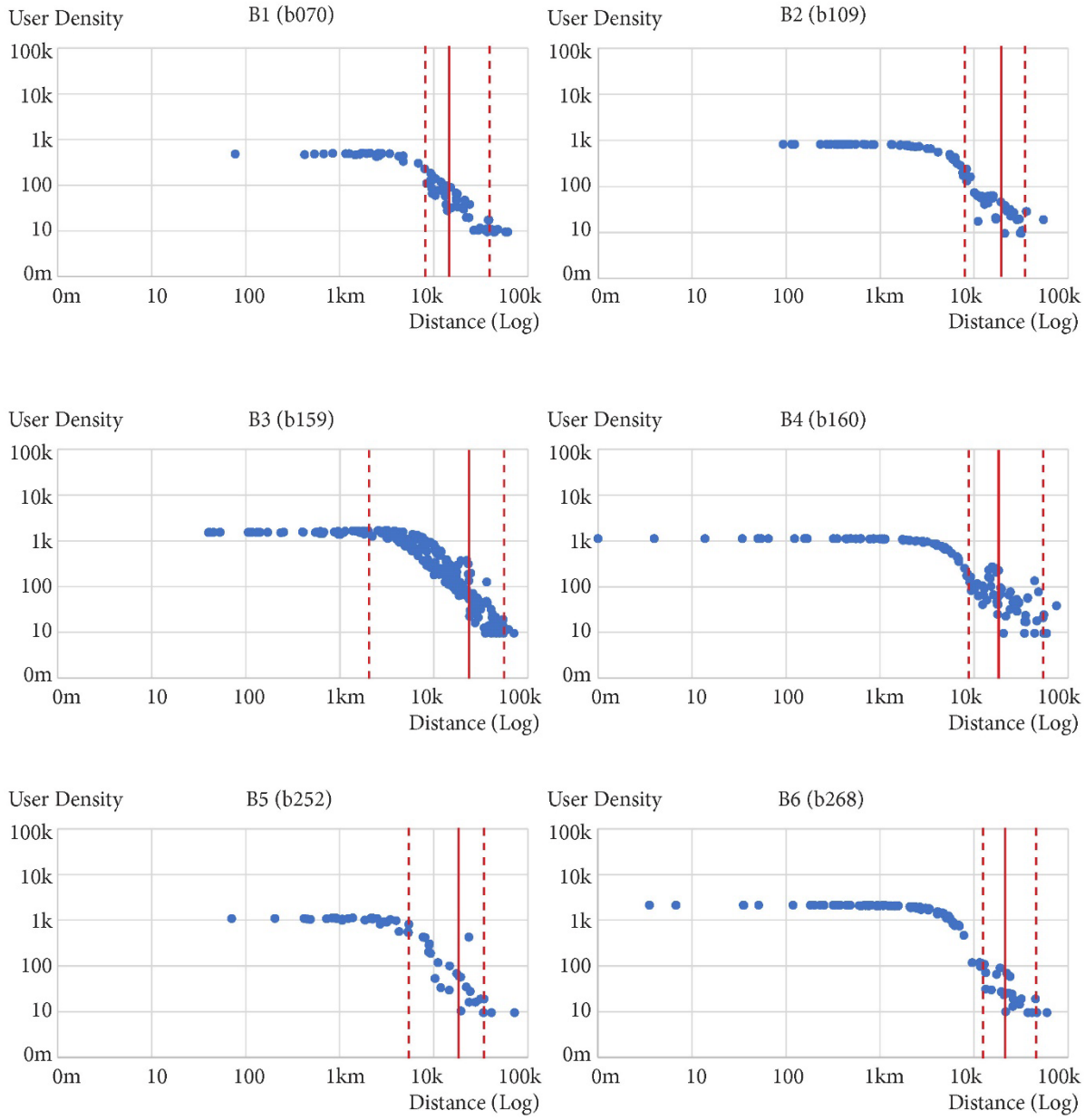


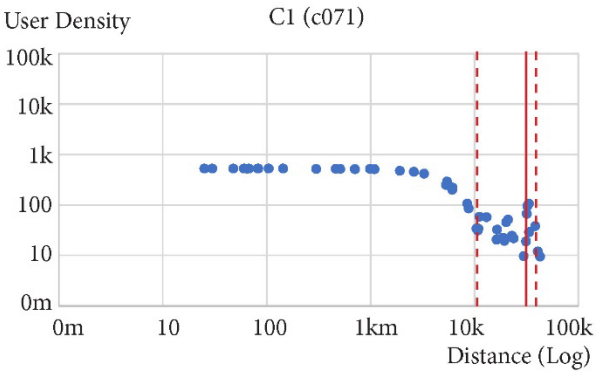
UPCA– Category D (10-50 ha).

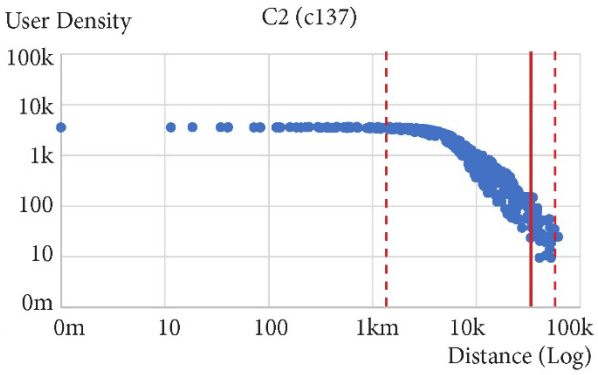


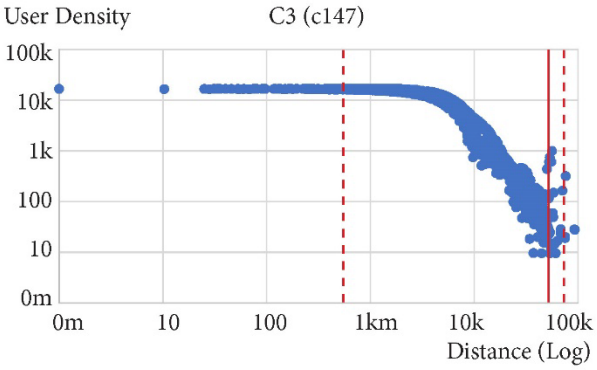
UPCA–Category E (50 ha and above).
Source: Konzatsu-Tokei ®, © ZDC.

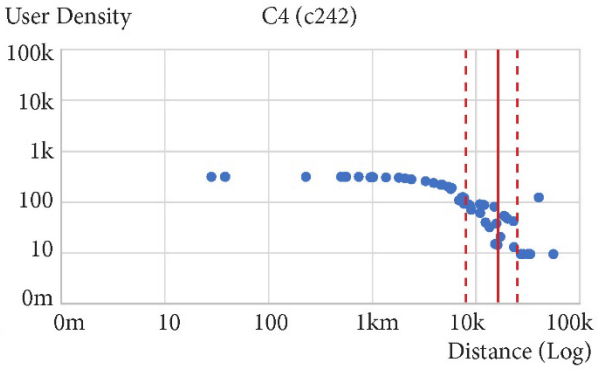
Appendix 3. Park user density – distance function.

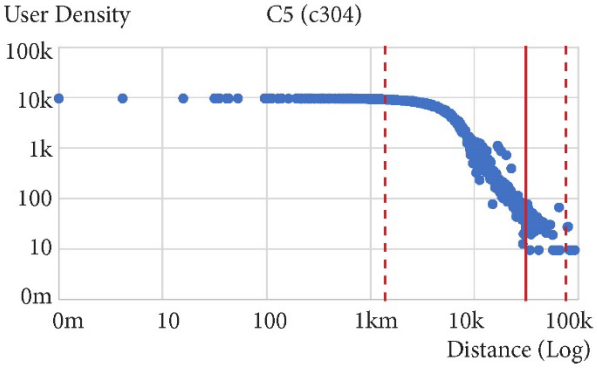


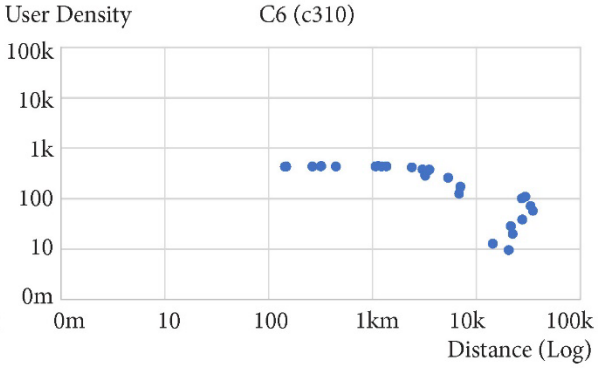

User Density
C1 (c071)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)

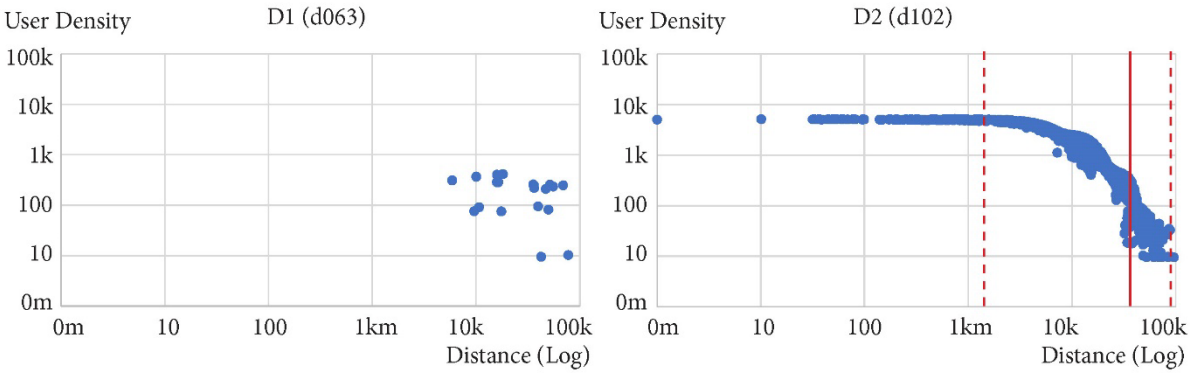

User Density
C2 (c137)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)


User Density
C3 (c147)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)

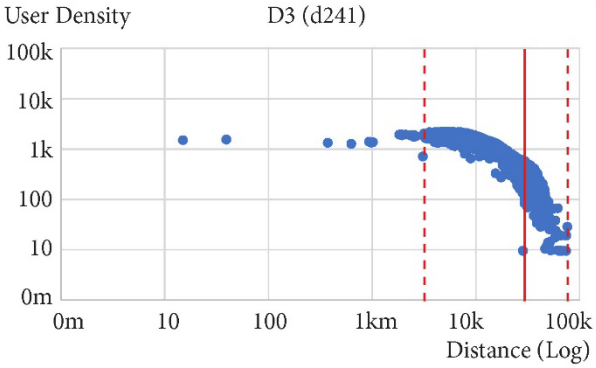

User Density
C4 (c242)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)

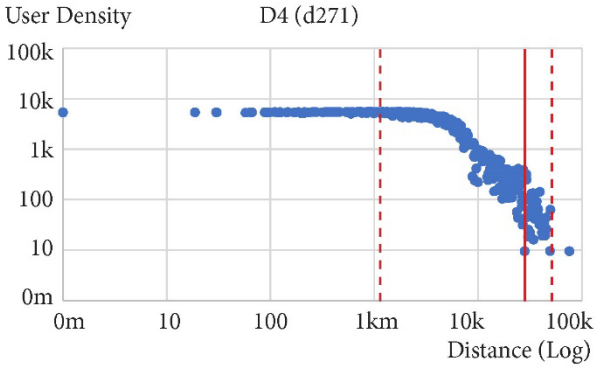

User Density
C5 (c304)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)

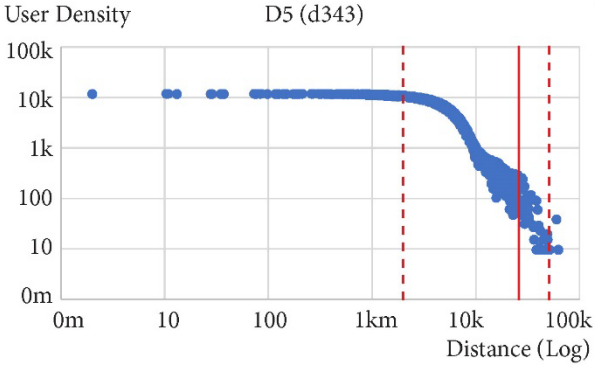

User Density
C6 (c310)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)

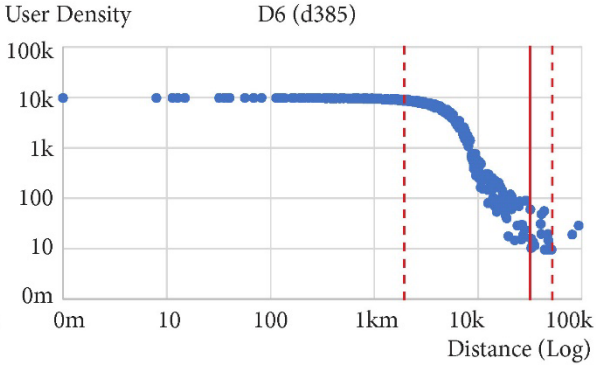

User Density
D1 (d063)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)

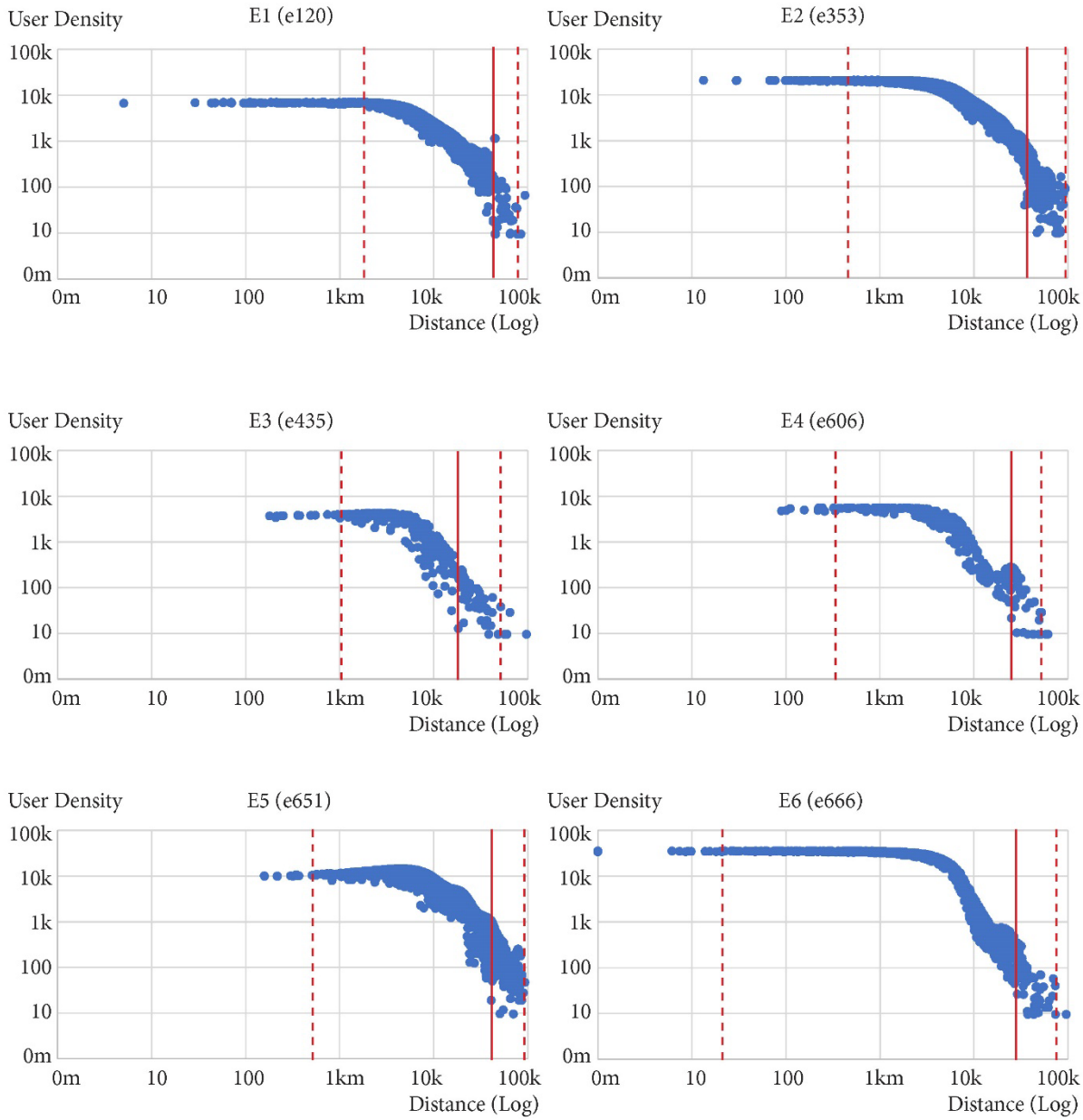
User Density
D2 (d102)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)


User Density
D3 (d241)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)


User Density
D4 (d271)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)

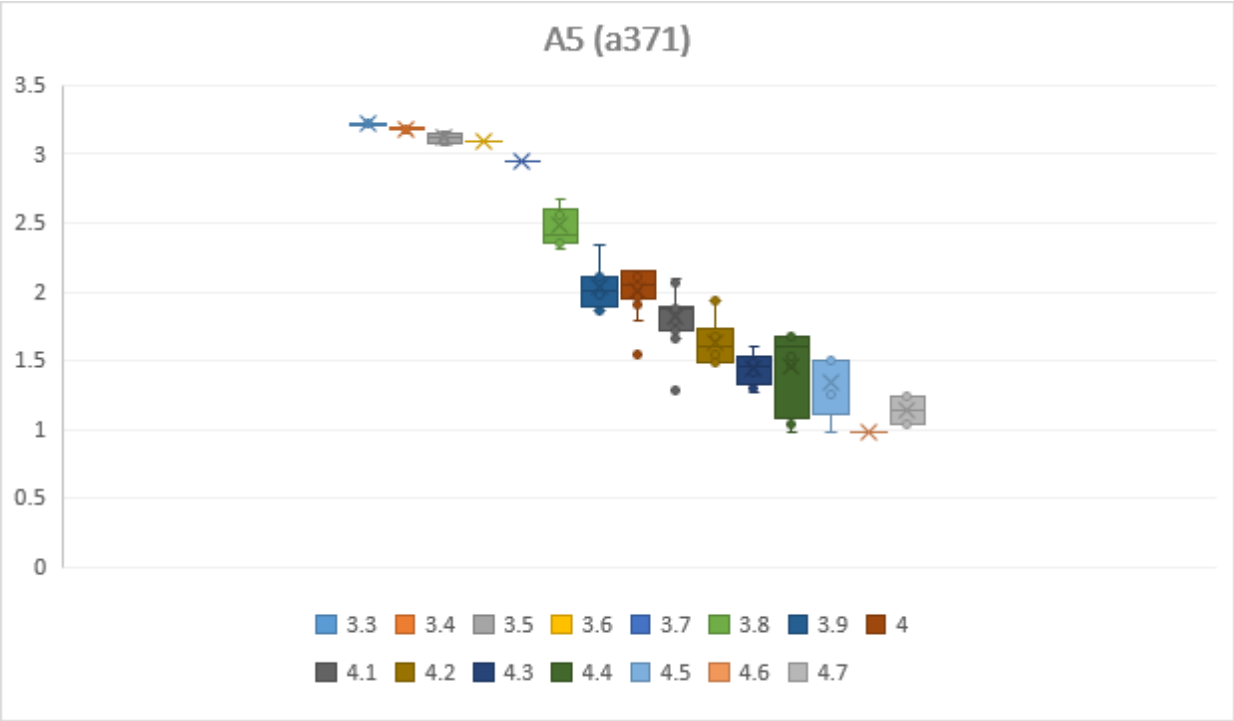

User Density
D5 (d343)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)


User Density
D6 (d385)
100k
10k
1k
100
10
0m
0m
10
100
1km
10k
100k
Distance (Log)



Source: Konzatsu-Tokei ®, © ZDC.

Appendix 4. Measure of bandwidth in the density-distance function chart.



In this box plot, x axis is the log-distance and the y axis is user density categorized in 0.1 log-distance intervals. The highest variance is 1.42 happened at log-distance 4.5 and the emergence of bandwidth happened at log-distance 3.8 end at 4.7.