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Urban Streetscape Changes in Portland, Oregon: A Longitudinal Virtual Audit

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Streetscape imagery has considerable potential for observing urban change. The literature lacks sufficient longitudinal studies, however, on urban change considering human perception and activities. We conducted a longitudinal virtual audit to observe the change in urban liveliness, human activities, and built environment by examining streetscape imagery taken in the late 2000s and the late 2010s in Portland, Oregon. Eleven untrained crowd workers were recruited to provide liveliness ratings of 24,242 streetscape images for both periods. Tabulation, mapping, and multilevel regression analyses were conducted to observe the distribution, changes in liveliness, and the factors affecting these changes. The results confirmed that the city had become livelier during the ten-year study period, which was spatially associated with the increase in pedestrians and cyclists and particular elements of the built environment, such as mid- and high-rise buildings and sidewalk signs. Although these results were somewhat expected, this study's value lies in confirming the potential of virtual audits conducted using Google Street View Time Machine for retrospectively examining subjective and objective urban change. Caution should be exercised, though, while interpreting urban change as temporal conditions (e.g., season, weather, and irregular events) can potentially bias the results in longitudinal studies. **Key Words: liveliness, Portland, streetscapes, urban change, virtual audit.**

As cities grow and decline over time, they experience numerous changes, including urbanization, suburbanization, and gentrification. Urban geography is fundamentally concerned with understanding the various aspects of these changes. Today, health geography, urban planning, and urban sociology researchers are using streetscape imagery (e.g., Google Street View [GSV]) to qualitatively observe and quantitatively characterize the minute details of urban landscapes (Schaefer-McDaniel et al. 2010; Aghaabbasi et al. 2018; Rzotkiewicz et al. 2018; Biljecki and Ito 2021; Cinnamon and Jahiu 2021; Y. Li et al. 2022). This study longitudinally develops this method to examine multifaceted urban changes.

Since the late 2010s, streetscape imagery has often been used to conduct systematic social observations (i.e., virtual audits) to characterize urban built environments (Biljecki and Ito 2021; Cinnamon and Jahiu 2021). For instance, several health geographers have employed this method to measure neighborhood walkability by observing microscale elements such as the presence or absence of sidewalks, street trees, and street furniture (e.g., benches, lights, and road signs) and their conditions (Schaefer-McDaniel et al. 2010; Aghaabbasi et al. 2018; Rzotkiewicz et al. 2018). Compared with traditional in-person audits, which are highly time-intensive and therefore require a narrow study area, virtual audits are more efficient (i.e., save time and cost less) and reliable (Rundle et al. 2011; Kelly et al. 2013; Pliakas et al. 2017; Rzotkiewicz et al. 2018). Moreover, using crowdsourcing to collect ratings by untrained auditors (Hara, Le, and Froehlich 2013; Hanibuchi, Nakaya, and Inoue 2019) and machine learning to evaluate imagery (Nguyen et al. 2018; Nguyen et al. 2019; Suel et al. 2019; Nagata et al. 2020) have helped expand the size of study areas. As the availability of streetscape imagery increased, virtual audit has rapidly expanded in recent years in many research fields. A recent systematic review that reviewed 250 papers provided a comprehensive picture of the research trends in this method (Biljecki and Ito 2021). They have concluded that street-view imagery is an entrenched component of urban analytics and GISience, and it is applied to myriads of research domains across the analysis of vegetation, transportation, health, and socioeconomic studies.

The use of historical images is promising but currently limited in audit studies to examine temporal changes in urban streetscapes (Biljecki and Ito 2021; Cinnamon and Jahiu 2021). Google Street View Time Machine (GSV-TM) provides archived images accumulated since the late 2000s, which can be used to retrospectively observe changes in urban streetscapes. Such information is useful not only for describing urban changes but also for analyzing changes in how people relate to places. For example, in the study of neighborhood and health, it can be useful information for causal inference between

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neighborhood environment and population health because modifications to the built environment can be regarded as interventions (Cândido et al. 2018). Limited longitudinal studies have been conducted to track urban changes (Biljecki and Ito 2021; Cinnamon and Jahiu 2021), except for some recent studies on traffic calming features (Cândido et al. 2018), food retailers (Cohen, Chrobok, and Caruso 2020), green view index (X. Li 2021), vacant land greening (Gobster et al. 2020), and gentrification (Hwang and Sampson 2014; Ilic, Sawada, and Zarzelli 2019; Ravuri 2022; Thackway et al. 2023).

Gentrification might be one of the most suitable topics for applying this method, as it often involves upgrades to the built environment (e.g., remodeled or newly built houses, condominiums, shops, and restaurants), an influx of affluent residents, and displacement of long-term residents. Thus, GSV audit can be a useful method to observe multidimensional understandings of gentrification by providing indicators of physical changes in addition to census-based socioeconomic indicators (Thackway et al. 2023). In fact, some recent studies have begun to use GSV to track physical changes in buildings and neighborhoods as a visual manifestation of gentrification (Hwang and Sampson 2014; Ilic, Sawada, and Zarzelli 2019; Ravuri 2022; Thackway et al. 2023). Gentrification, or urban change in general, might involve building upgrades and population changes, how people behave and use urban spaces, and the overall atmosphere and impression of the city. Therefore, more studies are needed to observe the diverse aspects of urban changes.

One such aspect is the nonbuilt environmental elements, namely, the activities and perceptions of people. Some cross-sectional studies have applied virtual audits to track the traffic flow at specific locations and people's transportation behaviors such as walking and cycling (Yin et al. 2015; Campanella 2017; Goel et al. 2018; Chen et al. 2020) and their perception or evaluation of the streetscape images such as liveliness, safety, and beauty (Naik et al. 2017; Zhang et al. 2018; Qi et al. 2020; Kang, Fan, and Jiao 2021; Larkin et al. 2021; Larkin et al. 2022). These studies are few, however, compared with those focusing on the built environment. Moreover, little longitudinal research has been conducted to track urban changes while focusing on people's activities and perceptions of urban places. Two exceptions are Naik et al.'s (2017) study regarding changes in the predicted street score (perception of safety) and Campanella's (2017) study examining the distribution of people in public spaces by counting the number of people, bicycles, and graffiti.

Changes in the built environment could accompany changes in people's behavior and perception. Hence, understanding whether GSV-TM is suitable for capturing such integrated changes in urban spaces through the lens of streetscape imagery is an important methodological concern. Therefore, in this study, we performed longitudinal virtual audits in Portland, Oregon, to observe its multifaceted urban changes. We chose Portland as our study site mainly because this city has experienced considerable urban growth and gentrification in recent years, and such changes in the streetscapes are expected to be reflected in the form of increased human activity and liveliness, as well as changes in the built environment. Considering this context, our study describes the changes in Portland's urban liveliness as perceived from the streetscape imagery between the late 2000s and the late 2010s to determine whether such changes are associated with the changes in the built environment and human activities captured in the streetscape images.

Urban liveliness is key to a vibrant, attractive, and livable city; the concept can be traced back to Jacobs's (1961) seminal work. In urban design and planning, cities and neighborhoods with lively streets are expected to have the ability to become more community-centered and civic-minded, healthy, inclusive, and ultimately more livable and sustainable (Mehta and Bosson 2021). Researchers have reported the various determinants of liveliness that cover human activity and built environment, such as the presence of humans, shop fronts, land-use mix, commercial and public seating, and community-gathering places (Mouratidis and Poortinga 2020; Qi et al. 2020; Mehta and Bosson 2021). Thus, the perception of liveliness, in combination with human activity and the built environment, is considered a good indicator of whether the multifaceted urban changes can be captured by the virtual audit relying on GSV-TM.

Methods

Sampling and Image Collection

Portland is the largest city in Oregon, with a population of approximately 650,000, and its metropolitan area has around 2.5 million people (according to the 2020 Census). The city has been developed along the Willamette River, which runs south to north and physically divides the city east and west (Figure 1). The city center has long been located on the west side of the river, although the recent urban redevelopment has expanded beyond the river (e.g., the Central Eastside). The population had increased from 583,776 in 2010 to 652,503 in 2020 (an increase of 11.8 percent, according to the census). Moreover, data from the American Community Survey 5-Year Estimates indicate that the percentages of the population of twenty-five years and older with a bachelor's degree or higher have increased from 41.1 percent (2006–2010) to 51.0

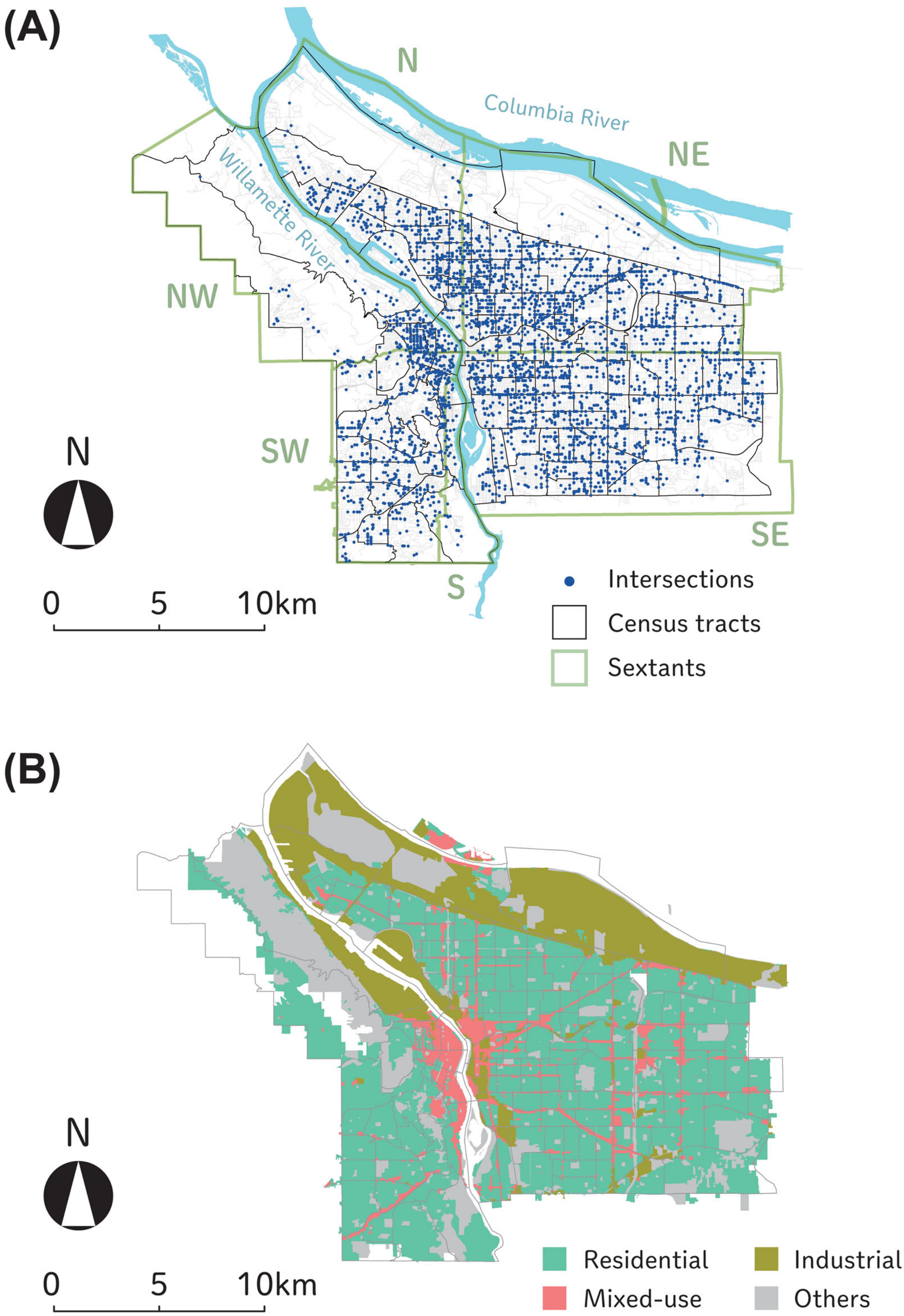

Figure 1 *Study area: (A) target tracts and intersections, (B) zoning classification.*

percent (2016–2020), and median household income (dollars) increased from \$48,831 (2006–2010) to \$73,159 (2016–2020), both of which can be indicators of gentrification.

The study area includes 142 census tracts with centroids that fall within the city of Portland (Figure 1). In correlation with the map in Figure 1 showing the distribution of zoning classification (residential, mixed-use, and industrial areas), population and (re)development are more concentrated in the city center, Downtown, and the Central Eastside. Nevertheless, we targeted the entire city, including outer Portland, to capture the variation and changes in the streetscape elements. To widely cover locations across Portland and to observe places where changes in both built- and nonbuilt environments are apparent while minimizing the number of images used for the manual audit, we randomly sampled up to twenty-five intersections from each of the 142 census tracts. The eligible intersections were three-way or more, excluding freeway, and where GSV images were available both in the late 2000s (2007–2009) and the late 2010s (2015–2018). All intersections were selected for the tracts where eligible intersections were less than twenty-five. The resulting sample contained 3,508 intersections. Although the sampled intersections seem somewhat concentrated due to the small areas of tracts in the central part, they were widely distributed across the city. The street-view images were obtained using the Street View Static API for each street direction of the sampled intersections in two time periods: the late 2000s and the late 2010s; that is, eight images were obtained from each four-way intersection. Consequently, we obtained 24,242 images in total. The numbers of images were as follows: 10,271 (2007), 1,850 (2009), 1,621 (2015), 6,140 (2016), 3,803 (2017), and 557 (2018) by year taken, and 4,588 (spring), 16,179 (summer), 2,662 (fall), and 813 (winter) by seasons. In the late 2000s, most images were taken in summer (86.1 percent), whereas no images were taken in winter. The distribution of seasons was relatively balanced in the late 2010s, although summer (47.3 percent) was still the most prevalent and winter (6.7 percent) was the least.

Conducting a Virtual Audit

A virtual audit was conducted manually by auditors. Several recent studies have recruited auditors via crowdsourcing (i.e., crowd workers) to conduct virtual audits, as their ratings have shown sufficient reliability (Hara, Le, and Froehlich 2013; Hanibuchi, Nakaya, and Inoue 2019). Hence, to conduct our virtual audit, we recruited eleven untrained crowd workers from the crowdsourcing platform Lancers, one of the largest crowdsourcing platforms in Japan. As these crowd workers were to manually audit the study site, we provided them with an easy-to-use checklist with brief instructions about the process.

As shown in Table 1, the virtual audit was designed to capture the features of streetscapes in the built environment (considering ten items such as sidewalks, street trees, and buildings) and human activities (pedestrians, cyclists, and people walking dogs), as well as the auditors' perceived impression of the images (i.e., subjective ratings of liveliness). We selected these items because (1) they were observable in GSV, (2) they were possibly related to the liveliness and thus could be good indicators of urban change, and (3) they were easily observable by even untrained crowd workers. A checklist for untrained crowd workers must be simple, easy to understand, and minimal in the number of audited items (Hanibuchi, Nakaya, and Inoue 2019). Thus, although the checklist is not comprehensive and not

Table 1 *A Summary of the checklist for virtual audit*

Variables	Description in the checklist	Categories
Perception		
Liveliness	Which is closer to your subjective impression? *Please answer based on how you feel when you see the image	Lively, ←, middle,→ , deserted
Human activities		
Pedestrians	The number of people walking. Do not include those sitting or in vehicles.	0, 1–4, 5–9, 10 or more
Cyclists	Cycling or walking a bike. Do not include parked bikes.	Yes, no
People walking dogs	The presence of dogs or not, regardless of their behavior.	Yes, no
Built environment		
Sidewalks	Sidewalks physically distinguished from the road.	Yes, no
Crosswalks	Crosswalks marked by paint.	Yes, no
Bike signs	Bike lane sign (symbols or text) painted on the street.	Yes, no
Surface problems	Holes, steps, or cracks on the street surface.	Yes, no
Street trees	Trees along the street (including trees in gardens or trees without leaves). Do not include mountains in the distance.	Many, some, few, almost none
Mid–high-rise buildings	Buildings of three stories or more. Do not include bridges or towers.	Yes, no
Sidewalk signs	Frame signs for shops placed on sidewalks.	Yes, no
Construction	Road or building construction sites.	Yes, no
Graffiti	Graffiti on walls, doors, or street. Do not include murals.	Yes, no
Spacious parking lots	Parking lot that seems to have space for 10 or more cars. Do not include street parking.	Yes, no

a validated tool for specific purposes (e.g., walkability), it was developed for the exploratory purpose of this study by referring to some existing audit tools such as Pedestrian Environmental Data Scan (Clifton, Livi Smith, and Rodriguez 2007) and Microscale Audit of Pedestrian Streetscapes-global (Cain et al. 2018). Except for the number of pedestrians, the presence of street trees, and people's perception of liveliness, responses were dichotomous (i.e., yes or no) to keep the checklist as simple as possible. The instructions provided with the checklist gave details for each item with relevant images as examples.

The 142 census tracts were assigned to eleven crowd workers (a maximum of twenty tracts per crowdworker), who rated all images taken in two periods in each tract. Hence, the difference in the ratings between the two time points at a certain place was not attributable to the differences in auditors. To avoid an order effect, images were randomly ordered within the tracts; thus, the auditors rated each image without knowing when it was taken.

We prepared a sample data set of 142 images (i.e., one image from each tract) to conduct a reliability test. Two trained auditors created a gold standard, and the percentages of the agreement were evaluated for each of the eleven crowd workers. Overall, the percentage of agreement was very good (89.3 percent), indicating that they were quite consistent in their ratings. These eleven crowd workers were unfamiliar with the streetscapes of Portland because they were recruited by the crowdsourcing platform in Japan. Their reliability, however, was almost the same as that of the other two auditors (89.1 percent), who were additionally chosen from Portland State University for the reliability test, suggesting that familiarity with the region did not result in bias (Zhu et al. 2017).

Main Outcome: Perception of Liveliness

The liveliness perceived from the streetscape imagery and the change in liveliness between the late 2000s and the late 2010s were the outcome variables in this study. We collected perception ratings for streetscape imagery by asking, "How lively is the area?" using a five-point scale ranging from *lively* to *deserted*. A supplemental explanation to the question was further noted: "Which is closer to your subjective impression? Please answer based on how you feel when you see the image." For each year in two study periods, the liveliness rating was coded from 5 (*lively*) to 1 (*deserted*), and the change in liveliness was defined as the score for the late 2010s minus the score in the late 2000s, which was treated as a continuous variable (ranging from −3 to 3, as there were no cases with ratings of −4 or 4).

Independent Variables: Human Activities and Built Environments

The independent variables included both human activities and built environment elements. For human activities, the virtual audit captured the number of pedestrians (0, 1–4, 5–9, and 10 or more), the presence of cyclists, and the presence of people walking dogs. Under built environments, the audit captured the presence of sidewalks, crosswalks, bike signs, surface problems, mid–high-rise buildings, sidewalk signs, constructions, graffiti, and spacious parking lots, as well as street trees (measured on a four-point Likert scale). In the cross-sectional regression analysis, the number of pedestrians and street trees were transformed into continuous variables and standardized to 0 indicating the lowest and 1 indicating the highest concentration. In the longitudinal analysis, all these variables were coded as 1 (*increased*), 0 (*unchanged*), and −1 (*decreased*).

We also considered seasons and weather, as they could affect the number of people on the streets and the auditors' impressions perceived from the imagery. The auditors marked the weather as fine or cloudy/rainy, depending on the cloud cover percentage (50 percent or more was regarded as cloudy/rainy). To consider the differences in season and weather between the two time periods while minimizing the number of categories, we created six categories of seasons (spring/fall to spring/fall, spring/fall to summer, spring/fall to winter, summer to spring/fall, summer to summer, summer to winter) and four categories of weather (fine to fine, fine to cloudy/rainy/unknown, cloudy/rainy/unknown to fine, cloudy/rainy/unknown to cloudy/rainy/unknown). Additionally, we used the years between the two time periods, regional prefixes (N, NW, NE, S, SW, SE), and zones (residential, mixed-use, industrial, others) as covariates representing basic temporal and geographical settings, which might be associated with the urban changes. The spatial data for prefixes, zones, street lines, and city boundaries were sourced from the PortlandMaps Open Data (see https://gis-pdx.opendata.arcgis.com/).

Analysis Procedure

First, we tabulated the liveliness, human activities, and built environment variables to show their overall distribution and temporal changes. Spatial distribution of the changes in liveliness and the number of pedestrians—one of the strongest predictors of liveliness—were then mapped using the kriging method of spatial interpolation and local Moran's I to observe the areas with increased or decreased liveliness over time. Three-level multilevel regression models were fitted to both cross-sectional data in the late 2000s and the late 2010s as well as longitudinal data between the 2000s and 2010s to investigate the factors associated with liveliness and its change. Considering the distribution of the dependent variables, ordered logit and linear models were used for cross-sectional and longitudinal data, respectively. We used the intersection (Level 2) and tracts (Level 3) as group variables and included a dummy variable for each auditor to adjust for personal differences in the ratings. There was no serious multicollinearity among the independent variables (all variance inflation factor equivalent scores of generalized variance inflation factor were less than two).

Results

Table 2 shows the overall distribution and differences of streetscape elements, as observed by the virtual audits in the late 2000s and the late 2010s. Responses regarding liveliness were more distributed toward *deserted* than *lively*, although the *middle* gained the most responses. Among the streetscape elements, sidewalks were the most prevalent (≥ 80 percent), whereas people walking dogs, cyclists, and graffiti were the least prevalent (≤ 2 percent). Pedestrians were present in only 10 percent or less of images in both periods. These results could reflect the stratified sampling of intersections by census tracts (i.e., the intersections were distributed across Portland, including all land-use areas). Thus, the images taken around the city center and populated areas were only one part of our samples. Regarding the changes over approximately ten years, the results confirmed that overall, many places have become livelier. The distribution of the responses shifted toward *lively* in the late 2010s: The number of places rated as *lively* increased by 53 percent, whereas those rated as *deserted* decreased by 17 percent. The number of pedestrians (more than one person), cyclists, and people walking dogs increased by 32 percent, 37 percent, and 69 percent, respectively. The number of built environment elements also increased: Bike signs and graffiti had more than doubled (increased by 162 percent) and almost doubled (increased by 91 percent), respectively.

Figures 2 and 3 present the spatial distribution of the changes in liveliness and pedestrians between the two study periods. Overall, the maps show a complicated distribution rather than simple trends of the places that became *livelier* or more *deserted*. For example, increased liveliness was observed in Humboldt and Boise (including areas surrounding Mississippi Avenue and Williams Avenue), North Pearl and Slabtown, Kenton, and Eastmoreland, whereas Downtown showed no increase in liveliness. Decreased liveliness was seen in southeast and southwest Portland neighborhoods, such as Hillsdale and areas around Hawthorne Boulevard, Division Street, and Powell Boulevard. Although the number of pedestrians is a strong predictor of liveliness (described later), the map showed different patterns: The increase in the number of pedestrians was concentrated in pedestrian-friendly commercial

Table 2 *Distribution and differences of the streetscape elements in the late 2000s and the late 2010s*

		The late 2000s		The late 2010s				
		n	%	*n*	%	Differences	Ratios	*p* value[a]
Liveliness	Deserted	1,512	12.5	1,250	10.3	–2.2	0.8	0.000***
	←	4,509	37.2	3,882	32.0	–5.2	0.9	
	Middle	4,891	40.4	5,539	45.7	5.3	1.1	
	→	1,117	9.2	1,309	10.8	1.6	1.2	
	Lively	92	0.8	141	1.2	0.4	1.5	
Pedestrians	0	11,205	92.4	10,910	90.0	–2.4	1.0	0.000***
	1–4	879	7.3	1,155	9.5	2.3	1.3	
	5–9	25	0.2	45	0.4	0.2	1.8	
	10 or more	12	0.1	11	0.1	0.0	0.9	
Cyclists	Presence	108	0.9	148	1.2	0.3	1.4	0.012*
People walking dogs	Presence	35	0.3	59	0.5	0.2	1.7	0.017*
Sidewalks	Presence	9,701	80.0	9,893	81.6	1.6	1.0	0.002**
Crosswalks	Presence	1,316	10.9	1,522	12.6	1.7	1.2	0.000***
Bike signs	Presence	224	1.8	588	4.9	3.0	2.6	0.000***
Surface problems	Presence	2,168	17.9	2,740	22.6	4.7	1.3	0.000***
Street trees	Almost none	641	5.3	430	3.5	–1.7	0.7	0.000***
	Few	2,527	20.8	2,372	19.6	–1.3	0.9	
	Some	7,062	58.3	7,513	62.0	3.7	1.1	
	Many	1,891	15.6	1,806	14.9	–0.7	1.0	
Mid–high-rise buildings	Presence	1,170	9.7	1,310	10.8	1.2	1.1	0.003**
Sidewalk signs	Presence	504	4.2	649	5.4	1.2	1.3	0.000***
Construction	Presence	194	1.6	218	1.8	0.2	1.1	0.234
Graffiti	Presence	123	1.0	235	1.9	0.9	1.9	0.000***
Spacious parking lots	Presence	773	6.4	984	8.1	1.7	1.3	0.000***

[a] p values by the chi-square test and Fisher's exact test.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

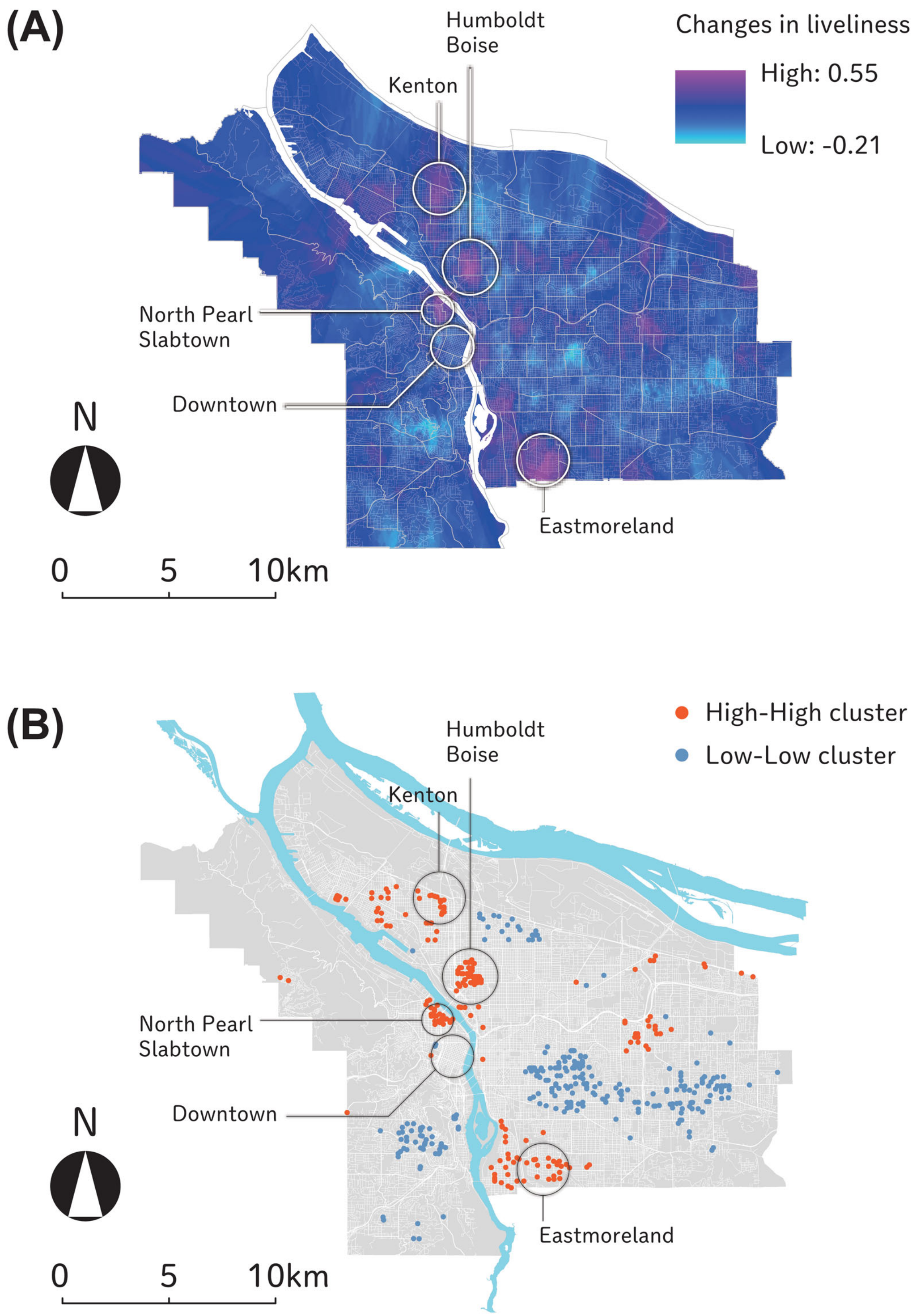

Figure 2 *Spatial distribution of the changes in liveliness by (A) kriging and (B) local Moran's I.*

areas in and around Downtown, as well as in NW 23rd, Kerns, and Hollywood, whereas some areas in north, northeast, and southeast Portland, as well as Providence Park near Downtown, showed a nonincrease or even a decrease.

Table 3 shows the results of the cross-sectional regression analysis of the association between liveliness and human activities, built environment elements, and other environmental variables in the late 2000s and the late 2010s. All audited streetscapes,

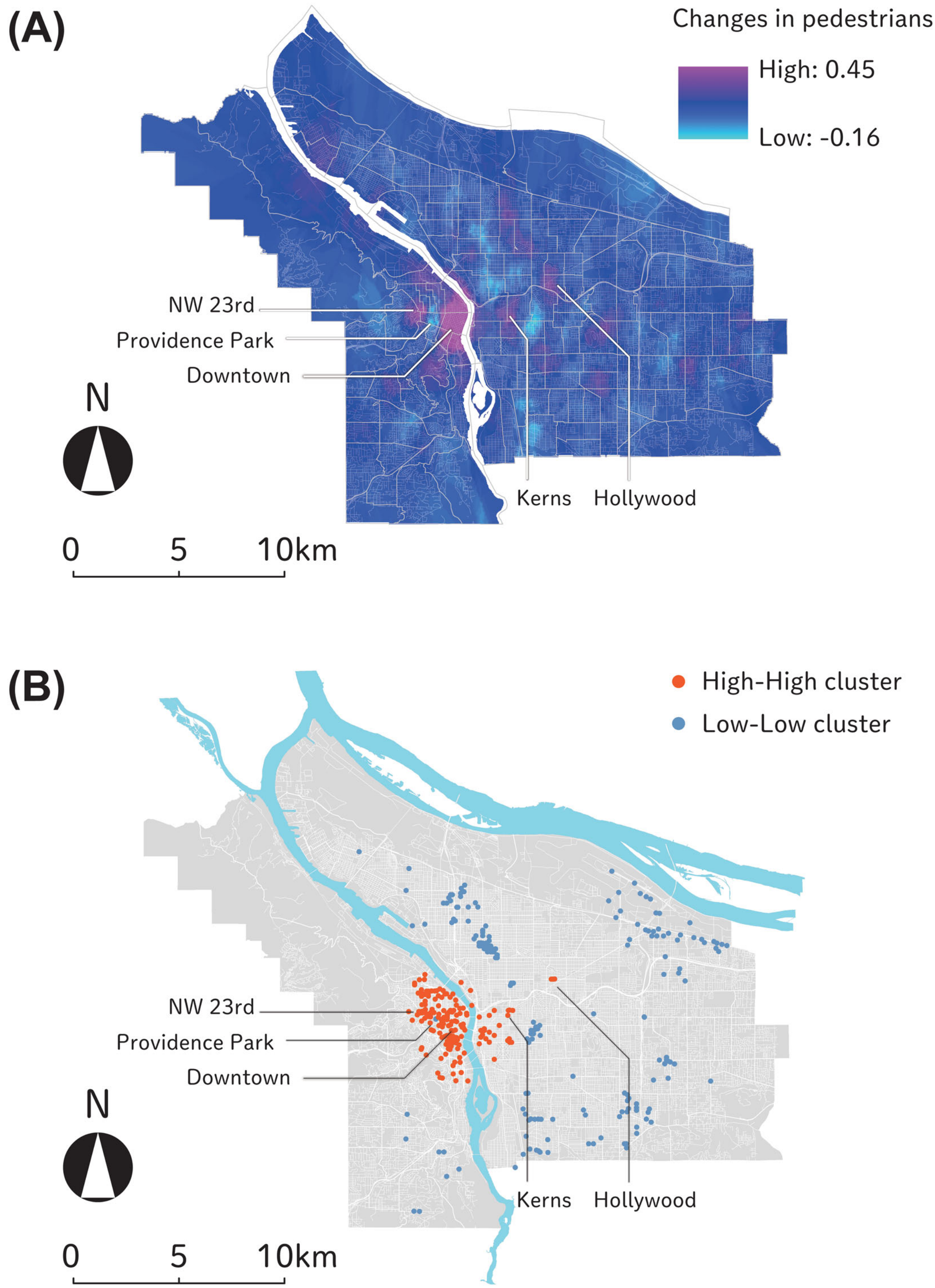

Figure 3 *Spatial distribution of the changes in pedestrians by (A) kriging and (B) local Moran's* I.

except for people walking dogs (only in the late 2000s), construction, and graffiti, were significantly and independently associated with the perception of liveliness. Images with more pedestrians, cyclists, sidewalks, crosswalks, bike signs, mid–high-rise buildings, sidewalk signs, and spacious parking lots,

Table 3 *Cross-sectional associations of liveliness with human activities and built environments in the late 2000s and the late 2010s, Portland*

	The late 2000s			**The late 2010s**		
	Coefficient	***SE***	***p* value**	**Coefficient**	***SE***	***p* value**
Pedestrians[a]	3.377	0.316	0.000***	2.243	0.286	0.000***
Cyclists	1.123	0.236	0.000***	0.765	0.202	0.000***
People walking dogs	0.133	0.409	0.745	0.707	0.324	0.029*
Sidewalk	1.078	0.078	0.000***	1.084	0.078	0.000***
Crosswalk	0.743	0.089	0.000***	0.551	0.081	0.000***
Bike sign	0.432	0.168	0.010*	0.227	0.107	0.033*
Surface problems	−0.265	0.067	0.000***	−0.146	0.062	0.018*
Trees on the street[a]	−1.257	0.119	0.000***	−0.524	0.125	0.000***
Mid–high-rise buildings	0.967	0.101	0.000***	0.913	0.097	0.000***
Sidewalk sign	0.753	0.118	0.000***	0.718	0.105	0.000***
Construction	0.051	0.191	0.789	0.023	0.178	0.897
Graffiti	0.052	0.226	0.817	0.059	0.171	0.732
Spacious parking lot	1.341	0.102	0.000***	1.168	0.092	0.000***
Prefix (ref. N)						
NW	0.807	0.360	0.025*	0.774	0.363	0.033*
NE	0.370	0.198	0.062	0.294	0.194	0.129
S	0.185	0.415	0.655	−0.067	0.411	0.870
SW	−0.198	0.263	0.450	−0.515	0.265	0.052
SE	0.419	0.223	0.060	0.232	0.222	0.296
Zone (ref. residential)						
Mixed-use	1.061	0.088	0.000***	1.181	0.088	0.000***
Industrial	0.122	0.167	0.465	0.162	0.163	0.322
Others	−0.071	0.144	0.623	0.005	0.141	0.971
Seasons (ref. spring/fall)						
Summer	−0.493	0.090	0.000***	0.155	0.067	0.020*
Winter				−0.309	0.137	0.024*
Weather (ref. fine)						
Cloudy/rainy/unknown	−0.466	0.061	0.000***	−0.578	0.057	0.000***
Random effects	**Variance**	***SE***	**ICC**	**Variance**	***SE***	**ICC**
Tract-level ($n = 142$)	0.697	0.100	0.126	0.743	0.105	0.138
Intersection-level ($n = 3{,}508$)	1.523	0.095	0.403	1.358	0.091	0.390
LR test (χ^2)	1640.12***			1570.1***		

Note: $n = 12{,}121$. Dummy variable for each rater was included but omitted from the table.
[a]Transformed and included as continuous variables.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

as well as fewer surface problems and street trees, were more likely to be perceived as livelier regardless of the time periods. Furthermore, streetscape images taken in the NW and the mixed-use zones were more likely to be rated as lively compared with the North sextant and residential zones, respectively. Compared to spring/fall, summer was negatively associated with liveliness in the late 2000s, whereas it showed a positive association in the late 2010s. Images taken on cloudy or rainy days were less likely to be rated as lively than fine days.

Table 4 represents the results of the longitudinal regression analysis of Portland's changes in liveliness levels between the late 2000s and the late 2010s. The changes in liveliness were significantly associated with changes in eight of thirteen streetscape elements. The places that experienced an increase in the number of pedestrians, cyclists, sidewalks, bike signs, mid–high-rise buildings, sidewalk signs, and spacious parking lots, and a decrease in the number of street trees were more likely to be perceived as livelier over time. Overall, except for the presence of crosswalks and surface problems, both the longitudinal and cross-sectional analyses had an overlap in the variables showing a significant association with liveliness. Years between two time points (positive), SW sextant (negative), summer to spring/fall (positive), fine to cloudy/rainy/unknown (negative), and cloudy/rainy/unknown to fine (positive) also showed significant associations.

Discussion

The results generally indicate that virtual audits using GSV-TM are a suitable method for retrospectively observing integrated urban changes, considering both objective and subjective aspects, with some methodological limitations. Overall, we found an increase in the number of lively places, human activities, and built environment elements. This finding might reflect Portland's urban changes due to population growth and urban redevelopment from the late 2000s to the late 2010s. Regression analyses also showed that such changes were spatially correlated: Thus, changes in liveliness at certain places were associated with changes in human activities and the built environment. Although the obtained results

Table 4 Longitudinal associations of the change in liveliness with those in human activities and built environments between the late 2000s and the late 2010s, Portland, Oregon

	Coefficient	*SE*	*p* value
Δ Pedestrians	0.113	0.015	0.000***
Δ Cyclists	0.107	0.037	0.004**
Δ People walking dogs	0.026	0.061	0.671
Δ Sidewalks	0.037	0.018	0.041*
Δ Crosswalks	0.010	0.022	0.631
Δ Bike signs	0.070	0.025	0.006**
Δ Surface problems	0.017	0.012	0.151
Δ Street trees	−0.028	0.010	0.004**
Δ Mid–high-rise buildings	0.111	0.023	0.000***
Δ Sidewalk signs	0.078	0.020	0.000***
Δ Constructions	0.018	0.030	0.558
Δ Graffiti	−0.025	0.033	0.452
Δ Spacious parking lots	0.152	0.021	0.000***
Years between the two time points	0.023	0.008	0.003**
Prefix (ref. N)			
NW	−0.030	0.037	0.418
NE	−0.035	0.024	0.144
S	−0.062	0.058	0.286
SW	−0.064	0.028	0.020*
SE	−0.039	0.024	0.109
Zone (ref. residential)			
Mixed-use	−0.029	0.016	0.073
Industrial	−0.002	0.028	0.954
Others	−0.011	0.028	0.706
Changes in seasons (ref. spring/fall to spring/fall)			
Spring/fall to summer	−0.036	0.033	0.282
Spring/fall to winter	−0.005	0.078	0.947
Summer to spring/fall	0.068	0.030	0.024*
Summer to summer	0.058	0.032	0.066
Summer to winter	0.025	0.038	0.522
Changes in weather (ref. fine to fine)			
Fine to cloudy/rainy/unknown	−0.094	0.016	0.000***
Cloudy/rainy/unknown to fine	0.119	0.015	0.000***
Cloudy/rainy/unknown to cloudy/rainy/unknown	0.031	0.017	0.077
Constant	−0.119	0.067	0.078
Random effects	**Variance**	**SE**	**ICC**
Tract-level ($n = 142$)	0.002	0.001	0.006
Intersection-level ($n = 3{,}508$)	0.031	0.003	0.098
LR test (χ^2)	143.58***		

Note: $n = 12{,}121$ Dummy variable for each rater was included but omitted from the table.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

were not unexpected, they were methodologically important, as we were able to retrospectively observe such changes through the lens of streetscape imagery.

Among individual neighborhoods, Humboldt and Boise (including areas surrounding Mississippi and Williams avenues), North Pearl and Slabtown, and Kenton became livelier during the decade. Humboldt and Boise are a part of inner northeastern Portland, where several gentrification studies have been conducted (Sullivan 2007; Sullivan and Shaw 2011; Goodling, Green, and McClintock 2015). North Pearl and Slabtown are recently redeveloped areas adjacent to the Pearl district, which has been redeveloped from a former warehouse district. Kenton is a neighborhood in North Portland and has been recently gentrified. Apart from these areas showing the most evident changes, however, we were unable to observe clear spatial patterns of the livelihood changes in Portland mainly because of the relatively small sample size in each tract (i.e., twenty-five intersections) as well as many areas being sampled from quiet residential areas. In addition, the authors' observations revealed that the increase in Eastmoreland's liveliness is mostly attributed to the visual effects of weather conditions: Most images in this area were taken during cloudy or rainy weather in the 2000s and fine weather in the 2010s. Thus, some changes can be reasonably explained in terms of urban redevelopment, whereas others could be attributed to irregular temporal conditions such as weather, indicating that maps showing changes in liveliness need careful interpretation.

Regarding human activities, the presence of pedestrians and cyclists increased, and so did the amount of street infrastructure (i.e., sidewalks and bike signs), which were all significantly associated with liveliness and its change. These results are consistent with Portland's general perception as a walkable and bikeable city (cf. Speck 2013) with the plan of twenty-minute neighborhoods (Gower and Grodach 2022). The presence of people walking dogs had also increased but was not associated with liveliness. As for the individual neighborhoods, commercial and mixed-use zones in Downtown and surrounding areas, including Old Town Chinatown, the Pearl District, and around NW 23rd, Kerns, and Hollywood, exhibited a large increase in the number of pedestrians. Despite the increase in pedestrians, Downtown showed no increase in liveliness (see Figure 3). This might be due to the timing of gentrification and the ceiling effect of liveliness ratings: The neighborhoods gentrified earlier, particularly near Downtown, might have been already perceived as lively in the late 2000s, and there was little room for increase. Despite being very close to Downtown, Providence Park showed an irregular decrease in the number of pedestrians (cool spot). A temporary situation caused this decrease: The images in the 2000s were taken just before or after a soccer game at Providence Park (home of the Portland Thorns and Portland Timbers). As exemplified by the cases of Eastmoreland and Providence Park, scholars must exercise caution while assessing urban streetscape changes in specific places because the availability of GSV images (i.e., frequency, timing, and route of image collection) is neither uniform nor random, and thus could reduce their accuracy and lead to a biased estimation of the change (Curtis et al. 2013; Smith, Kaufman, and Mooney 2021).

Among the built environment elements, the presence of mid–high-rise buildings, sidewalk signs, and spacious parking lots had increased, and they were positively associated with liveliness and its change. This finding could reflect the (re)development of both residential and commercial (or mixed-use) areas: In the past few decades, the number of newly constructed and remodeled condominiums, shops, and restaurants has increased, particularly in the neighborhoods around Downtown and the Central Eastside. Although parking lots are often regarded as representing inactive street frontage, which is related to reduced pedestrian activities (Ewing et al. 2016), they can be evaluated as relatively livelier when compared to the streetscapes of less populated areas, which are often included in this study (i.e., few or no built environment elements in most images; see Table 2). This could explain some areas' increased liveliness in East Portland (near I-205 and the airport), because many new shopping centers have been developed with huge parking lots. Street trees showed a negative association with liveliness and its change, probably because extensive green spaces often seen in Portland's residential areas might inhibit the sense of liveliness (Mouratidis and Poortinga 2020).

The associated factors with liveliness were almost the same for cross-sectional analyses between the late 2000s and the late 2010s and very similar between the cross-sectional and the longitudinal analyses. The only differences between the two cross-sectional analyses were people walking dogs, which was only significantly associated with liveliness in the late 2010s, and the seasons of images taken (i.e., opposite directions of association between the two time periods). The former was probably due to the few applicable cases in the 2000s (see Table 2). Although the reasons for the opposite directions were unclear for the latter, a highly skewed distribution (e.g., no images taken in winter in the late 2000s) might have contributed to the result. The results indicate the importance of considering seasons when examining subjective impressions from the GSV images. As expected from the similar results between the two time periods, the longitudinal analysis also showed similar independent variables being significantly associated with changes in liveliness, whereas the presence of crosswalks and surface problems were the exceptions.

This study has some methodological limitations that should be addressed in future research. As mentioned earlier, transient elements could affect the observation of streetscape changes. Researchers have repeatedly highlighted the difficulties in measuring temporal features as they are changeable in the short run (Aghaabbasi et al. 2018). Thus, seasonality and weather conditions are the factors that make temporal analysis unreliable (Cinnamon and Jahiu 2021). In addition, the differences stemming from the images being taken at different dates or times of the day cannot necessarily be interpreted as a meaningful change, as exemplified by Providence Park regarding the number of pedestrians around the soccer stadium. Thus, caution should be exercised in interpreting the differences in the streetscapes by considering the possibility of errors or biases. Nevertheless, this study confirmed the importance of seasonality and weather in affecting the perception of the streetscape imagery. The seasons and weather and their differences between the two time periods are all associated with the perception of liveliness and its change (as in the case of Eastmoreland), indicating the importance of considering these conditions in longitudinal studies using streetscape imagery.

Another shortcoming is that we had to limit the number of intersections for sampling and not include locations other than intersections (i.e., on the street segment between intersections) due to the limited resources for manual audit. For the same reason, each image was audited by one crowd worker, although we checked reliability among auditors by using a sample data set and controlled the auditor effects in the regression models. The checklist used in this study was developed for exploratory purposes; thus, it is neither comprehensive nor validated. Developing a validated tool covering multifaceted elements of streetscapes, including perception, while keeping easy-to-use nature suitable for untrained auditors will be required. Furthermore, to increase the location and expand the study areas, further studies should be conducted using deep learning models combined with crowdsourcing to automate the scoring of perceptions of the built environment (Larkin et al. 2022). A larger sample size might allow for the generation of aggregated values (e.g., increased liveliness at tract or block group level) and link them to the other indexes such as density, land-use diversity, and street connectivity, or the degree or timing of gentrification defined by census indicators, which will lead to broader and comprehensive analyses of urban changes. Additionally, further studies should be conducted in other cities with different spatial morphologies and gentrification experiences to determine how they compare with Portland.

Conclusion

Although many recent studies have examined a cross-section of streetscapes as reflected in GSV imagery, few studies have observed longitudinal streetscape changes, which need to be extracted using historical images taken at the same place at different times. This study conducted a longitudinal virtual audit to examine the changes in Portland's liveliness levels as perceived from the streetscape imagery taken in the late 2000s and the late 2010s. Using the audit data in two time periods, we confirmed that the city became livelier overall over approximately ten years, which was associated with the changes in human activities (e.g., increase in pedestrians) and the built environment (e.g., increase in mid- and high-rise buildings and sidewalk signs). Thus, a longitudinal virtual audit using GSV-TM has considerable potential for enabling a retrospective examination of integrated urban changes considering both objective and subjective aspects. The methods have some limitations, however, such as the spatially and temporally biased availability of GSV images and the difficulties in observing transient features, particularly nonbuilt environment features, as they are susceptible to seasonality and weather conditions. More studies are needed to improve image collection (e.g., combining multiple sources in addition to GSV) and measurement (e.g., automation using deep learning models for perception scoring). ■

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