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Unmanned aerial vehicles (UAVs) in behavior mapping: A case study of neighborhood parks

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ABSTRACT

Behavior mapping is an effective tool for the direct observation of the interaction between people and places. However, current approaches have shortcomings that introduce location inaccuracies and hinder micro-context recording of observed activities. This study explores the applicability of unmanned aerial vehicles (UAVs) in behavior mapping. First, we suggest a protocol for the use of UAVs in behavior mapping. Then, as a case study, we explore neighborhood park uses using the behavior maps and quantitative information collected from 30 neighborhood parks in Salt Lake County, UT, USA. Inter-rater reliability tests of identifying user attributes (e.g., gender, age group, activity level) and geocoding produced high Kappa statistics and location precision. The case study results show different park usage by sex, age groups, and activity types across different times. For example, we observed only a few seniors and more males than females, a gap that becomes larger among children and teenage groups. User density was higher in picnic areas and playgrounds and lower in lawns, baseball fields, and water features.

This study demonstrates that UAV-based behavior maps can provide both quantitative and qualitative data. Summary statistics, along with digital maps, provide accurate patterns of park use. It also enables qualitative, design-focused explorations such as different people-place interaction patterns by user attributes and time. As a reliable and effective tool for behavior mapping, UAVs can support practitioners' data-informed and responsive design and management efforts.

1. Introduction

Understanding who visits a neighborhood park and which activities they engage in can support specific programming or potential renovation in the park. When accumulated, such information generates knowledge on people-place interaction in parks, a foundation for evidence-based design and planning for landscape architects and park planners.

Among many tools such as visitor counting, survey, and interview, behavior mapping is effective when exploring the interaction between people and place (Bechtel et al., 1987; Ittelson et al., 1976; Moore and Cosco, 2007). The behavior map is developed to assess whether different locations are used or not, at what time, by which type of people, and what activities are engaged in (Moore and Cosco, 2010; Ng, 2016). Using behavior mapping, a researcher can collect both quantitative and qualitative information, which allows for a more nuanced understanding of design and its consequences.

However, existing behavior mapping tools—whether paper-and-pencil, PDAs, or tablet PCs—inject some degree of error when recording the exact location of observed activities on a map (Goličnik and Thompson, 2010; Marušić and Marušic, 2012). Still photography or video recording may address this problem and also enable post-validation of the data (Burke, 2006; Spink et al., 2013; Yalowitz and Bronnenkant, 2009), but these methods are inefficient in capturing visitors over larger spaces, which raises cost-effectiveness issues when surveying neighborhood parks or larger green spaces. The lack of reliable and cost-effective tools may contribute to the general lack of understanding of park use dynamics and appropriate interventions. This, in turn, could result in the underutilization of neighborhood parks (Cohen et al., 2016).

While various techniques—both analog and digital—have been explored for behavior mapping, the utility of Unmanned Ariel Vehicles (UAVs) has not been studied in the context of public space use. UAV, also called a drone or Unmanned Aircraft Systems (UAS), means an aircraft operated without direct human intervention from within or on the aircraft (U.S. FAA, 2019). The use of UAVs in behavior mapping may be efficient in capturing behavior across a larger area in a shorter amount of time. A UAV using video recording could establish the exact

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location of individuals as well as more accurate attribute information; thus, the use of UAVs could be reliable and informative in behavior mapping to study micro-scale design implications. Using UAV gathered imagery, people-place interaction could be explored by user attributes and activity types such as gender, age group, physical activity level, time (time of day, the day of the week, season, etc.). This study explores the applicability of UAVs in the behavior mapping of neighborhood park use.

First, we review existing behavior mapping techniques and the potential of a UAV-based approach. Then we develop a protocol that includes defining the area of observation, the observed behaviors, and a system for recording and coding. This protocol is then applied to create behavior maps and explore people-place interaction in neighborhood parks in Salt Lake County, Utah, USA. Lastly, we discuss the practical implications of the new tool for evidence-based design and planning in supporting data-informed and responsive design and management of urban green space.

2. Literature review

Behavior mapping is a method used in environmental psychology and related fields for observing people's behaviors and movements systematically associated with components and attributes of the built environment (Cosco et al., 2010; Bechtel and Zeisel, 1987; Ittelson et al., 1976). It is an unobtrusive, objective, and direct observational method for recording the location of subjects and measuring their activity levels simultaneously (Cosco et al., 2010; Moore and Cosco, 2007). Environment and behavior researchers began developing the behavior mapping method in the late 1960s to study the influence of the physical environment on the behavior of individuals and groups (Barker, 1968; Ittelson et al., 1976).

Behavior mapping is advantageous to survey methods such as questionnaires or interviews as it allows a researcher to directly observe phenomena in their natural settings with very limited or no influence on the observed subjects (Moore and Cosco, 2010; Ng, 2016). For social perception reasons, people may not always provide candid answers to questions about their activities, especially if the activity in question is illegal or against the social norm (Ng, 2016). Further, concurrent direct observation may be more accurate than a retrospective survey, especially for those with limited memories (e.g., children or seniors) (Ng, 2016). Third, researchers can also collect contextual information concurrently with the observation of people's behaviors. Thus, this method allows for the empirical evaluation of correlations between the affordances of behavior settings and individuals' activities (Cosco et al., 2010).

Affordance and behavior setting are two important concepts in behavior mapping theory. Affordances are the behavioral possibilities provided by an environmental feature, or behavior setting, to an individual. Hence, a behavior setting possesses affordances. This perception-action framework introduced by Gibson (1979; Fjørtoft, 2004) allows an environment to be described by its function rather than its form. Behavior settings are discrete ecological units where the physical environment and behavior are thus connected in time and space (Barker, 1968; Heft, 2001). It subdivides an area in terms of afforded behavior so that environment and behavior can be linked directly, which is essential for understanding the impact of design on behavior and for guiding design interventions. As a unit of analysis, the behavioral setting provides a common language for linking design to research by disaggregating the built environments into functional parts such as pathway, sandpit, gathering place, vegetable garden, and so on. Understanding behavior settings forms the foundation for designing places that better suit people's purposes (Lynch and Hack, 1984). Behavior mapping is the most effective tool for understanding behavior settings and their affordances.

The benefits of behavior mapping can be highlighted in longitudinal studies such as quasi-experimental designs to assess the effectiveness of design interventions or to assess the influence of seasonality in the usage of spaces (Cosco et al., 2010).

Behavior mapping has been applied in various settings including schools (Fjørtoft, Kristofferson, & Sageie, 2009; Ledingham and Chappus, 1986; Rivlin and Rothenberg, 1976), neighborhood open space (Hampton et al., 2010), playgrounds and outdoor play areas (Cox et al., 2018; Moore and Cosco, 2007; 2010; Refshauge et al., 2013; Drown and Christensen, 2014), museums or zoos (Yalowitz and Bronnenkant, 2009), residential care settings (Milke et al., 2009), hospitals (Bernhardt et al., 2004; Lincoln et al., 1996), and grocery stores (Larson et al., 2005; Sorensen, 2003). Ittelson et al. (1976) conceived of four uses of this method—describing the distribution of behaviors throughout a particular space; comparing two different situations; identifying general patterns in the use of space; providing quantitative predictions of behaviors in a new facility.

Traditionally, behavior mapping is conducted manually with printed maps (Beeken and Janzen, 1978; Moore, 1986; Moore and Young, 1978; Kinoshita, 2007). The use of digital tools in behavior mapping was introduced by Van Andel (1984). Digital tools include geographic information systems, video recording, radio frequency identification systems, a global positioning system (GPS), and motion, infra-red light, and ambient sound sensors (Fjørtoft et al., 2009; Intille, 2012; Larson et al., 2005; Whyte, 1980). Initially, digital tools have been used in the recording, behavioral coding, and analysis aspects of behavior mapping. For example, researchers have used handheld devices such as personal digital assistants (PDAs) to record behavior mapping data in the field with mobile GIS applications (Simpson, 2007; Wener, 2002; Bahillo et al., 2015). Compared with the paper-and-pencil techniques, digital behavioral coding and analysis systems can be more accurate by eliminating the need for subsequent data entry or transcription and are less intrusive (Hecht, 1997). As data recorded using behavior mapping may lose its connection with the behavior setting when summarized in a matrix for common analytical tools, GIS is becoming more commonly used as an analytic tool to maintain the setting and behavior interactions (Fjørtoft et al., 2009; Goličnik, and Thompson, 2010; Simpson, 2007). GIS-based maps also provide an opportunity for further data validation and the use of spatial analytic techniques. The use of these, and other, digital tools in the observational aspects of behavior mapping is a more recent phenomenon only now being explored in the literature.

Still, the recording of field observations, regardless of whether manual or digital tools are used, raises a reliability issue as the accuracy of manually recording the location of observed activities on a map will have some degree of error (Goličnik and Thompson, 2010; Maruhšić and Marušic, 2012). New techniques which automate the recording of locations and field observations reduce this potential for error and increases accuracy. Still and video photography has been used in behavior mapping for some time, but its use in combination with automated user identification methods is more recent and can provide useful data regarding people's use of and their movement within spaces. The majority of this research has been focused on pedestrian tracking in street, campus, and open environments (Stuart et al., 2013), and is not necessarily behavior mapping as much as it is automated tracking. Automated video tracking methods often require those who are observed to possess a sensor, such as a RFID or GPS tag, or have a fiduciary marker to facilitate tracking, extensive image calibration to reduce distortion impacts, little to no signal occluding of the observed, homogeneity of the characteristics of the observed, and are less able to observe individuals over larger spaces (Burke, 2006; Yalowitz and Bronnenkant, 2009; Stuart et al., 2013). Multiple overlapping camera views address some of these issues and allow for behavioral observation of people automatically and less-intrusively (Spink et al., 2013), but require complex systems of cameras operating in concert with video detection applications (Sharifi et al., 2017). Most importantly, overhead camera views are most efficient and accurate for these systems and are the most difficult to acquire, particularly in open space settings.

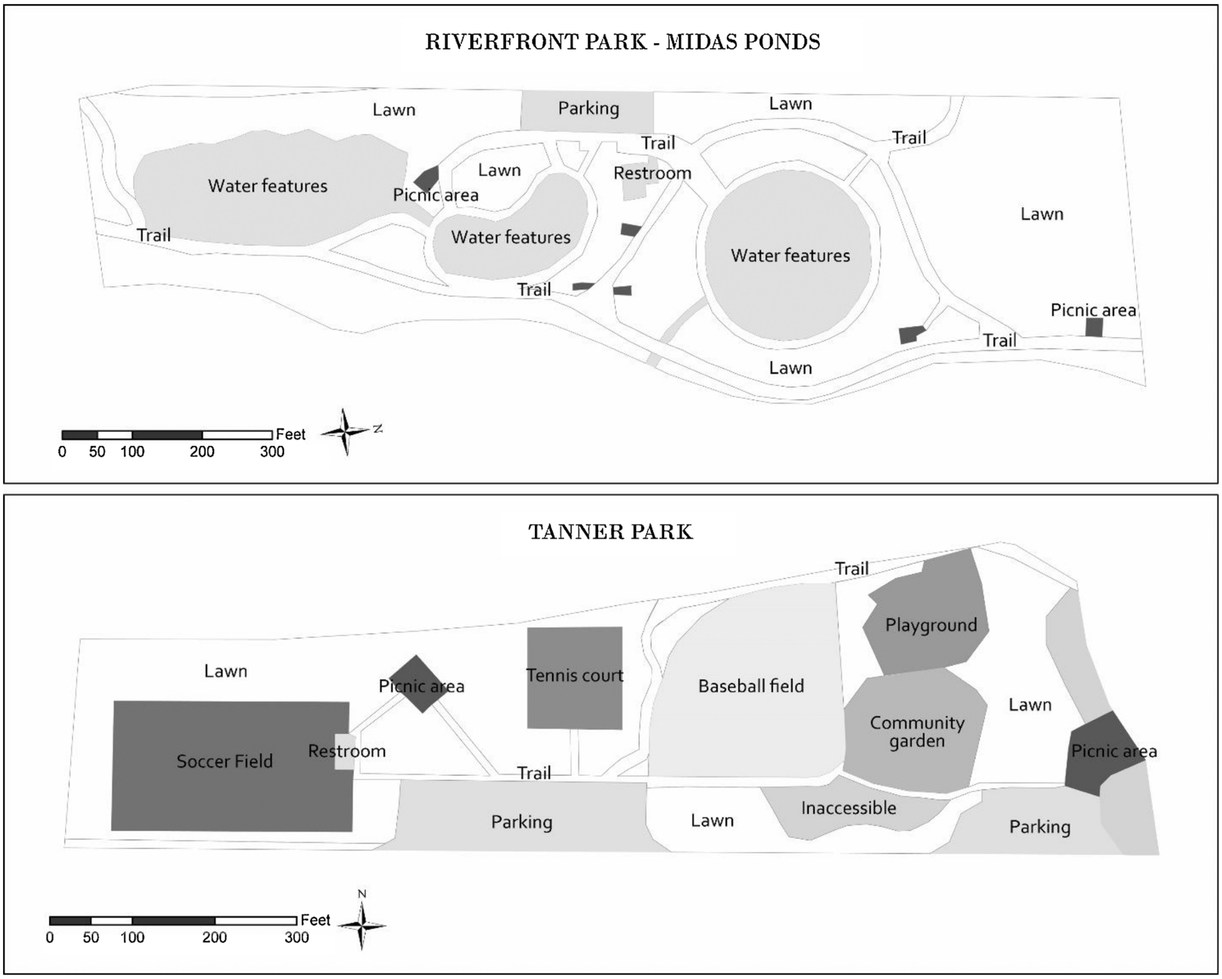


Fig. 1. Examples of behavior setting map used in this study.

The use of GPS is becoming popular for tracking movements (Coutts, 2008; Orellana et al., 2012; Oswald et al., 2010; Shoval et al., 2008). The need to carry an external device is, however, likely to increase reactivity. The increasing popularity of smartphones has made it economically feasible for their users and behavioral scientists to record and log their users' daily activities (Bahillo et al., 2015). Nevertheless, the use of GPS is more appropriate for individual-centered mapping, or behavioral tracking, instead of place-centered mapping (Sommer and Sommer, 2002), particularly in public spaces.

Park and Ewing (2017) suggests the possibility of UAVs in behavior mapping to address these shortcomings in other methods and tools. The use of UAVs in behavior mapping may be more efficient in capturing behavior across a larger area in a shorter amount of time. Park and Ewing (2017, 2018) report that even after including the time spent video coding, UAV observation may reduce the time required with the traditional on-the-ground observation by 20–40 %. A UAV equipped for video recording could facilitate establishing the exact location of individuals as well as more accurate attribute information; thus, the use of UAVs could be more reliable and informative in behavior mapping to study micro-scale design implications.

Previous studies find that UAV-based counting of people in public space is reliable and valid compared to traditional on-the-ground protocols (Gaszczak et al., 2011; Ma et al., 2016; Portmann et al., 2014; Park and Ewing, 2017, 2018). For example, Park and Ewing (2018) showed that UAV-recorded video supported the survey of spatial patterns of pedestrians in street environments. This study explores the applicability of UAVs in behavior mapping, specifically by conducting a case study of UAV-enhanced behavior mapping of neighborhood park use.

3. Protocol development

To employ behavior mapping, it is necessary to clearly define the area of observation (behavior settings), the types of activities (affordances), and a system for recording and coding. Ittelson et al. (1970) identify five elements of behavior mapping: 1) a base map identifying the essential physical features of interest, 2) behavioral categories with their definitions and codes, 3) a schedule of observation, 4) a systematic procedure of observation, and 5) a system of coding and counting. Note that the steps are not necessarily chronological. This study refines the Ittelson et al. (1970)'s five elements of behavior mapping in the context of UAV-based behavior mapping.

3.1. Creating a base map in GIS

For UAV-based behavior mapping, the base map is best constructed in a GIS. Attention should be paid to software compatibility with the UAV software suite to facilitate data sharing and integration. The essential features of interest are the behavior settings, or the individual area with environmental features that are likely to affect the behaviors of interest (e.g., pathways, gathering spaces, trees, buildings, etc.). Behavior maps may need to be refined and confirmed by field observations as people's actual behavior spills across lines on the ground (e.g., children playing in and around a playground). Depending on the survey purpose, the recording document can be in forms other than a map; a spreadsheet table in which rows representing physical locations and columns representing behavior would suffice (Bechtel and Zeisel, 1987).

In this study, behavior maps were constructed for 30 parks in Salt Lake City, Utah, using ESRI's ArcGIS Desktop 10.6. Publicly available 1-meter orthoimagery, which was the same as that used within the UAVs software operating system, was used as the base data for identifying and delineating the behavior settings. The parks are classified according to the presence of fifteen behavior settings—lawn, trail, basketball field, baseball field, tennis court, skateboarding area, other sports field, playground, picnic area, parking area, restroom/service facility, water features, garden, outdoor stage, and inaccessible area (see examples in Fig. 1).

3.2. Defining behavioral categories and developing a system of coding

The next step is to define the behaviors relevant to each behavior setting in the context of the research problem under investigation. These behavioral categories must be explicit, precise, mutually-exclusive, and observable. In addition to sometimes being developed in concert with the definition of the behavior settings, the development of behavioral categories might also involve an iterative observational approach—categorizing observed standard patterns of behaviors, combining observational categories into analytic categories, and revising the observational categories as needed. User behavior can also be coded according to research-defined categories for target behavioral phenomenon. For example, in playground observations, Refshauge and Petersen (2013) and Refshauge et al. (2015) use four types of play—-functional, dramatic, constructive, and games. Shirazi (2018) mapped outdoor activities in neighborhoods for walking, sitting, standing, playing, conversation, cycling, running, and fixing. Goličnik, and Thompson (2010) coded park users' behaviors using 42 specific categories such as sitting, stopping, jogging, lying down, fishing, etc.

This study adopts SOPARC (System for Observing Play and Recreation in Communities; McKenzie et al., 2006) as a systematic observation schema for collecting behavioral phenomenon data on park users and their physical activities. SOPARC uses "momentary time sampling techniques" in which researchers systematically and periodically scan individuals and contextual factors within pre-determined target areas (behavior settings) (McKenzie et al., 2006). The reliability and the validity of this method have been tested and confirmed in numerous studies (Baran et al., 2014; Chung-Do et al., 2011; Cohen et al., 2011; Rung et al., 2011). During an area scan (i.e., an observation sweeping from left to right), the activity of an individual is coded as sedentary, moderate, or vigorous. Summary counts also describe the number of users by gender and age group.

A major difference between traditional SOPARC and the UAV-based approach is that a UAV-recorded video allows for researchers to play, pause, rewind, and fast-forward to capture the attributes and behaviors of each park user. Thus, a video assessor may watch each person in the video as long as necessary to estimate personal attributes (e.g., gender, age group, activity level) and identify their behavior. Then, the assessor may geocode that person in GIS at the location(s) where their behavior is most relevant and/or apparent.

3.3. Defining a schedule of observation

To assess public park-use patterns spatially as well as temporally, behavioral observations need to be conducted throughout the time period of interest. Cohen et al. (2011) recommend four days/week and four times/day for a robust estimate of public park user characteristics. They also suggest that six observations—three times a day and twice a week, as done in the present study—provide an excellent level of reliability for estimating whole park use patterns (Cohen et al., 2011).

In this study, each park was observed six times; three different times during a day (morning: 8–10 AM, early afternoon: 12 noon-2 PM, late afternoon: 4–6 PM) on two different days of a week (one weekday and one weekend). UAV-based observation in each park took 10 − 15 min, enabling the observation of five to six parks per two-hour observation period.

External influences such as climate, seasonal effects on activity, and special events are also important control variables, which the researcher(s) should attempt to either exclude or hold constant during the observation period. UAV observation is normally available on days in which no rain or strong winds occur.

3.4. Establishing an observation procedure

UAV-based behavior mapping entails the use of a UAV carrying a fully-stabilized video camera. Each observation is conducted in four steps. First, in a preliminary visit, an operator sets a flight path and specific waypoints according to the park boundaries and obstacles. The flight path is saved and repeated for consistency during each observation. During this step, the boundaries of behavior settings may also be adjusted to reflect any observed behavioral patterns. An important aspect of this step is to identify areas that cannot be observed from a flying UAV (e.g., under a group of big trees, indoor areas). These areas are identified for on-the-ground observation using the same coding system. The UAV pilot could do the additional on-the-ground observation immediately after the flight. Then, the data from the on-the-ground observation should be digitized in GIS in the same way that data from the UAV-recorded video would be. This step may serve as pilot testing to identify any problems that need to be rectified before data collection begins. It can also identify how much time is needed to conduct the UAV-based data collection of each park.

Second, during each observation, the researcher(s) may begin by recording contextual information such as weather (e.g., temperature and wind) and park conditions (e.g., organized event). Observer training should be conducted to ensure the replicability of the observation procedure.

The third step involves data collection where the UAV is automatically flown through the preset waypoints and records the park users. The flight height can be set to 10–15 meters (30–40 feet), a compromise between data accuracy, flight safety, and less obtrusiveness (Park and Ewing, 2017), while allowing for slight adjustments depending on the presence of obstacles.

The final step involves coding the observed behaviors. After the on-site flights, a video assessor geocodes park-user data in GIS software by watching the recorded video files and coding the established measures and spatial locations. Park-user data is coded by type—gender (female, male), age group (child, adult, senior), activity level (sedentary, moderate, vigorous), and geocoded according to the fifteen predetermined behavior settings in each park. The video assessor reviews the video footage for each observed person as long as necessary to establish personal attributes (e.g., gender, age group, activity level) and identify their behavior. Then, the assessor may geocode that person in GIS at the location(s) where their behavior is most relevant and/or apparent. This process is repeated for each individual observed within the behavior settings of interest.

Minimizing the "observer effects" is an important criterion in any direct observation, including behavior mapping, because an obtrusive observer may affect the behavior of the observed (Bechtel, 1967). Observing the subjects at an appropriate distance is a common strategy (Winkel and Sasanoff, 1966; Hill, 1984). A flying UAV is highly likely to be noticed by park users. Reactivity can be a problem when people are aware that they are being observed in a setting. Reactivity may be reduced by pre-flying the area before the actual recording so that the users become accustomed to the presence of the UAV. In this study, we counted the number of park users stopping their activity to watch the UAV, and found that the observer effect occurred for 0.3 persons per park on average (0.8 % of total users). For those few people—especially children—who watched the flying UAV, the wide camera angle of the UAV enabled the researchers to capture their behaviors before they became aware of the UAV.

Behavior mapping is advantageous to survey methods such as questionnaires or interviews as it allows a researcher to directly observe phenomena in their natural settings with very limited or no influence on the observed subjects

3.5. Data extracting and analysis

Sanoff (1971) proposed three ways of analyzing behavior maps: (1) behavioral density refers to the total frequency of all types of activities at a place; (2) activity profile refers to the frequency of specific types of activities occurring at a place; and (3) behavioral range refers to the range of different activities occurring at a place. Ittleson et al. (1970) suggest several patterns that can be examined through behavior mapping. Peaking indicates that certain areas are consistently used primarily for a single type of activity. Constancy indicates that certain behaviors tend to remain constant over many different conditions. Reciprocity refers to spaces where an increase in behavior in one space is associated with a decrease in that behavior in another space.

Behavior mapping is also commonly used to produce descriptive statistics such as the number and percentage of observed behaviors in individual behavior settings, characteristics of users by location and activity, and observed activity over time. The numeric data (counts) can be used in statistical modeling (Zacharias et al., 2004).

4. UAV-based behavior mapping: a case study

4.1. Study site and behavior mapping process

In this application of the use of UAVs in behavior mapping, we used a UAV, DJI Phantom 4 Professional, carrying a fully-stabilized 4 K video camera to conduct the observations. Each observation in a park was conducted in four steps (Fig. 2): 1) In a preliminary visit, an operator set a flight path and specific waypoints according to the park boundaries and obstacles; 2) the data collection began by jotting down contextual information such as weather (e.g., temperature and wind), park facilities, and conditions (e.g., organized event); 3) the UAV automatically flew through the preset waypoints and recorded the area; and 4) the video data was reviewed to extract the behaviors of interest which were coded in GIS. The reliability and validity of this observation method were tested by Park and Ewing (2017).

The case study was conducted in the fall of 2017. To understand park-use patterns across different times, each park was observed six times; three different times during each day (morning: 8–10 AM, early afternoon: 12 noon-2 PM, late afternoon: 4–6 PM) on two different days of a week (one weekday and one weekend). The observer made every attempt to observe each park during a single week, but when the weather was inclement, the observation was rescheduled for the next available day (i.e., same time of day and day of the week). The first author of this paper obtained approval from the Institutional Review Board (IRB) at the University of Utah, and every UAV operation followed safety regulations set forth by the Federal Aviation Administration. The video data was stored in a password-protected server and only accessible to the researchers. This study selected 30 neighborhood parks in Salt Lake County, Utah, based on their diversity in park attributes (e.g., size, park type) and neighborhood conditions. The diversity in park and neighborhood settings are important for the generalizability of the results. For example, park-use patterns in an affluent White-dominant neighborhood could be much different from those in a poor non-White-dominant neighborhood. To focus on the use of neighborhood parks, not regional parks which likely exhibit different use patterns and user characteristics, this study limited the park size to between 2 and 20 acres (Cohen et al., 2016).

4.2. Reliability test

We first tested the inter-rater reliability of the UAV observation. Inter-rater reliability is the extent to which two or more raters (or observers) agree. Cohen's kappa statistic is an appropriate measure of inter-rater reliability for categorical variables (Cohen, 1960; McHugh, 2012); thus, it was used to test the reliability of identifying a park user's gender, age group, and physical activity level. A kappa statistic over 0.8 is considered "almost perfect," and the value between 0.6 and 0.8 is considered "substantial."

Two observers concurrently watched a video file from the UAV, and digitized park users in a GIS and coded their personal attributes independently. The two observers did not discuss the subjects during this process. A total of 155 park users were digitized from twelve video files. The kappa statistics are 0.92 [CI: 0.86 – 0.98] for gender, 0.87 [CI: 0.80 – 0.93] for age group, and 0.78 [CI: 0.69 – 0.86] for activity level, respectively. Thus, we conclude that the UAV-based observation of park users demonstrates "substantial" to "almost perfect" levels of inter-rater reliability.

Second, we examined the inter-rater reliability of the park users' locations. The differences of the geocoded location of park users between two raters show a mean of 1.04 m (minimum: 0.04, maximum: 4.31, standard deviation: 0.93). The National Standard for Spatial Data Accuracy (NSSDA), published by the Federal Geographic Data Committee (1998), recommends root-mean-square error (RMSE) to estimate positional accuracy, computed as the square root of the average of the set of squared differences between two location values (e.g., coordinates). We followed the NSSDA recommendation to compute our location precision. As a result, the computed RMSE between two observers is 1.39 m. The digitizing error represents only 0.6 % of the sample park users (1 out of 155) being placed in a different behavior setting between the two video assessors.

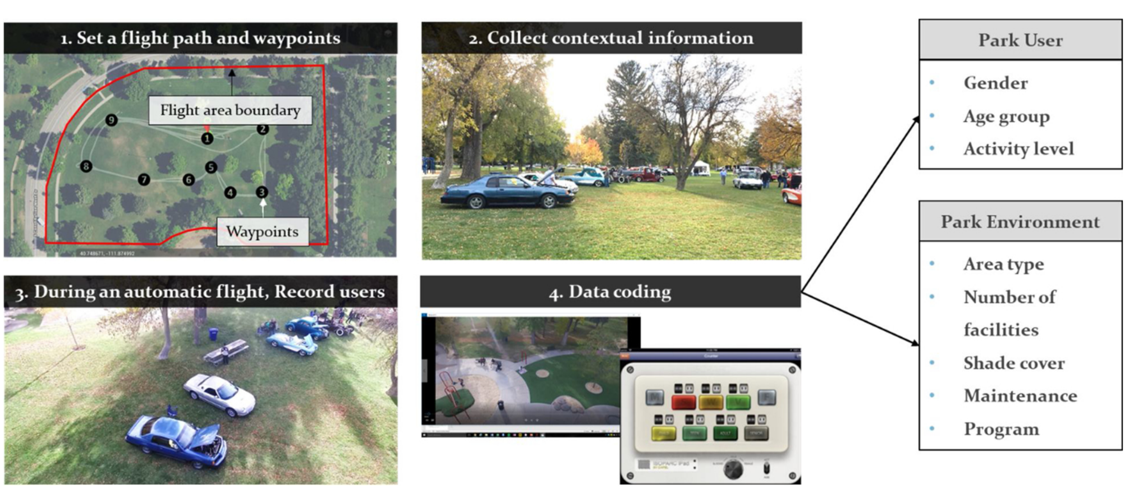


Fig. 2. UAV observation process.

Table 1
User density (per acre) between user group attributes.

	Child	Teen	Adult	Senior	Total	X^2 value
Female	0.44	0.09	0.71	0.04	1.28	49.9 ($p < .001$)
Male	0.67	0.16	0.68	0.06	1.56	
Total	1.11	0.25	1.39	0.10	2.85	
	Child	Teen	Adult	Senior	Total	X^2 value
Sedentary	0.37	0.08	0.88	0.05	1.40	436.2 ($p < .001$)
Walking	0.43	0.10	0.44	0.04	1.02	
Vigorous	0.30	0.06	0.07	0.00	0.43	
Total	1.11	0.25	1.39	0.10	2.85	
	Sedentary	Walking	Vigorous		Total	X^2 value
Female	0.69	0.46	0.13		1.28	57.3 ($p < .001$)
Male	0.70	0.56	0.30		1.56	
Total	1.40	1.02	0.43		2.85	

4.3. User-user relationship

Table 1 shows user density—the number of people per acre—-between different user attributes in the 30 neighborhood parks observed. Overall, there were more male users (1.56 per acre) than female users (1.28 per acre). Adults (1.39/acre) were most prevalent, followed by children (1.11/acre). Seniors (0.10/acre) and teenagers (0.25/acre) are rarely observed. In terms of activity level, sedentary activities (1.40/ acre) are most observed, followed by walking (1.02/ acre) and vigorous activities (0.43/acre).

There was a significant gender gap among the children and teenager groups, with more males observed. On the other hand, there were slightly more female adults than males in the observed parks. Different physical activity levels were relatively evenly distributed in children and teenage groups. However, sedentary activities are the dominant activity type in adult and senior groups. Vigorous activities were observed most in children (0.30/acre) and rarely observed in seniors. Chi-square tests with Yates' continuity correction (Yates et al., 1999) show that all these group-wise differences are statistically significant at $p < .001$ level (Table 1).

The digitally-coded maps enable further spatial analyses. One application is to measure interpersonal distances (Hall, 1966). Hall (1966) proposes a series of interaction distance zones between two persons—"intimate" distance (0–1.5 feet; 0 to 0.46 m), "personal" distance (1.5–4.0 feet; 0.46–1.22 meters), "social" distance (4.0–12.0 feet; 1.22–3.66 meters), and "public" distance (over 12.0 feet; over 3.66 m). For example, on a weekday afternoon in Fitts Community Park (Fig. 3) the shortest distance between any two persons is 0.79 feet (24 cm; intimate interaction), and the average is 10.7 feet (3.26 m; social encounter distance). Out of 110 people observed, 11 % (n = 12) were within intimate distance of another person, 45 % (n = 51) were within personal distance, 30 % (n = 33) within social distance, and 13 % (n = 14) within public distance. This suggests that this park supports strong personal associations and social interactions between individuals.

4.4. User – behavior setting relationship

Fig. 4 shows the user frequency and density by behavior setting type. The average number of users per each observation session is highest in soccer/football fields (195.2), followed by playgrounds (125.0) and lawns (74.3). The average user density is highest in picnic areas (125.2 per acre), followed by playgrounds (110.6 per acre) and skateboarding areas (76.5 per acre). In addition to the relatively-low user frequency, lawn is one of the least dense areas (4.7 per acre). Baseball field and water features (e.g., creek, fountain) are not popular in terms of both total number of users and their density, although very few of the observed water features were designed for active participants.

Table 2 shows user density (per acre) by type of behavior setting, gender, age group, and activity level. Different uses of behavior settings by user attributes were observed. More exercise-oriented places such as baseball fields, skateboarding areas, soccer/football fields, and tennis courts were more occupied by male users while female users more occupy picnic areas and playgrounds (Fig. 5). Chi-square tests with Yates' continuity correction (Yates et al., 1999) show that all group-wise differences between behavior setting types and gender, age groups, and activity levels are statistically significant at $p < .001$ level (Table 2). Fig. 5 shows an example of gender-related differences where more males are observed in a skateboarding area while more females are in and around a playground.

Different behavioral settings showed preferences by different age groups (Table 2). Adults were dominant in most behavior settings, such as picnic areas, tennis courts, and trails, while playgrounds are dominated by children. Soccer fields, lawns, and playgrounds appear to be used by both children (players) and adult (guardians/observers). Skateboarding areas were used more by children and teenagers than other age groups. Seniors are observed more frequently in picnic areas, playgrounds, and trails than other behavior settings. Fig. 6 is an example of a typical weekend afternoon observation showing children occupying playgrounds, lawns, and a creek; adults found in and around picnic areas and trails; and trail use by a few seniors.

The levels of physical activity are also significantly different according to behavior settings (Table 2). Walking is more prominent than either sedentary or vigorous activities in baseball fields, basketball courts, playgrounds, and trails. Sedentary activities such as sitting, standing, and lying are more observed in picnic areas, soccer fields (by the spectators), and water features (e.g., creek, fountain) than other activity types. In lawns, playgrounds, and parking areas, both sedentary and walking are similarly observed. Vigorous activities such as running or active exercise are more observed in skateboarding areas and tennis courts, compared with moderate or sedentary activities. As an example, Fig. 7 demonstrates differences in the use of behavior settings in terms of physical activity levels: vigorous activities are observed in a tennis court, a playground, and a lawn, while sedentary activities are more common in a picnic area.

4.5. User-time relationship

Temporal patterns are apparent by user groups. The density of male and female visitors followed a similar pattern—peaked at weekend lunch and afternoon, while there were slightly more females in weekday morning and lunchtime (Fig. 8). Weekday afternoon was the only time when children, not adults, was the dominant age group in neighborhood parks. The number of teenagers also peaked during weekday afternoons. Senior visitors were most observed on weekends at lunchtime, although the presence of seniors was mostly stable across observations. While sedentary behaviors were most observed during weekend sessions and moderate-level physical activities such as walking were slightly more or as frequent as sedentary activities during weekdays.

4.6. Temporal variation

Parks are more used during weekends (2.20/acre) than weekdays (1.44/acre). Late afternoon is most occupied during weekdays (3.00/acre) while the early afternoon is more popular on weekends (5.41/acre, followed by 4.47/acre for the weekend afternoon). Several behavior settings and their varying occupancy rates by time are presented in Fig. 9.

Following the expected pattern, weekday afternoon and weekend lunchtime and afternoon are the most popular time for lawn, playground, and skateboarding areas (Fig. 9). Changes in user density

Fig. 3. User location map of Fitts Community Park.

between peak hours and non-peak hours are more pronounced for picnic areas, playgrounds, soccer fields, and skateboarding areas. Picnic areas were dominantly used during weekend lunch and afternoon while being almost empty in the morning. Soccer/football fields were most used weekend morning and lunch times while being almost empty during other time periods. Tennis courts were highly utilized throughout the day only during the weekend. The use of trails was relatively stable across different time periods. In Fig. 10, two behavior maps representing different days of a week show that during a weekday, the trail was used for children's commuting and the playground was occupied, while during a weekend, more visitors are found, especially in a picnic area.

Figs. 5 to 7 are examples indicating that lawn areas are typically empty, but those near a picnic area or a playground attract people. This suggests that people in activity spaces may overflow into the surrounding lawns, or that park features function as a behavioral anchor for users. A lawn next to a picnic area in Fig. 7 (Lodestone Park) was used for vigorous physical activities by a group using the picnic area, which is confirmed in the UAV-captured video data (Fig. 11a). A further examination of the left-side map in Fig. 10 (a weekday afternoon)

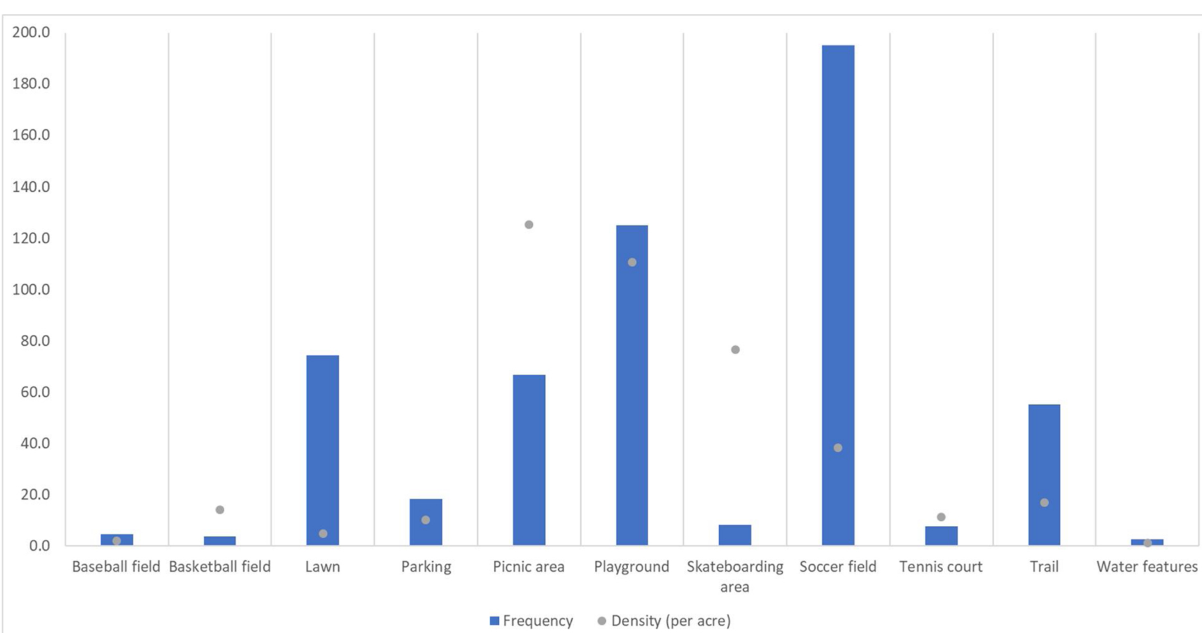


Fig. 4. User frequency and density (per ha).

Table 2
User density (per acre) by place type, gender, age group, and activity level.

	Female	Male	Child	Teen	Adult	Senior	Sedentary	Walking	Vigorous
Baseball field	0.07	0.25	0.09	0.00	0.24	0.00	0.09	0.20	0.04
Basketball field	1.23	1.12	0.45	0.22	1.67	0.00	0.78	1.00	0.56
Lawn	0.34	0.46	0.31	0.09	0.37	0.02	0.30	0.32	0.18
Parking	0.74	0.92	0.21	0.18	1.21	0.06	0.82	0.82	0.03
Picnic area	11.24	9.63	2.86	2.39	14.37	1.25	16.71	3.96	0.21
Playground	9.95	8.48	11.35	0.66	6.14	0.27	6.68	8.04	3.71
Skateboarding area	1.56	11.19	6.25	5.47	1.04	0.00	3.64	1.56	7.55
Soccer/football field	2.51	3.87	2.55	0.54	3.11	0.19	3.93	1.66	0.80
Tennis court	0.59	1.30	0.17	0.17	1.46	0.08	0.17	0.63	1.09
Trail	1.32	1.51	0.79	0.23	1.58	0.23	0.67	1.78	0.38
Water features	0.08	0.12	0.08	0.00	0.10	0.01	0.13	0.05	0.01
Total (per acre)	1.28	1.56	1.11	0.25	1.39	0.10	1.40	1.01	0.43
X^2 value	85.7 ($p < .001$)		549.1 ($p < .001$)				597.9 ($p < .001$)		

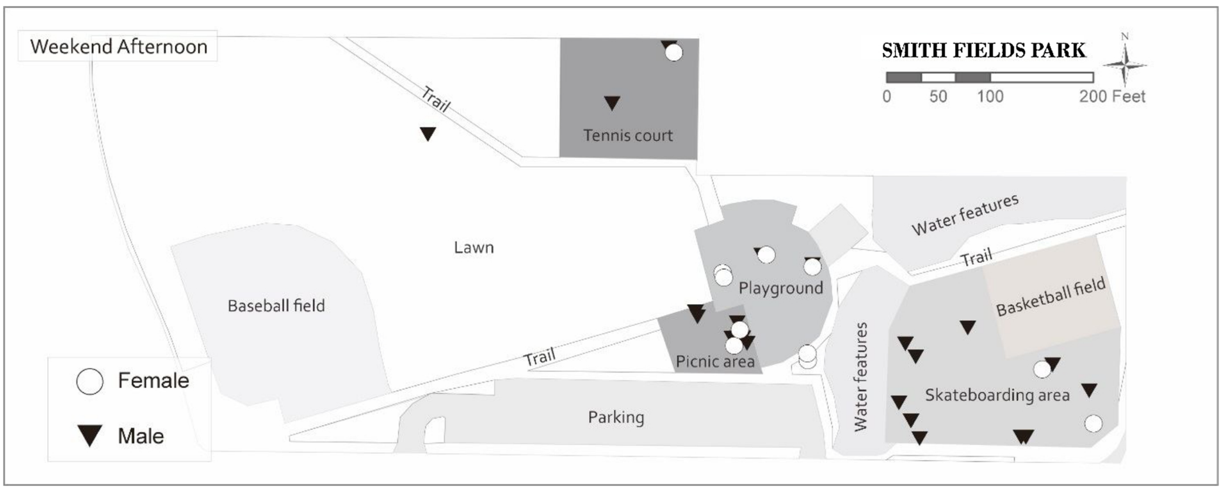


Fig. 5. Behavior map of park users by sex.

reveals that kids are walking back home along a trail in the park, as confirmed in Fig. 11b.

5. Discussion and conclusions: toward evidence-based design and planning

This study developed a generalizable protocol for UAV-based behavior mapping of neighborhood parks and demonstrated its applicability using a case study of its use across 30 neighborhood parks in Salt Lake County, UT. People-place interactions were explored according to different user attributes, physical activity levels, and time.

This study shows that the use of UAVs can enhance our understanding of park-based behaviors through behavior mappings. UAVs can record video data over a large area within a short period of time. Each UAV observation in this study took about 10 – 15 min, enabling five to six parks per two-hour observation period. The coding of the recorded video took approximately 20 min for each park's observation. For the neighborhood parks of this study, ranging from 2 to 20 acres,

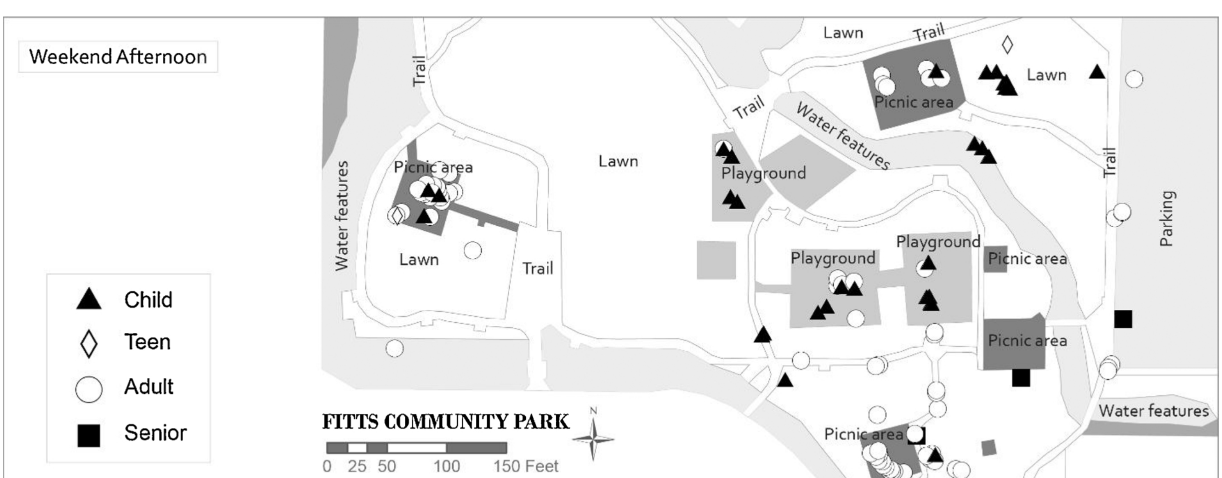


Fig. 6. Behavior map of park users by age group.

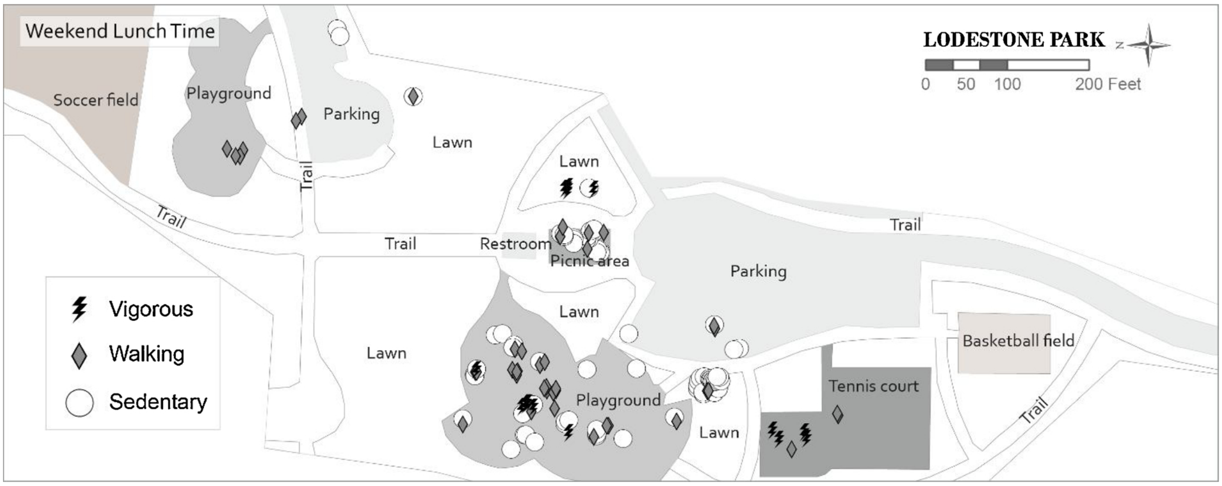


Fig. 7. Behavior map of park users by level of physical activity.

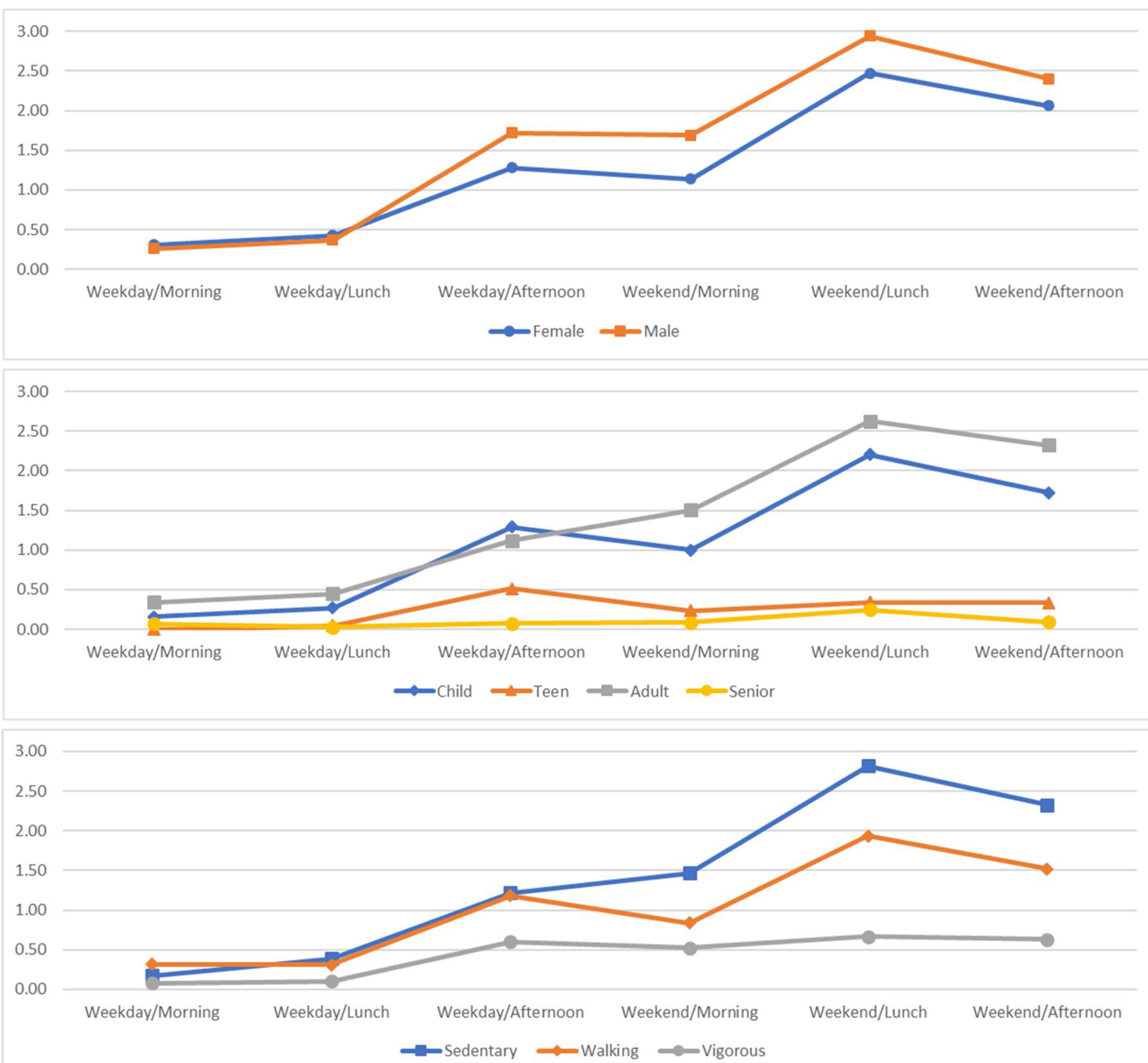


Fig. 8. User density (per ha) by time and user group.

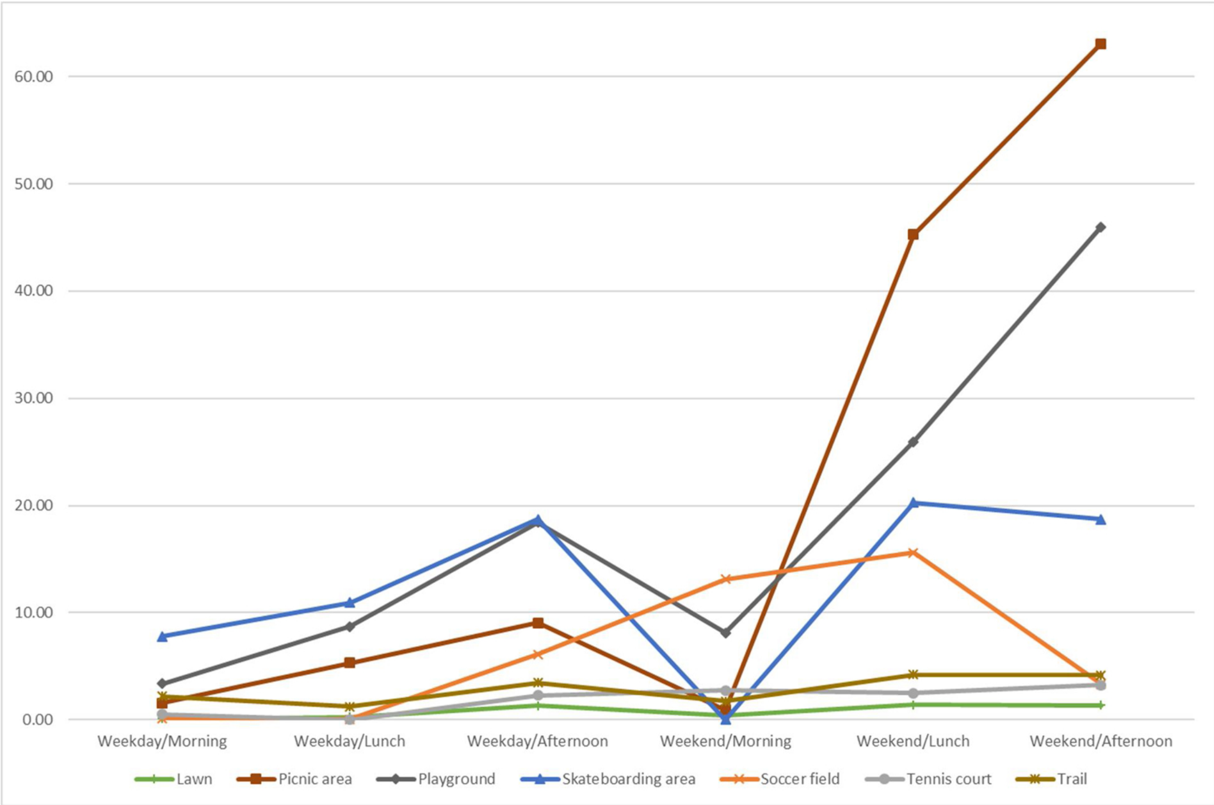


Fig. 9. User density (per acre) by time for select behavior settings.

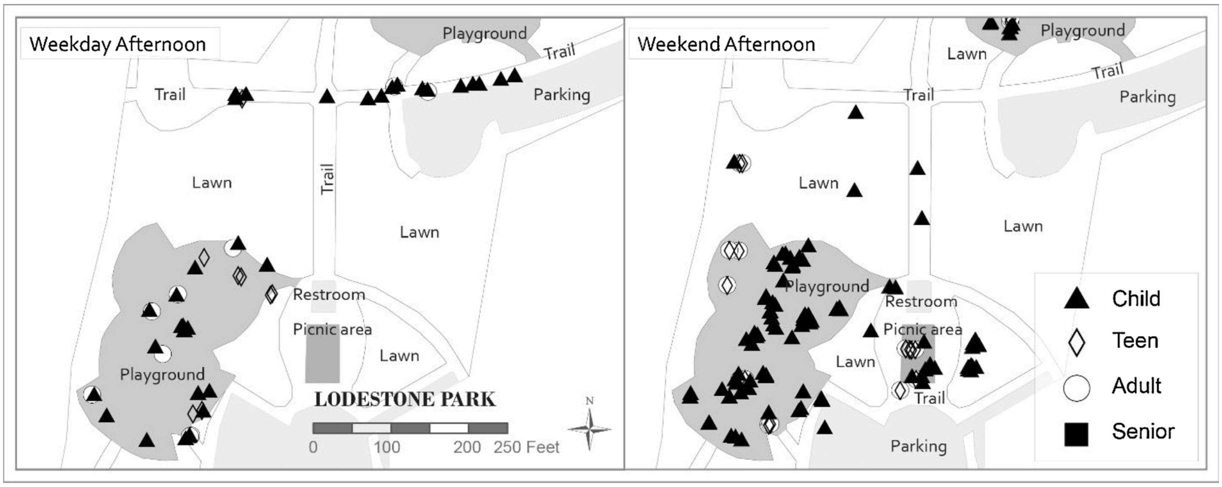


Fig. 10. A comparison of behavior maps between different days of a week.

(a) weekend afternoon (b) weekday afternoon

Fig. 11. UAV-captured images in Lodestone Park.

every park was observed in a single UAV flight. This confirms Park and Ewing (2017)'s study showing that the UAV observation could save person-hours significantly, even after accounting for the time spent on video counts.

The locations of park users were geocoded in GIS, which can be verified by other researchers later by watching the same video files. This advancement in human detection and tracking from UAV-recorded video data may allow for improved accuracy of the data (Gaszczak et al., 2011; Ma et al., 2016; Portmann et al., 2014). Automated tracking technologies, when applied to the identification of individuals and their locations, may further improve the accuracy and reduce the time necessary to geocode locations during behavior mapping.

The UAV-recorded video provides a convenient and useful means for extracting information on user attributes and their behaviors. In this study, we were able to estimate and code the sex, age group, and physical activity level of each user. Depending on a study's purpose (e.g., understanding social behaviors by different ethnic groups), user attributes may include race, ethnicity, and disability (Kaczynski et al., 2011; Spengler et al., 2011; Van Dyck et al., 2013), and behaviors may be coded more specifically such as sitting, standing, playing, lying down, fishing, etc. (Golicnik and Thompson, 2010; Shirazi, 2018).

As demonstrated by this case study, UAV-based behavior maps can provide both quantitative and qualitative data. Summary statistics, along with digital maps, provide accurate patterns of park use. For instance, this study showed disproportional usage of neighborhood parks by gender, more males than females, a gap which becomes larger among children and teenager groups, and age with the percentage of seniors (3.5 %) out of all park users, a much lower value than the County population average of 8.7 %. User density is higher in picnic areas and playgrounds and lower in lawn, baseball fields, and water features. In addition, this study shows that park occupancy is different by sex, age group, and activity type across different times.

The digitally-coded maps allow for geospatial analyses. Fig. 3 shows one such example to measure interpersonal distances (Hall, 1966). This type of analysis can contribute to both a better understanding of patterns of personal distance and social interactions in public spaces, and whether design practices indeed support the intended patterns of interactions (Ozdemir, 2008; Veitch and Arkkelin, 1995). Such analysis can further distinguish interaction distances by behavior settings; for example, intimate or personal distance may be expected in a picnic area or a playground while social or public distance may be observed in a lawn or a trail.

Fig. 12 shows that the original behavior map with point data (Fig. 12a) can be converted into raster formats such as a hot spot map (Fig. 12b) or a point density map (Fig. 12c). We used the "Optimized Hot Spot Analysis" tool for Fig. 10b and "Point Density" tool for Fig. 10c in ArcGIS Desktop 10.6. Such raster maps can be overlaid with other data such as topography (elevation, aspect, slope) to understand associations between park use patterns and ecological conditions of environments.

In addition to quantitative inquiries, UAV-based behavior maps also enable qualitative, design-focused explorations. Different people-place interaction patterns can be explored by user attributes and time. For example, a future study might look at neighborhood environments beyond a park boundary and examine how park use is associated with surrounding built and natural environments.

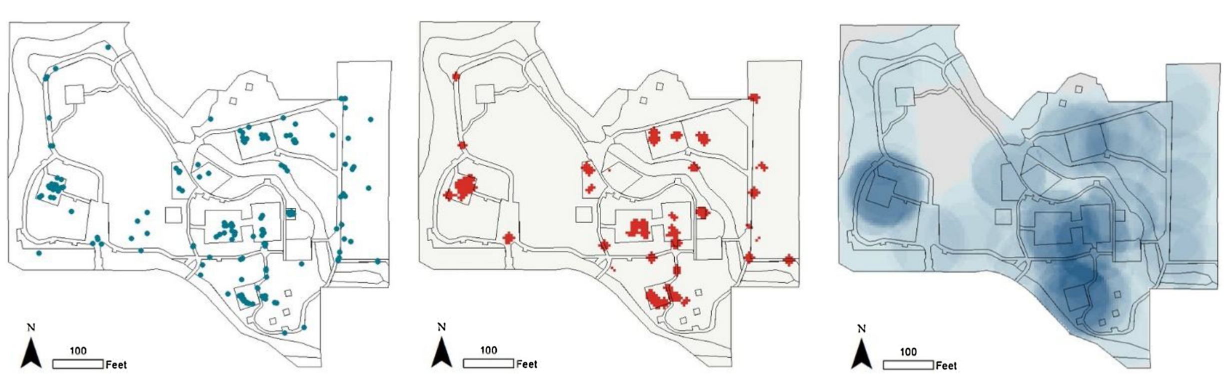
The UAV-based behavior mapping is not the panacea for capturing all people-place dynamics, of course. The user attributes—gender, age group, race/ethnicity—are only assumed by the video assessor, which may raise reliability issues (Park and Ewing, 2017). On the other hand, user survey such as a questionnaire or interview would allow for more precise user information, although they may not capture user behaviors, at least their natural behaviors. Thus, UAV-based direct observation and user survey could complement each other to enable a more comprehensive understanding of stated and revealed park use dynamics.

Flying a UAV in neighborhood parks entails several limitations; 1) a remote pilot may need prior approval or a waiver from an aviation agency (e.g., U.S. Federal Aviation Administration or European Aviation Safety Agency) for a night-time flight or a flight over a crowd, 2) UAVs do not perform well during rainy or windy days, and 3) while a UAV can cover a larger area effectively and have fewer blind spots, areas under a group of trees, especially in a dense forest, would not be completely recorded by the UAV. To find a balance among survey efficiency, data coverage, and data accuracy, a researcher may combine a UAV observation with on-the-ground observation, especially for areas unseen from a bird-eye-view or for specific situations such as rainy or windy days, as suggested by the protocol in this study. Further, while data collection may be more efficiently conducted by UAV, interpretation, particularly at greater detail feasible by UAV-recorded video, may take longer to code post-collection.

In sum, the use of UAVs in behavior mapping can contribute to both design practice and research. Accurate and informative behavior maps may be examined through multiple strategies such as description, modeling, quasi-experiments, and evaluation and diagnosis to produce new knowledge (Swaffield and Deming, 2011).

Additionally, the spatial data may be used to relate human behaviors to environmental attributes and model and predict those behaviors. Field experiments, or quasi-experimental strategies, can also benefit from the accurately geocoded data from UAV observation. An example is 'post-occupancy evaluation' (Cooper Marcus and Francis, 1998), in which a researcher compares park use patterns before and after certain design interventions and assess the design effectiveness.

The visualization of a behavior map itself may help designers understand the outcomes of their design practice more intuitively and meaningfully, contributing to better evidence-based design (Hamilton and Watkins, 2009; Zeisel, 2006). "Research on design," such as the current study using the UAV-based behavior maps, is carried out on



(a) original point data (b) hot spot analysis (c) point density analysis

Fig. 12. Converting an original map into raster maps.

landscape design products such as parks, gardens, or other types of public space and mainly relies on observation or case study methods (Lenzholzer et al., 2013). Park usage and environment-behavior relationships can be compared across different parks and communities and used to generate empirically-tested knowledge. The knowledge produced by such design research can help designers base design decisions on credible evidence and achieve the best possible outcomes.

Aided by more accurate and informative data, practitioners could identify environmental layouts, design attributes, and programming that contribute to more visitors, more health-promoting behaviors, and more social interactions in the designed space. We hope that design professionals will see UAV-based behavior mapping, supplemented by other data collection techniques, as an aid for developing evidence-based practice and for applying their creative skills for the best possible design solutions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Keunhyun Park: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Keith Christensen:** Investigation, Writing - review & editing. **Doohong Lee:** Data curation, Visualization, Writing - review & editing.

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