Manuscript

Urban Analytics and City Science

EPB: Urban Analytics and City Science
2022, Vol. 0(0) 1–15

DOI: 10.1177/23998083211064624
journals.sagepub.com/home/epb
SAGE

Analyze the usage of urban greenways through social media images and computer vision

Yang Song
Department of Landscape Architecture and Urban Planning, Texas A&M University, College Station, TX, USA

Huan Ning
Department of Geography, University of South Carolina, Columbia, SC, USA

Xinyue Ye
Department of Landscape Architecture and Urban Planning, Texas A&M University, College Station, TX, USA

Divya Chandana and Shaohua Wang
Department of Informatics, New Jersey Institute of Technology, Newark, NJ, USA

Abstract

Urban greenway is an emerging form of urban landscape offering multifaceted benefits to public health, economy, and ecology. However, the usage and user experiences of greenways are often challenging to measure because it is costly to survey such large areas. Based on the online postings from Instagram in 2017, this paper used Computer Vision (CV) technology to analyze and compare how the general public uses two typical greenway parks, The High Line in New York City and the Atlanta Beltline in Atlanta. Face and object detection analysis were conducted to infer user composition, activities, and key experiences. We presented the temporal patterns of Instagram postings as well as the group gatherings, smiling, and representative objects detected from photos. Our results have shown high user engagement levels for both parks while teens are significantly underrepresented. The High Line had more group activities and was more active during weekdays than the Atlanta Beltline. Stronger sense of escape and physical activities can be found in Atlanta Beltline. In summary, social media images like Instagram can provide strong empirical evidence for urban greenway usage when combined with artificial intelligence technologies, which can support the future practice of landscape architecture and urban design.

Keywords

Urban greenway, park usage, computer vision, social media, place quality

Corresponding author:
Xinyue Ye, Department of Landscape Architecture and Urban Planning, Texas A&M University, Architecture Center Bldg C, 3137 TAMU, College Station, TX 77840, USA.
Email: xinyue.ye@tamu.edu

Introduction

The greenways are urban linear parks that are often developed on vacant lands and properties of railway lines, power lines, or edges of water bodies (Paneerchelvam et al., 2020). They create essential linkages between city neighborhoods and accommodate various recreational needs (Watson, 2003). Cities design walking paths, bike trails, water trails, gardens, agricultural facilities as parts of greenways for public use. Greenways also connect natural habitats and mitigate biodiversity loss and fragmentation in urban areas (Ahern, 2013). Recently, greenways have gained increasing popularity in the US and the world as an emerging form of development (Akpinar, 2016). Previous studies have demonstrated that greenways could encourage more physical activities, increase interactions with nature, and contribute to more job opportunities (Cohn and Scott Shafer, 2009; Dallat et al., 2014).

It is important to understand how the greenway has been used and what is affecting its usages to maximize its benefits (Hamilton et al., 2017). Research showed associations between size, proximity, number of amenities, and number of programs with positive park usages and physical activities (Bedimo–Rung et al., 2005). On the other hand, poor maintenance, safety issues, lack of access points, and ineffective event programming could negatively affect greenway usages, especially for minority groups (Boone et al., 2009). While these features and attributes are essential, the subjective factors and direct experiences were found to be stronger indications for successful parks and public spaces (Fongar et al., 2019). For example, the perception of accessibility was found to be more important than proximity measures such as network distance (Wang et al., 2015). The perceived qualities and nature-relatedness of green spaces were better predictors of park visit frequency for local communities than objective measures such as the percentage of vegetation areas, size of parks, and number of facilities (Flowers et al., 2016). Therefore, investigating park experiences and uses directly from the users' perspective is crucial. Without such knowledge, researchers and administrators will have little empirical evidence from users to evaluate planning and design interventions.

In recent years, growing numbers of studies have used social media to assess place preferences and engagements from users (Heikinheimo et al., 2017; Wang et al., 2019). The abundance of big data offers a broader coverage on the human experiences of places across time and space (Chen et al., 2020; Ye et al., 2020). Powered by AI technology such as natural language processing (NLP) and computer vision (CV), researchers can automate the data analytics process in tackling complex problems using emerging new big urban data (Jamonnak et al., 2020; Li, 2020; Ning et al., 2021). Researchers have found that social media data were helpful to offset the limitations of conventional survey techniques due to the expense and infrequencies (Li et al., 2017; Wang et al., 2016; Ye et al., 2016). There are also strong links between geo-located photos and empirical visitations (Donahue et al., 2018; Sessions et al., 2016). Online reviews and photograph postings of specific locations could describe the user experiences at the site level (Song et al., 2021). By investigating iconic public spaces such as parks and streets, several empirical studies have identified user perceptions and usages that could support future practice in urban design and landscape architecture (Song et al., 2020b).

The long-term usage and experiential patterns of users are key to understand the impact of urban greenways. Sim et al. (2020) have recently compared the differences in the uses of three elevated greenway parks through field observations and surveys. But each park was only studied for two weekdays and two weekend days. Existing literature rarely gathers big datasets to study the user experiences of urban greenways. This paper utilizes social media data on Instagram with Computer Vision technology to investigate and compare two urban greenway parks' usage patterns during 2017. The well-known Atlanta Beltline (Atlanta, GA) and the High Line (New York, NY) were chosen as our case study sites. Our study objectives are (1) to examine the efficacy of using

Instagram data and CV technology on understanding the greenway usage; (2) to detect meaningful scenes and activity types based on the visual content of Instagram photos; (3) to analyze the temporal patterns of different CV detections and identify their indications for park users and their experiences.

Methodology

Study site and data collection

Atlanta Beltline (Figure 1) is a project that transforms a former railway corridor into a multi-use trail around the core of Atlanta, GA. The whole beltline reaches 33 miles along with playgrounds, parks,

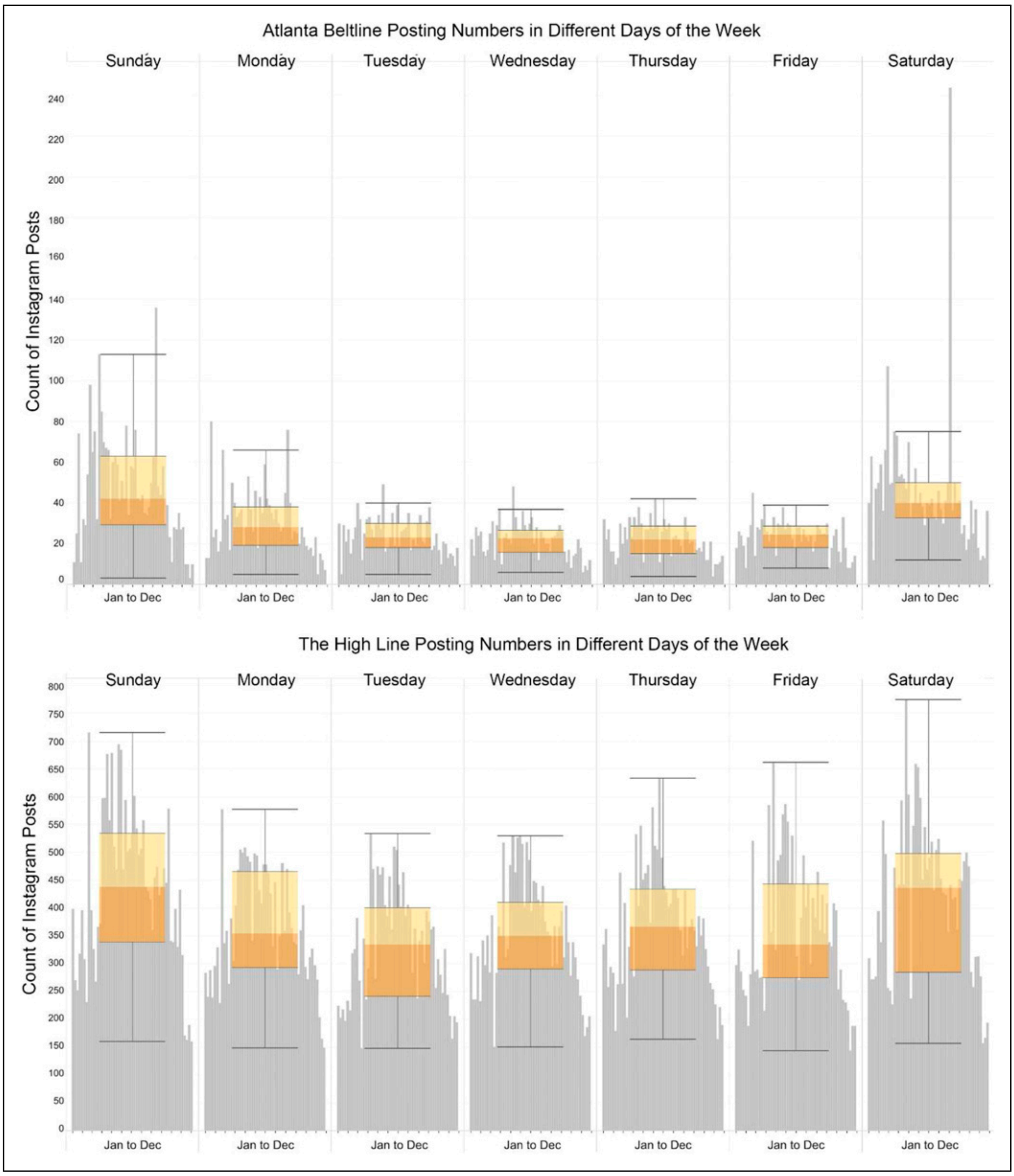

Figure 1. Weekday posting numbers throughout the year of 2017.

shopping centers, and public arts. This study focused on the eastside section of the Atlanta Beltline, which was first opened to the public with three miles of trails. The High Line (Supplementary Figure S1) is built on a historic and elevated railroad track in New York City, NY, with gardens, seatings, food vendors, viewing decks, and art displays. These two greenway parks are both located in the central downtown area of the city. They are among the most influential projects in the US with enormous recognition by the public. Both have won multiple awards for their excellent design and management (ASLA Professional Awards,2010; Atlanta Beltline Awards, 2020).

As one of the most popular social media platforms globally, Instagram is considered a self-representation and personality crafting platform where users post their everyday lives and moments (Rettberg, 2017). Instagram has outperformed other platforms such as Twitter and Flicker in predicting park visitations (Tenkanen et al., 2017). This study uses Instagram as our primary data source for the year of 2017. We used the location tag “Atlanta Beltline” to collect 11,198 Instagram posts from 7765 unique users for Atlanta Beltline. And we collected 137,055 posts from 94,715 unique users for the High Line using the location tag “The High Line.” The location tags are chosen by users when then physically located in or around the parks. However, no specific geo-location information (GPS coordinates) were included for privacy reasons.

Facial detection

Computer vision has been a key component of the AI advances in recent years. We reviewed the current state-of-art object detection approaches in computer vision (Liu et al., 2020), and used these techniques to infer park usages. There are two types of widely used CV technology included in this study. The first is face detection which was used to provide inferences of user behaviors and emotions which has been well developed in recent years (Masi et al., 2018; Zheng et al., 2020). Commercial companies (e.g., FacePlusPlus) provide publicly accessible APIs that take a photo as the input then return the attributes of detected faces (Supplementary Figure S2), such as gender, age, and expression (Smile vs not smile) with accuracies relatively close to the performance of human raters (Jung et al., 2018). It has been used in many studies (Patil et al., 2018) as a reliable tool.

Object detection

The second technology is object detection through a pre-trained YOLOv3 detector (Redmon and Farhadi, 2018), which identifies the bounding boxes or boundaries of target objects. Popular object detectors such as YOLO (Redmon and Farhadi, 2018) and SSD (Liu et al., 2016) are based on multi-layer Convolutional Neural Network (CNN), and require a mass amount of training data. COCO (Lin et al., 2014) dataset is a widely used CV dataset in object detection research, which contains 80 common object types such as person, backpack, bottle, and dog. In this study, we used a pre-trained YOLOv3 model to detect four target categories (handbag, vehicle, bike, and pet) out of seven COCO object types. Although these categories are not direct records of user activities, they could be used as proxy measures to indicate park usage and experiences (see Table 1). We selectively excluded other COCO object types including (1) streets or indoor objects (stop sign, laptlop,etc.) that our model did not detect enough amount of them in park settings; (2) objects with significant accuracy issues (bench, cake, book, etc.); (3) objects unrelated with our study (bowl, teddy bear).

Per our knowledge, the performance of YOLOv3 on Instagram photos for outdoor public spaces is unknown. Therefore, we tested the reliability of our objective detection task through manual validation. 3% of the entire dataset was taken out as the validation set, and four human annotators checked whether the class of a returned bounding box is correct and whether there is a missing object. Finally, we evaluated our CV model performance through the precision, recall, and F1 Score calculated as below

$$Precision = \frac{true\ positive}{true\ positive + false\ positive} \tag{1}$$

$$Recall = \frac{true\ positive}{true\ positive + false\ negative} \tag{2}$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

Results

Object detection accuracy

Our analysis of park users is based on the premise of adequate accuracy performance in object detection results. Except for the pet category of the High Line, all detections have high precision scores (Table 2), which indicate the high accuracy of positively detected objects. The vehicle and bicycle (Supplementary Figure S3) detection are very precise, given that their F1 scores are all larger than 0.8. Pet category is very accurate for Atlanta Beltline (F1 = 0.84). However, the High Line presents a low precision score (F1 = 0.4) with many false positives witnessed from fuzzy objects, human hair at night, dazzle effects, or art sculpture in photos (Supplementary Figure S3). The handbag category has a lower F1 score of around 0.5. This is mostly from the lower recall score with

Table 1. CV detection categories and COCO object types.

Categories	COCO object types	Indications on park users	Rationale
Vehicle	Car Truck Bus	Sense of wilderness or escape from city life	Too many vehicles around means the location is close to roads or traffic which are unlikely to make people feel secluded from the city and experience the wilderness of nature
Bicycle	Bicycle	Biking/exercising activities	Bringing a bike in a greenway is a strong indication of a biking trip for exercising purposes
Pet	Cat Dog	Jogging/walking activities	Pets are active and promote more physical activities
Handbag	Handbag	Sightseeing or walk around the area	Females bring handbags to relax and socialize with people. Few will bring handbags for exercising

Table 2. Accuracy measures of different CV detection categories.

Study site	CV detection category	Average of precision	Average of recall	F1 score
Atlanta beltline	Vehicle	0.85	0.82	0.83
	Pet	0.78	0.90	0.84
	Handbag	0.90	0.37	0.52
	Bicycle	0.93	0.72	0.81
The high line	Vehicle	0.85	0.82	0.83
	Pet	0.28	0.80	0.41
	Handbag	0.90	0.40	0.55
	Bicycle	0.92	0.72	0.81

many false negatives where the model could not detect smaller Handbags for people in the distance (Supplementary Figure S3). Overall, the YOLOv3 model produces acceptable results for our dataset and the following analysis.

General stats and distributions

The posting numbers on Instagram could give us a general idea about the site's activity levels (Song et al., 2020a). Atlanta Beltline dataset identified 5771 female and 3279 male faces, 5800 posts have no faces. As Figure 1 shows, the Weekend days had more postings than weekdays. The average posting number for a weekend day was 46.6 (coefficient of variation 42%), which was about double the amount for a weekday with average posting number of 24.4 (coefficient of variation 31%). For the High Line dataset, 47,391 female and 36,917 male faces were identified; while, 55,693 posts had no faces. The difference between weekday and weekend is less than the Atlanta Beltline. The average posting number for the High Line on a weekend day was 429.5 (coefficient of variation 32%); while, the average weekday posting stood at 355.4 (coefficient of variation 30%). The High Line showed lower volatility, given its lower coefficient of variation. This could also be seen from daily posting patterns in Figure 1, where the High Line did no't have big spikes and drops as the Atlanta Beltline did.

Facical attributes and detected objects

As Figure 2 shows, the left *Y* axis represents the ratio of smiles in detected faces. Both pink and blue curves of Atlanta Beltline (combined average 70%) show higher values than The Highline (combined average 58%). This indicates that user faces in Atlanta Beltline Instagram photos are more likely to smile than The High Line. There was also a consistent pattern that female faces had higher ratios of smiling (roughly 1.5 times of male) for both sites. People take pictures when they are happy, and smiling faces are normal in social media photos like Instagram or Facebook. However, smile intensities represented in social media photos are strong predictors of long-term well-being (Seder and Oishi, 2012). The long-term patterns of smiling faces detected from Instagram photos could be an indirect indication of how park visitations contribute to user well-beings. Although the number of smiling faces detected in Instagram postings cannot represent all users, we believe this analysis still has the potential to compare user sentiment for different sites or different times when other variables were controlled.

Since our CV algorithms only detect foreground faces, we detect major faces in the photo that are usually friends or companions during the trip. Therefore, we use the face counts in each photo as a measure of social interactions. When three and more faces are seen in a photo, we count it as social activities. 1–2 faces photos were categorized as family or companion activities. The 2017 distribution charts (Figure 3) show that more photos with 1–2 faces (gray color) were detected than photos with 3+ faces (pink color) for both sites. The High Line has a higher percentage of photos with 3+ faces (average 14.0%) than Atlanta Beltline (average 6.65%). The peak for photos of 3+ faces is in early Sept. in the Atlanta Beltline, versus late May for the High Line.

The compositions of user age groups and genders are shown in Figure 4. 18–34-year-olds are the biggest age group for both genders and sites. 12–17-year-olds, mostly teenagers, are the least seen group across all categories. A discernible difference between the two sites is the male group between 35 and 64, where the High Line recorded a higher percentage (19.25%) than Atlanta Beltline (14.62%). Moreover, 18–34 females of the Atlanta Beltline recorded a higher rate (40.21%) than the High Line (33.73%).

The weekly results for the percentages of four object categories are illustrated in Figure 5. Because our CV model detects cars, buses, trucks as far as 500 ft away, a photo of streets or roads can record very high numbers of vehicles. The vehicle category in the High Line dominated other categories, with an average of 90.3% as lots of photos include the streets in Downtown Manhattan.

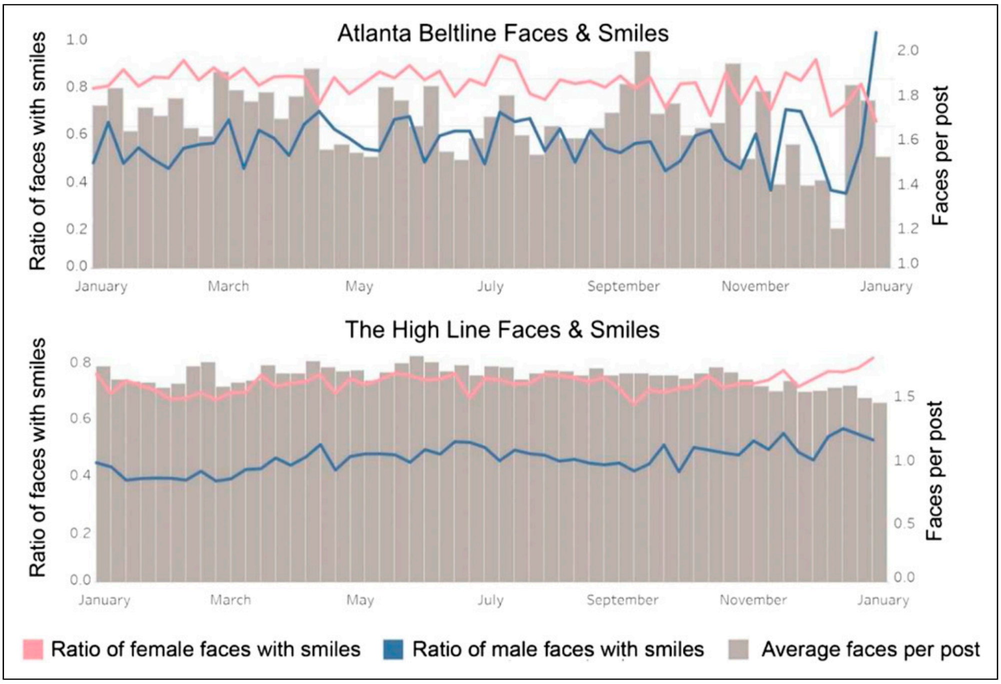

Figure 2. Weekly distributions between average faces (right *Y* axis) and ratio of smiles in detected faces (left *Y* axis).

For the Atlanta Beltline, the categories are more even as the vehicle counted an average of 46%, the pet counted an average of 22.5%, and the bicycle counted 25.9%. The handbag category was the least category in the Atlanta Beltline, while, as the second biggest category in the High Line. Regarding overall distributions, the bicycle category in both sites generally started to increase from January and to peak in the summer months during August or September. The pet category did not show strong patterns for both sites as we did not see significant seasonal differences.

Discussion

Visitations and users

Park engagement. Assuming Instagram postings correlate with the overall real visitation well as seen in previous research (Donahue et al., 2018). The number of photos in our dataset could help indicate the overall park engagement levels for different times. Overall, both the High Line and Atlanta Beltline users recorded significantly higher Instagram postings comparing to a similar study of Freeway park in downtown Seattle (Song and Zhang, 2020). This showed the strong engagement levels and interactions in these two parks and demonstrated how greenways could attract public usage as green infrastructure investment.

From Figure 2, the posting numbers in the winter season are low for the High Line (lower bars on both sides of the distributions). This is different from Bryant Park according to a previous study (Song et al., 2020b) which has shown the highest park engagement during the holiday season in Winter. Our manual readings of Instagram photos also found a lack of activities during winter festivals such as Thanksgiving and Christmas. Cold and windy climate plus dormant plants may have affected the High Line's attractiveness to people.

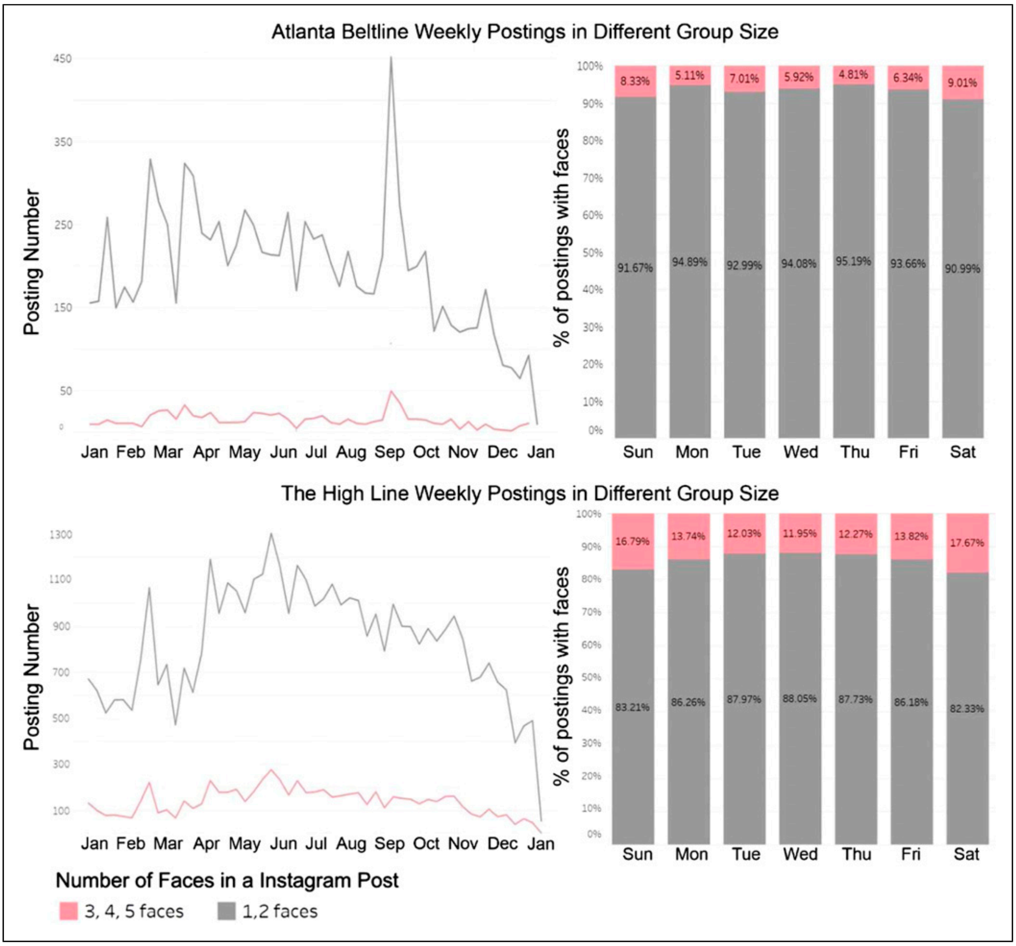

Figure 3. Distributions of postings in different group size.

It is common sense that more people visit parks during weekend than weekdays. But the High Line had more weekday postings than Atlanta Beltline according to Figure 1. Located in Manhattan, NYC which has a denser and a more walkable street network. For many local residents, the High line is very accessible to their home or workplace, allowing them to plan short-time trips there during the weekdays. On the other hand, Atlanta Beltline Eastside was located around single-family housing and automobile-oriented commercial developments. The density around the Atlanta Beltline is a lot lower than the High line. Trips to the Atlanta Beltline requires longer time and will not be feasible for many residents during the weekdays.

User compositions. Our user composition results generally align with previous studies (Sim et al., 2020; Veitch et al., 2015). We saw more females than males in both sites (Figure 4). The 64% for females is also higher than the overall female user percentage (51%) on the Instagram platform (Chen, 2020). Most users were adults in the age groups between 18 and 64, while, children, teens, and the elderly were minor. Especially for teens (13–17), both parks only recorded an average of 0.19% of the total. It is common that teens do not take as many Instagram photos as adults with only 3.3% of all Instagram users were teens (Chen, 2020). However, this is still significantly higher (17.3

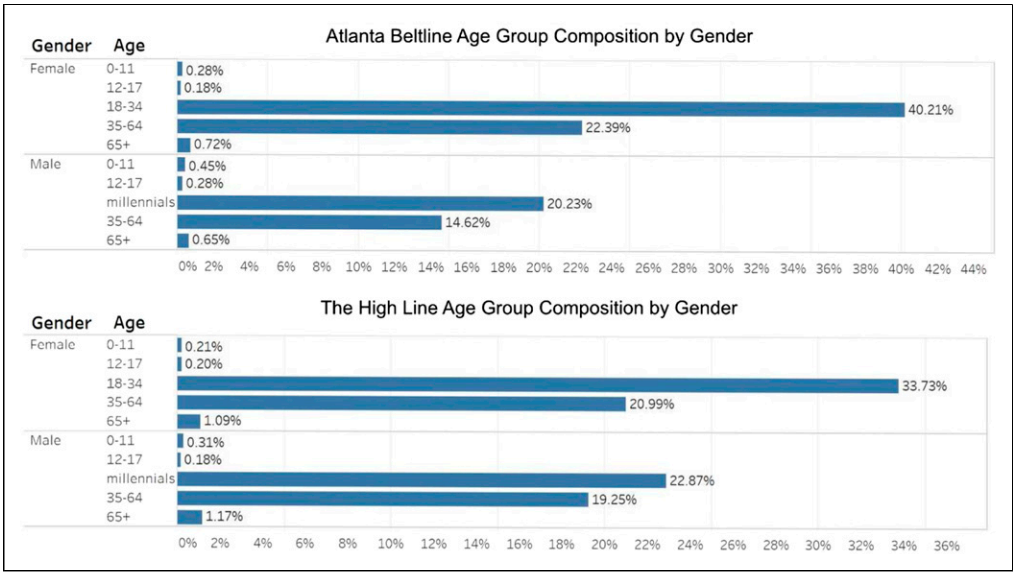

Figure 4. Age group analysis of faces detected.

times) than the teens detected in our data. Both parks lack recreation facilities for teenagers such as basketball courts, mountain biking, and skateboard. It is essential to serve the underserved age groups and design for inclusive greenways.

Indications on user experiences, activities, and interactions

User smiles. Likewise, our results of smiling faces could indicate how the experiences in the two parks mentally impact the users. As Figure 2, both sites generally present stable ratios of smiles in detected faces; there is no significant difference between cold and warm seasons. People shown in the High Line are less likely to smile than those in the Atlanta Beltline. And females tend to smile more than males consistently throughout the year at both sites. This could be a sign that both parks meet female users' needs more than male users.

Group activities. Supportive social interactions have been consistently linked to mental health (Antonucci et al., 2010). From Figure 3, both sites have shown considerable group activities (3+ faces). The ratio of group images almost reached the level of larger city parks such as Lincoln Park in Chicago (Tinsley et al., 2002). The High Line has attracted a higher percentage of group activities than the Atlanta Beltline. The big spike of group activities during September in Atlanta Beltline may come from a famous art Parade activity. The High Line, on the other hand, was developed from an old railway track which has limited width. Big spikes of events and gatherings were rarely seen, but tours, yoga classes, and small concerts or art exhibitions frequently took place there. Overall, our results proved that greenways, if designed and programmed appropriately, were not just trails or paths for mobility purposes but also public spaces that could provide a considerable amount of social interactions and events.

Park users through objects detected. Regarding our object detection results (Figure 5), we found all four categories are useful to inform park usage and experiences directly or indirectly. The number of vehicles in photoes can be associated with visitors' restorative experiences, as people are more

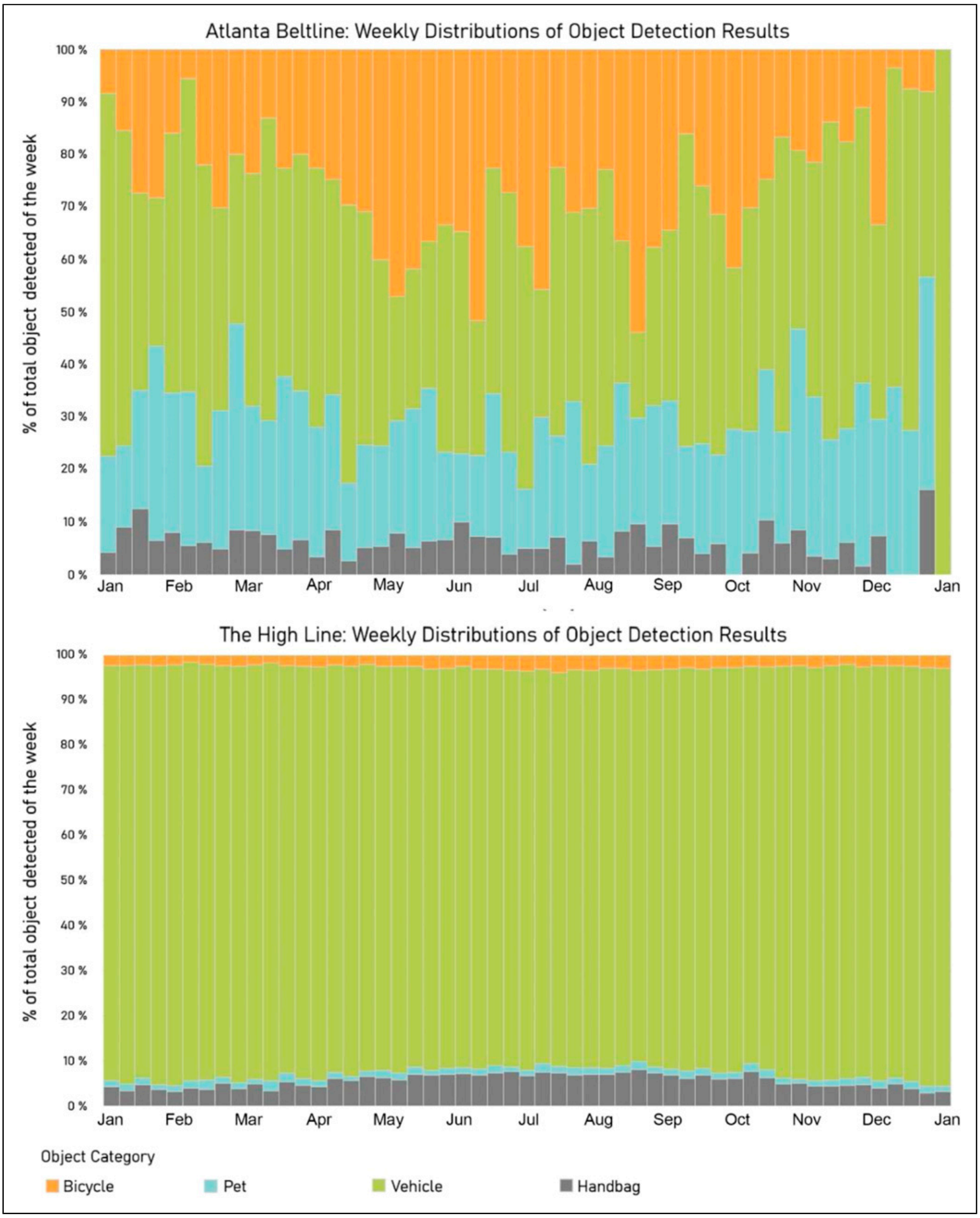

Figure 5. Distributions of object detection results by percentage compositions.

likely to feel an escape from the city and the sense of wilderness in nature (Zoderer et al., 2020). The Vehicle category was the most seen element in people's Instagram posts in the High Line, and we found that people like to take photos at the intersection between the High Line and the streets below. In comparison, Atlanta Beltline was secluded from city traffic with few vehicles seen. Handbags are indirect indications of likely trip purposes of Female users who normally with their Handbags when attending social events, taking a walk, sight viewing, or relaxing instead of exercising. So more handbags seen in the High Line may indicate a lower level of usage of physical exercises for females. This resonates with Sim et al. (2020) who found that the High Line could not accommodate high-intensity physical activities. Elevated urban greenways have limitations to support physical activities since facilities such as bike lanes, skate ramps, drainages, and fences are usually more expensive to construct. Pets and Bicycles are not so productive to compare our two cases since the High Line has so few of them. However, they are good indications for physical activities shown in Atlanta Beltline.

Significances and limitations

In our opinion, understanding public space usage is one of the most fundamental works in landscape architecture and urban design because it will be challenging to plan and design spaces for people without knowing how people are using them. However, most urban park managers do not have the resources to collect comprehensive or even preliminary data on park users (Godbey et al., 2005; Walls, 2009). Researchers are also constrained in collecting large data samples for an extended period (White et al., 2019). This is especially true for urban greenway studies given their long lengths and extensive coverages in cities.

We presented a possible solution at scale by showing the potential of using Instagram data as a proxy to investigate greenway park usages in urban cities. Similar to previous visual preference survey methods (Nassauer et al., 2009), Instagram postings, which are self-reported experiences and represent real user engagements, provide rich visual content that could reveal park visitations patterns, users, activities, and social interactions (Donahue et al., 2018; Kang et al., 2019; Sessions et al., 2016). They are great resources for landscape architecture and urban design research studying topics in sense of place, cultural landscapes, mental health, physical activities, place activation, etc. (Shaw et al., 2016; Ye and Liu, 2018).

Computer Vision, as an important emerging technology, will transform how researchers perceive human-environment relationships. Ready-to-use CV technologies, such as pre-trained YOLO models, are widely available to the public and can be used in many settings (urban, rural, indoor, outdoor, etc.) especially for urban designers and landscape architects who have few computer science background.

Future studies should develop customized CV datasets to correctly detect water features, sculptures, seatings, food items, take-out bags, cell phones, strollers, playgrounds, sports field, etc. Technologies in vision-based human activity recognition could be applied on detecting jogging or sitting in social media photos. Scene studies could be developed to analyze “views” or what constitutes a scene ”worthy of a post?" It is also important to compare the different perceptions between local residents and tourists. Human perceptions are an important component for urban studies. Our research did present some indirect links between sentiment and smiles, group size and social interactions, vehicle numbers, and restorative experiences (escape from the city). However, future studies may look for ways to integrate social media data with surveys or interviews to directly measure human perceptions.

Like many other social media studies (Ghermandi and Sinclair, 2019), our data was limited to certain demographics with Instagram accounts even though the Instagram usage rate is growing. Some amount of advertising account, bots, and fake account could also confound our results (we exclude some during our manual browsing). We do not know if our data reflect local residents or tourists and did not standardize through local population. Our face detection results may not reflect all users since only 42% of our Instagram photos have human faces. The difficulties of defining exact spatial boundaries that our data represents also lead to selection bias in our results. The difficulties of obtaining specific geo-location info from Instagram posts limit the applicability to inform park design and planning. The CV techniques only effectively detect several frequent activities. We are not able to depict the full picture of how the parks were used. Regarding to the gender and age inference, an earlier assessment by Jung et al. (2018) shows that the results from FacePlusPlus are reliable on gender (accuracy >0.92), but less confident on age (average minimum error = −0.89, average maximum errors = 6.4). A new assessment of current face attributes detection is needed to reflect the performance of the evolving technology. Lastly, our park activity indications were made based on empirical assumptions. For example, if we see pets in a photo, we assume the users were walking a dog or likely having more physical activities. This might not always be the case.

Conclusion

In this study, we examined and analyzed the usage of two influential greenway projects, including the High Line in New York City and Atlanta Beltline in Atlanta. By harnessing Instagram posting data and CV technology, we gain insights on who are the greenway users and how the greenway was used.

In summary, common characteristics found in two parks include (1) both greenways have shown strong value to attract public use as we found high Instagram engagement levels; (2) a considerable amount of group activities were detected, indicating the potential of enhanced social interactions and events of greenway; (3) more female users were found, and they tend to be more satisfactory to greenway experiences than males; and (4) less than expected teenager users were shown, indicating the lack of teenager amenities.

Major differences of the two greenways include (1) Atlanta Beltline is showing lower weekday visitations relative to the weekend days. This difference may come from lower connectivity and urban density in Atlanta Downtown area where people have to plan for longer trips to visit the park. (2) Since The High Line is elevated, users could see city street scenes from above. More vehicles were seen in Instagram photos of The High Line, indicating a weaker sense of connection with nature and escape of the city. (3) The High Line has shown fewer physical activities than Atlanta Beltline, such as running and biking. Elevated greenways may be limited to accommodate high-intensity physical activities.

These common and different characteristics that we found could potentially inform future designing and managing greenway parks. They also showed the promising usage of social media photos to understand urban greenways and the potential of applying artificial intelligence, such as pre-trained CV models, as an analytical tool to understand the user behavior of the built environments in urban areas.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The research was supported by National Science Foundation (NSF) under grants SMA-2122054 and OAC-2112356, Texas A&M University Harold L. Adams Interdisciplinary Professorship Research Fund, and College of Architecture Faculty Startup Fund. The funders had no role in the study design, data collection, analysis, or preparation of this article.

Supplemental Material

Supplemental material for this article is available online.

References

Ahern J (2013) Urban landscape sustainability and resilience: the promise and challenges of integrating ecology with urban planning and design. *Landscape Ecology* 28(6): 1203–1212.

Akpinar A (2016) Factors influencing the use of urban greenways: a case study of Aydın, Turkey. *Urban Forestry & Urban Greening* 16: 123–131.

Antonucci TC, Fiori KL, Birditt K, et al. (2010) Convoys of social relations: integrating life-span and life-course perspectives. In: Lamb, M. E. and Freund, A. M. (eds) *The handbook of life-span development, social and emotional development*. Hoboken, NJ: John Wiley & Sons, Vol. 2, 434–473. DOI: 10.1002/9780470880166.hlsd002012

Atlanta Beltline Awards (2020). Atlanta Beltline Awards. https://beltline.org/tag/atlanta-beltline-awards/

Bedimo-Rung AL, Mowen AJ and Cohen DA (2005) The significance of parks to physical activity and public health: a conceptual model. *American Journal of Preventive Medicine* 28(2): 159–168.

Boone CG, Buckley GL, Grove JM, et al. (2009) Parks and people: an environmental justice inquiry in Baltimore, Maryland. *Annals of the Association of American Geographers* 99(4): 767–787.

Chen J (2020) *Important Instagram Stats You Need to Know for 2020*. Available at: https://sproutsocial.com/insights/instagram-stats/.

Chen X, Li G, Yang L, et al. (2020) Profiling unmanned aerial vehicle photography tourists. *Current Issues in Tourism* 23(14): 1705–1710.

Chon J and Scott Shafer C (2009) Aesthetic responses to urban greenway trail environments. *Landscape Research* 34(1): 83–104.

Donahue ML, Keeler BL, Wood SA, et al. (2018) Using social media to understand drivers of urban park visitation in the Twin Cities, MN. *Landscape and Urban Planning* 175: 1–10.

Dallat MAT, Soerjomataram I, Hunter RF, et al. (2014) Urban greenways have the potential to increase physical activity levels cost-effectively. *European Journal of Public Health* 24(2): 190–195.

Fongar C, Aamodt G, Randrup TB, et al. (2019) Does perceived green space quality matter? linking Norwegian adult perspectives on perceived quality to motivation and frequency of visits. *International Journal of Environmental Research and Public Health* 16(13): 2327.

Flowers EP, Freeman P and Gladwell VF (2016) A cross-sectional study examining predictors of visit frequency to local green space and the impact this has on physical activity levels. *BMC Public Health* 16(1): 420–428.

Ghermandi A and Sinclair M (2019) Passive crowdsourcing of social media in environmental research: a systematic map. *Global Environmental Change* 55: 36–47.

Godbey GC, Caldwell LL, Floyd M, et al. (2005) Contributions of leisure studies and recreation and park management research to the active living agenda. *American Journal of Preventive Medicine* 28(2): 150–158.

Hamilton K, Kaczynski AT, Fair ML, et al. (2017) Examining the relationship between park neighborhoods, features, cleanliness, and condition with observed weekday park usage and physical activity: a case study. *Journal of environmental and public health* 2017: 7582402.

Heikinheimo V, Minin ED, Tenkanen H, et al. (2017) User-generated geographic information for visitor monitoring in a national park: a comparison of social media data and visitor survey. *ISPRS International Journal of Geo-Information* 6(3): 85.

Jamonnak S, Zhao Y, Curtis A, et al. (2020) GeoVisuals: a visual analytics approach to leverage the potential of spatial videos and associated geonarratives. *International Journal of Geographical Information Science* 34(11): 1–21.

Jung S-G, Kwak AJ, Salminen H, et al. (2018) *Assessing the Accuracy of Four Popular Face Detection Tools for Inferring Gender, Age, and Race*. Stanford, CA: ICWSM.

Kang Y., Jia Q., Gao S., et al. (2019) Extracting human emotions at different places based on facial expressions and spatial clustering analysis. *Transactions in GIS* 23(3): 450–480.

Li S., Ye X., Lee J., et al. (2017) Spatiotemporal analysis of housing prices in China: a big data perspective. *Applied Spatial Analysis and Policy* 10(3): 421–433.

Li X (2020) Examining the spatial distribution and temporal change of the green view index in New York City using Google street view images and deep learning. *Environment and Planning B: Urban Analytics and City Science* 48(1): 2039–2054.

Lin TY, Maire M, Belongie S, et al. (2014) Microsoft coco: Common objects in context. In: European conference on computer vision, Zurich, Switzerland, 6–7 and 12 September 2014. Cham: Springer, 740–755.

Liu L, Ouyang W, Wang X, et al. (2020) Deep learning for generic object detection: a survey. *International Journal of Computer Vision* 128(2): 261–318.

Liu W, Anguelov D, Erhan D, et al. (2016) Ssd: Single shot multibox detector. In: European conference on computer vision, Amsterdam, The Netherlands, 8–16 September 2014. Cham: Springer, 21–37.

Masi I, Wu Y, Hassner T and Natarajan P (2018) Deep face recognition: A survey. *In 2018 31st SIBGRAPI conference on graphics, patterns and images (SIBGRAPI)*.

Nassauer JI, Wang Z and Dayrell E (2009) What will the neighbors think? Cultural norms and ecological design. *Landscape and Urban Planning* 92(3–4): 282–292.

Ning H, Ye X, Chen Z, et al. (2021) Sidewalk extraction using aerial and street view images. *Environment and Planning B: Urban Analytics and City Science*. Published online. DOI: 10.1177/2399808321995817

Paneerchelvam PT, Maruthaveeran S, Maulan S, et al. (2020) The use and associated constraints of urban greenway from a socioecological perspective: a systematic review. *Urban Forestry & Urban Greening* 47: 126508.

Patil PPR, Pramod R and Sandhya S (2018) A General Approach on Facial Feature Extraction and Face Attributes. *In 2018 3rd International Conference on Computational Systems and Information Technology for Sustainable Solutions (CSITSS)*.

Redmon J and Farhadi A (2018) Yolov3: An Incremental Improvement. *arXiv Preprint*.

Rettberg JW (2017) Self-representation in social media. In: Burgess J, Marwick A and Poell T (eds) *SAGE handbook of social media*. Thousand Oaks, CA: SAGE, 429–443.

Seder JP and Oishi S (2012) Intensity of smiling in Facebook photos predicts future life satisfaction. *Social Psychological and Personality Science* 3(4): 407–413.

Sessions C, Wood SA, Rabotyagov S, et al. (2016) Measuring recreational visitation at US national parks with crowd-sourced photographs. *Journal of Environmental Management* 183: 703–711.

Shaw SL, Tsou MH and Ye X (2016) Human dynamics in the mobile and big data era. *International Journal of Geographical Information Science* 30(9): 1687–1693.

Sim J, Bohannon CL and Miller P (2020) What park visitors survey tells us: comparing three elevated parks—the high line, 606, and high bridge. *Sustainability* 12(1): 121.

Song XP, Richards DR and Tan PY (2020a) Using social media user attributes to understand human–environment interactions at urban parks. *Scientific Reports* 10(1): 1–11.

Song Y, Fernandez J and Wang T (2020b) Understanding perceived site qualities and experiences of urban public spaces: a case study of social media reviews in Bryant Park, New York City. *Sustainability* 12(19): 8036.

Song Y, Wang R, Fernandez J, et al. (2021) Investigating sense of place of the Las Vegas Strip using online reviews and machine learning approaches. *Landscape and Urban Planning* 205: 103956. DOI: 10.1016/j.landurbplan.2020.103956.

Song Y and Zhang B (2020) Using social media data in understanding site-scale landscape architecture design: taking Seattle Freeway Park as an example. *Landscape Research* 45(5): 1–22.

Tenkanen H, Di Minin E, Heikinheimo V, Hausmann A, Herbst M, Kajala L and Toivonen T (2017) Instagram, Flickr, or Twitter: Assessing the usability of social media data for visitor monitoring in protected areas. *Scientific reports* 7(1): 1–11.

Tinsley HE, Tinsley DJ and Croskeys CE (2002) Park usage, social milieu, and psychosocial benefits of park use reported by older urban park users from four ethnic groups. *Leisure Sciences* 24(2): 199–218.
Veitch J, Carver A, Abbott G, et al. (2015) How active are people in metropolitan parks? An observational study of park visitation in Australia. *BMC Public Health* 15(1): 610.
Walls M (2009) *Parks and Recreation in the United States: Local Park Systems.Resources for the Future*. Available: http://www.rff.org/research/publications/parks-and-recreation-united-states-local-park-systems. Viewed (accessed 06 March 2016).
Wang D, Brown G, Liu Y, et al. (2015) A comparison of perceived and geographic access to predict urban park use. *Cities* 42: 85–96.
Wang Y, Jiang W, Liu S, et al. (2016) Evaluating trade areas using social media data with a calibrated huff model. *ISPRS International Journal of Geo-Information* 5(7): 112.
Wang Z, Lam NS, Obradovich N, et al. (2019) Are vulnerable communities digitally left behind in social responses to natural disasters? An evidence from Hurricane sandy with Twitter data. *Applied Geography* 108: 1–8.
Watson D (2003) *Time-saver Standards for Urban Design*. New York, NY: McGraw-Hill Professional Pub.
White MP, Alcock I, Grellier J, et al. (2019) Spending at least 120 minutes a week in nature is associated with good health and wellbeing. *Scientific Reports* 9(1): 1–11.
Ye X, Li S, Yang X, et al. (2016) Use of social media for the detection and analysis of infectious diseases in China. *ISPRS International Journal of Geo-Information* 5(9): 156.
Ye X and Liu X (2018) Integrating social network and spatial analyses of the built environment. *Environment and Planning B: Urban Analytics and City Science* 45(3): 395–399. DOI: 10.1177/2399808318772381
Ye X, Zhao B, Nguyen TH, et al. (2020) Social media and social awareness. In: Annoni A, Guo H, Goodchild MF (eds) *Manual of Digital Earth*. Singapore: Springer, 425–440.
Zheng X, Guo Y, Huang H, Li Y and He R (2020) A survey of deep facial attribute analysis. *International Journal of Computer Vision* 128(8): 2002–2034.
Zoderer BM, Carver S, Tappeiner U, et al. (2020) Ordering “wilderness”: Variations in public representations of wilderness and their spatial distributions. *Landscape and Urban Planning* 202: 103875.
ASLA Professional Awards (2010). ASLA Professional Awards. Available at: https://www.asla.org/2010awards/index.html

Author Biographies

Yang Song is an assistant professor in Department of Landscape Architecture and Urban Planning at Texas A&M University. His research interests lie in the intersection of environmental psychology, urban design, and public health.

Huan Ning is a doctoral student in Department of Geography at University of South Carolina. His research expertise is on remote sensing and computer vision.

Xinyue Ye holds Harold Adams Endowed Professorship in Department of Landscape Architecture and Urban Planning and directs Urban Data Science Lab at Texas A&M University. His research expertise is on human dynamics and urban informatics.

Divya Chandana is a master student in Department of Informatics at New Jersey Institute of Technology. Her research expertise is on computer vision and web programming.

Shaohua Wang is an assistant professor in Department of Informatics at New Jersey Institute of Technology. His research spans the study of software engineering from system, empirical, and machine learning perspectives.