



## Research article

## Urban land use cover changes in three developed cities of the United States: San Diego, Denver, and Buffalo

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## HIGHLIGHTS

- Land cover change was studied in Buffalo, NY, Denver, CO, and San Diego, CA since the Great Recession.
- Increases in developed classes and decreases in green areas were minimal given increases in population and demand for development in the years following the Great Recession.
- Some clustering in development at a small spatial scale was found in San Diego and at a larger spatial scale in Denver.

## ARTICLE INFO

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## ABSTRACT

Using imagery available through Google Earth Pro and a point sampling methodology, changes in land cover for three U.S. cities were assessed, beginning during the Great Recession (2007) and extending through to 2018. The cities were Buffalo (New York), Denver (Colorado), and San Diego (California), and 11 land cover classes were used to characterize each. The novel contributions of this work, and the innovative contributions to science include an analysis of urban land cover change in the years since the Great Recession, and the use of point pattern analysis on sample points that changed from non-developed in 2007 to developed in 2018, to determine whether a spatial pattern of land cover class change was evident. An initial assumption was made that forest cover change in these three cities would be minimal since the Great Recession. In fact, forest cover decreased by less than 1% in all three cities with the greatest decrease in Buffalo. Over the post-recession study period, increases in the developed land classes were evident in all three cities at the expense of grasses, tree cover, and other land classes. Some clustering of new development activities was noticed at a relatively small scale in San Diego, while some dispersion of new developed activities was noticed at a larger scale in Denver. Among other factors, changes in population, economics, and land use are factors that influence land cover change with specific impacts on forest cover, and therefore in the provision of urban forest benefits to the environment and society.

## 1. Introduction

Urban areas are dynamic systems that can undergo continuous alteration of use (dominant activity) and cover (material on the surface) over time, and these characterizations can be important in the management and planning of urban landscapes (Hermosilla et al., 2012). Urban land uses include features related to the presence and expansion of cities (buildings, roads, powerlines, airports, etc.), features needed to maintain or support growth (agricultural areas, water), and other features (forests) that would be beneficial for ensuring a healthy environment (Zhang

et al., 2010). Over time, land uses can change; forests for example can often transition into developed features such as roads, buildings, and other human infrastructure (Bettinger and Merry, 2019; Auch et al., 2016). Socio-economic forces (financial instruments and tools that allow people to carry debt) have been noted as important mechanisms that can influence changes in land use in the United States (Sealey et al., 2018). For example, tighter credit availability during the recent Great Recession has been suggested to have negatively influenced both unemployment and the ability of people to obtain loans to purchase houses (Bandyopadhyay et al., 2018).

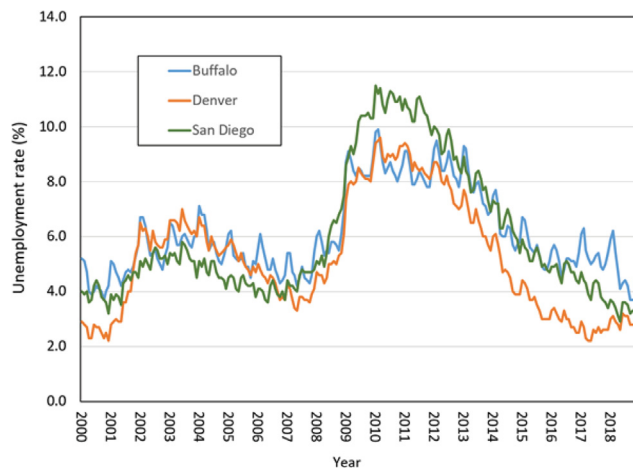
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**Figure 1.** Unemployment rates for Buffalo (New York), Denver (Colorado), and San Diego (California), 2000–2019 (US Bureau of Labor Statistics, 2022).

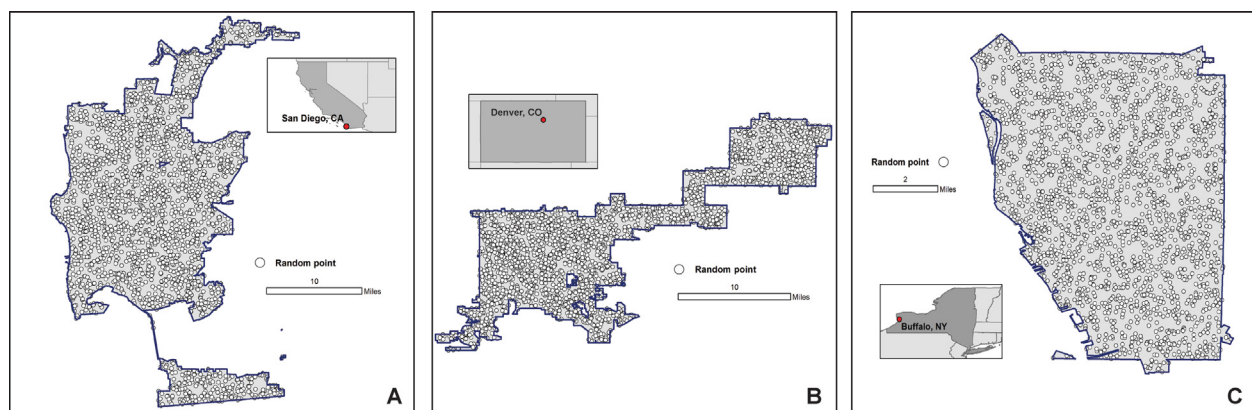
While concerns about land use changes typically focus on its impact on people's quality of life and public health such as childhood obesity and social cohesion (Bell et al., 2008; Ulmer et al., 2016), the impact of changes in land use on the environment can be just as important. Increases in air pollution and noise levels are often associated with changes in land use resulting from fewer and unequally distributed green areas (Lederbogen et al., 2011; Lin et al., 2015). Therefore, it is important to understand the current and historic land use patterns of cities as they are fundamental inputs for city leaders in the decision-making process addressing the needs of a community (Anderson et al., 1976). As one resource, urban trees provide a wide range of environmental, social, and economic benefits and play an important role in climate change mitigation efforts within cities and at larger scale. As urban development expands to accommodate a growing population, urban forests and other green areas are becoming more valuable as they can help mitigate issues associated with such growth (e.g., urban heat island, air quality, and noise pollution, etc.) (Nowak et al., 2021; Nowak and Greenfield, 2018). Estimates of the current land uses and types of cover are indicators of the condition and character of the land that when tracked over time, can serve to inform stakeholders of potential drivers of change. For example, changes in tree cover or other green areas within a city might be correlated with improving or declining economic conditions. The former condition (improving economic conditions) might reveal needs for changes in land use to support housing development, urban farming, and transportation expansion, among others; the latter condition (declining economic conditions) might reveal changes in land use associated with

land abandonment, which in turn may result in a natural or purposeful reversion of open areas to areas covered by shrubs or trees.

Urban forests are admittedly just one of many different types of urban land uses, yet they constitute a key component of urban ecosystems as they add diversity to elements and characteristics of the other different land uses. A parking lot that is positioned next to a grassy field, a patch of trees, and a large building creates a heterogeneous environment that has implications for aesthetic values, wildlife habitat, erosion potential, noise potential, and many other issues of interest to society. With this in mind, one might define urban forests as an urban green infrastructure with a diverse arrangement of tree species and other vegetation. An urban forest might further include grassy areas, individual trees, groves, groups of trees in parks and along sidewalks and road verges, green belts, and entire forested areas in and around a city (Pearlmuter et al., 2017; Endreny, 2018). In contrast to roads, houses, airports, lakes, and other landscape features, the definition of an urban forest can be elusive. In Europe, for example, urban forests are viewed as urban green spaces where trees may have been planted and are subsequently managed, and wooded places where aesthetic values and recreational pursuits are important (Konijnendijk, 2003). As one piece of a broader landscape matrix, urban forests provide many regulating, cultural, and supporting ecosystem services such as climate and noise amelioration, community connections, and others previously mentioned.

While again just one of many different types of urban land uses, tree cover is one important aspect of urban areas that city planners monitor. Even though the correlation between human population density and abundance of tree cover or developed features in an urban area depends on local environmental and socio-economic conditions (Locke and Grove, 2016), city leaders and local populations are often interested in increasing vegetative cover. The success of initiatives to increase vegetative cover may depend on the ability and capacity of city leaders to monitor and evaluate the current state of land uses and understand the factors that influence land use change. Tree cover and other green areas are just a few land use classes that managers might monitor when assessing changes in the local environment and the associated impacts on human well-being.

There are two general methods for detecting urban land uses: 1) A census-based approach that utilizes remote sensing methods to capture multispectral satellite imagery and algorithms to process and categorize the complete set of information, and 2) A sampling-based approach which is based on the examination of sample points or sample areas in conjunction with remotely sensed imagery (Kaspar et al., 2017). The former approach might require specialized skill to process and interpret (classify using supervised or unsupervised methods and associated algorithms) an entire study area using multispectral imagery (satellite-, aerial-, or drone-derived). Here, an algorithm, perhaps with some assistance (training areas) conducts the work of land classification. The latter



**Figure 2.** The city maps with random points (A: San Diego; B: Denver; C: Buffalo).

**Table 1.** Land cover classes and descriptions of each class used in Buffalo, Denver, and San Diego.

Class	Class Description
Grass	Athletic grass (baseball and soccer fields, golf course fairways, and putting greens)
	Business grass (grass within commercial, school, and church properties)
	Cemetery grass
	General grass (grass that is neither recreational nor athletic)
	Grass parking lot
	Highway grass (grass in medians, off-ramps, and adjacent to highways and interstates)
	Leisure grass (recreational grass not used for athletic activity)
	Powerline grass (grass within a powerline right-of-way)
	Residential grass
Developed areas	Athletic facilities (stadium seating, tennis courts)
	Buildings (residential and commercial structures)
	Cemented surfaces (bricking, empty cement lots not used for parking, cemented patios)
	Commercial (paved lots associated with a commercial function like storage)
	Driveways (paved residential driveways)
	Parking lots
	Power plants
	Residential hardscapes
	Swimming pools
	Sidewalks
Water treatment facilities	
Transportation	Airports
	Dirt roads
	Railroads
	Paved roads
Bare ground	Bare ground (dirt plots of land, dirt lots, and dirt driveways)
	Rocks
	Sand (sand and sand traps on a golf course)
Shrubs	Naturally occurring shrubs
	Landscape shrubs
Trees	Coniferous trees
	Deciduous trees
Crop/Pasture	Agricultural crop land including farms
	Pastures (both commercial and non-commercial)
Nursery/ Orchard	Plant and tree nurseries
	Fruit orchards
Water	Natural water (lakes, rivers, and ponds)
	Reservoirs and man-made ponds
Marsh	Marshlands
Other	Junk piles
	Unmanaged grassy area
	Solar panels (not attached to a building)

approach, however, allows one to obtain a similar level of accuracy while using faster, less expensive, and simpler procedures that involve viewing geographic points placed upon remotely sensed imagery, and subsequently interpreting the land use at those points (Hostetler et al., 2013). Here, a human, perhaps with some assistance (definitions, guides, or templates) conducts the work of land classification. The effectiveness of using either approach has been demonstrated in several studies involving assessments of land cover transition (e.g., Bettinger and Merry, 2019; Nowak and Greenfield, 2012; Nowak et al., 2013). Richardson and Moskal (2014) suggested that in comparison to census-based landscape classification methods, random sampling provides more unbiased results in detecting land cover changes, although it may require a large number of point samples to provide an acceptable level of statistical confidence.

King and Locke (2013) did not find a significant statistical difference in detecting land cover changes between census-based and sampling approaches, yet Parmehr et al. (2016) found a 4.5% variation in urban tree canopy maps developed using landscape classification techniques that combined multispectral satellite imagery and LiDAR data, and a point sampling approach that used high resolution aerial imagery. One advantage of using a point sampling approach in conjunction with high resolution aerial imagery is that fine-scale developmental activities (e.g., sidewalks, individual trees) which may otherwise be lost through classification of satellite imagery (e.g., Landsat) should facilitate a more precise quantification of land uses and help contribute to our understanding of how people in society manage land and whether significant recent changes in management have occurred. The results of this study aim to guide city forest planners in determining a sustainable path to maintain and increase green cover and to develop forest management plans that generate desired environmental and socio-economic benefits of a particular urban community.

The objectives of this study are to estimate recent land cover and land use changes associated with urban forest cover in three moderately large cities distributed across the conterminous United States: San Diego (California), Denver (Colorado), and Buffalo (New York). A point sampling approach that uses high resolution aerial imagery in Google Earth Pro was employed. The analysis involves a range of time that begins with the Great Recession (2007–2009), when financial instruments and tools that allow people to carry debt were limited and extends to the current time (or latest availability of aerial images) by using the point sampling method. The Great Recession resulted in varying effects (usually declines) in revenue, budgets, employment, investment, and economic development activities in states and local governments of the United States. Some of the most affected sectors of the economy were government, real estate, and construction, and in some areas building permits declined considerably (Bardhan and Walker, 2011; Hinkley and Weber, 2021). The selected cities are quite different concerning their position within the geography of the country, local climatic conditions, and their history of development. While the Great Recession ended officially in mid-2009, some national (U.S.) measures of economic activity did not return to pre-recession levels until 2013 (Frone, 2018), while local unemployment rates may have taken a few years longer to return to pre-recession levels (Figure 1). The selected cities have also undergone different developmental histories. For example, the population of Buffalo has been declining along with the city's basic industries, while the population of Denver and San Diego have been increasing over the last decade. These changes likely influence demand for housing and infrastructure (e.g., utilities, road access, etc.).

## 2. Methods

The methodology of this study began with the selection of three diverse urban areas, and the time frame within which to study their land uses. In discussing the time frame of the study, concerns over the availability of aerial imagery and a desire to study responses to recent global economic challenges were considered. The method for estimating land uses and land use change was then selected, along with the associated statistical procedures to determine the magnitude and significance of the results.

### 2.1. Area of study

Three United States cities were included in the land cover assessment presented here: San Diego (CA), Denver (CO), and Buffalo (NY) (Merry, 2022). These cities were chosen because they are different in their geography, climate, and landscape characteristics. The area studied included the officially designated, specific municipalities of the three cities, and not the broader, more generally (or locally) known metropolitan area of each. For the purpose of this paper, their history of development from the Great Recession in 2007 through 2018 is

**Table 2.** Percent change of land cover classes between 2007 and 2018 in San Diego.

	2018												2007	
	Land class	Grass	Developed	Transportation	Bare ground	Shrub	Tree	Crop/Pasture	Nursery/Orchard	Water	Marsh	Other	Total	SE
2007	Grass	9.91	0.96	0.22	0.30	0.35	0.04	0.04	-	-	-	-	11.83	0.007
	Developed	0.13	24.74	-	0.04	-	-	-	-	-	-	-	24.91	0.009
	Transportation	0.09	0.04	10.83	0.04	0.13	-	-	-	-	-	-	11.13	0.007
	Bare ground	0.57	0.70	0.13	1.52	0.48	0.04	-	-	-	-	-	3.43	0.004
	Shrub	0.17	0.17	0.13	0.30	34.61	0.09	0.04	-	0.04	-	-	35.57	0.010
	Tree	0.22	0.26	-	-	0.09	6.26	-	0.04	-	-	-	6.87	0.005
	Crop/Pasture	0.30	-	0.09	0.04	-	-	1.00	0.04	-	-	-	1.48	0.003
	Nursery/Orchard	-	0.04	-	0.04	-	-	-	0.48	-	-	-	0.57	0.002
	Water	-	-	-	-	-	-	-	-	3.96	0.09	-	4.04	0.004
	Marsh	-	-	-	-	-	-	-	-	-	0.17	-	0.17	0.001
	Other	-	-	-	-	-	-	-	-	-	-	-	-	-
2018	Total	11.39	26.91	11.39	2.30	35.65	6.43	1.09	0.57	4.00	0.26	-		
	SE	0.007	0.009	0.007	0.003	0.010	0.005	0.002	0.002	0.004	0.001	-		

highlighted. In addition, these cities all have populations over 250,000 and the average density of people living within each city ranged from 3, 698 to 7,206 people per square mile. Of the three cities, San Diego is the 8<sup>th</sup> largest city by population in the United States with a little over 1.4 million residents in 2018, while Denver is the 19<sup>th</sup> with a population of about 716,000 in 2018 and Buffalo the 88<sup>th</sup> with a current population of about 256,000 in 2018 (US Census Bureau, 2020a; US Census Bureau, 2020b). The size of each city's municipal area varies according to how they are defined by local government administrators; populations within the surrounding greater metropolitan areas of these cities could be two to four times greater than the official city area in which we concentrate this study.

2.2. Point sampling

In this study, we employed a simple random sample design in conjunction with aerial interpretation (expert recognition and knowledge) procedures to estimate land covers. A vector geographic information system (GIS) database of each city's physical boundary was acquired from the city GIS data repository websites. These databases were

projected to the Universal Transverse Mercator (UTM) system using the appropriate UTM zones: UTM 17N (Buffalo), UTM 13N (Denver), and UTM 11N (San Diego). Within each city's physical boundary, 2,300 points were randomly distributed using ArcGIS 10.6 (Figure 2). A single point is described by the northing and easting values of its position within the appropriate UTM zone. A Google Earth KML file was then created from the set of 2,300 points for interpretation across multiple years. A detailed assessment of the proportions of major land uses suggested that as the number of sample points exceeded 91.8% +/- 1.5% (San Diego), 92.6% +/- 1.4% (Buffalo), and 81.7% +/- 2.1% (Denver), the value of these proportions, with 99% confidence, was largely unchanged. It may have been possible, with respect to the major land use classes that had more sample points, that a 99% confidence level could have been met with fewer samples. However, the trade-off of using more sample points, involving additional time and yet greater statistical precision, was considered worthwhile for estimating the conditions of, and transitions involving, minor land use classes.

We employed the imagery available within Google Earth Pro for this analysis. While the imagery was generally available for more recent years, it was not available across all three cities; therefore, the years 2019

**Table 3.** Changes of land cover classes in time series from 2007 to 2018 in San Diego.

Land cover classes	2007–2008	2008–2009	2009–2010	2010–2011	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	2017–2018	Net change (2018–2007)	Average change per year
Grass	0.13	0.04	0.17	-0.04	-0.26	0.04	-0.03	-0.13	-	0.09	-0.17	-0.43	-0.04
Developed	0.17	0.09	0.17	0.17	0.13	0.13	0.22	0.26	0.39	0.17	0.09	2.00***	0.18
Transportation	-	0.04	-0.04	0.04	0.04	-	-0.09	0.22	0.09	-	-0.04	0.26	0.02
Bare ground	-0.22	-0.26	-0.22	-0.04	-0.04	-0.13	0.39	-0.17	-0.39	-0.13	0.09	-1.13**	-0.10
Shrub	-0.13	0.09	0.09	-0.04	0.13	0.04	-0.22	-0.13	0.17	0.04	0.04	0.09	0.01
Tree	-	-	-	0.04	-	-0.04	-	-	-0.30	-0.09	-0.04	-0.43	-0.04
Crop/Pasture	-	-0.04	-0.17	-0.13	-	-0.04	-	-	-	-0.04	0.04	-0.39*	-0.04
Nursery/Orchard	-	-	-	-	-	-	-	-	0.04	-0.04	-	-	-
Water	0.04	-	-	-	-0.09	-	-	-	-	0.09	-0.09	-0.04	-
Marsh	-	-	-	-	0.09	-	-	-	-	-0.09	0.09	0.09	0.01
Other	-	0.04	-	-	-	-	-	-0.04	-	-	-	-	-

\*Changes significantly different from zero as  $p < 0.05$ .

\*\*Changes significantly different from zero as  $p < 0.01$ .

\*\*\*Changes significantly different from zero as  $p < 0.001$ .

**Table 4.** Percent change of land cover classes between 2007 and 2018 in Denver.

2018													2007	
Land class	Grass	Developed	Transportation	Bare ground	Shrub	Tree	Crop/Pasture	Nursery/Orchard	Water	Marsh	Other	Total	SE	
2007	Grass	26.43	1.17	0.57	1.17	1.09	0.30	0.39	0.04	0.13	-	0.09	31.39	0.010
	Developed	0.17	26.39	0.09	0.26	-	0.04	-	-	-	-	-	26.96	0.009
	Transportation	0.09	0.04	14.22	0.17	0.04	-	-	-	-	-	-	14.57	0.007
	Bare ground	1.00	0.39	0.22	0.96	0.17	-	0.09	-	0.04	-	-	2.87	0.004
	Shrub	0.43	0.04	0.04	0.09	1.13	-	0.04	-	-	-	-	1.78	0.003
	Tree	0.57	0.22	0.04	0.04	-	8.30	-	-	0.04	-	-	9.22	0.006
	Crop/Pasture	0.35	0.17	0.04	0.30	0.13	-	10.00	-	-	-	0.09	11.09	0.007
	Nursery/Orchard	-	-	-	-	-	-	-	-	-	-	-	-	-
	Water	-	-	-	0.04	-	-	-	-	1.17	-	-	1.22	0.002
	Marsh	-	-	-	-	-	-	-	-	-	0.09	-	0.09	0.001
	Other	0.04	0.35	-	0.04	-	-	-	-	-	-	0.39	0.83	0.002
2018	Total	29.09	28.78	15.22	3.09	2.57	8.65	10.52	0.04	1.39	0.09	0.57		
	SE	0.009	0.009	0.007	0.004	0.003	0.006	0.006	0.000	0.002	0.001	0.002		

and 2020 were omitted from the analysis. Google Earth Pro imagery viewed at low-eye altitude (e.g., 5 km above ground or lower) are acquired from local or federal government sources such as the U.S. Department of Agriculture National Agriculture Imagery Program (NAIP) or sources such as DigitalGlobe, GeoEye-1, Ikonos, and others (Taylor, 2014). Prior to delivery through Google Earth Pro, the imagery is aggregated and sharpened; therefore, spatial resolution is difficult to define (Bettinger and Merry, 2019). The approximate spatial resolution for image interpretation purposes using Google Earth Pro imagery is about 2 m or less (Bettinger and Merry, 2019). Throughout the United States, imagery available through Google Earth Pro is less frequent, and often too coarse for interpretation of small features prior to about 2007. This date coincides, fortunately, with the advent of the Great Recession.

Land cover classes were developed based on preliminary visual assessments of the land cover contained in each city. Once the interpretation of sample points began, a land cover class for each point was assigned. An initial image interpretation effort was conducted by an intern who had been trained in interpretation methods. One hundred percent of the sample points were then re-interpreted by a person with significant experience in remote sensing and image interpretation. Each sample point was assigned one of 41 classes that were aggregated into 11 broad classes for analysis (Table 1). Some land cover classes (e.g., sidewalks) required close inspection of the imagery (low-eye altitude in Google Earth Pro), while other land cover classes (e.g., various types of grasses) required a broader perspective (higher eye altitude); therefore, a standard elevation above ground level was not employed in these efforts.

Seven image interpretation principles were employed when examining the aerial imagery in Google Earth Pro: *size, color, shape, shadows, pattern, texture, and convergence of evidence* (Paine and Kiser, 2012). An eighth image interpretation principle, *time*, was also of assistance in overcoming some of the challenges related to image interpretation thanks to the time series of imagery made available through Google Earth Pro. Of the broad land cover classes, developed areas included structures (i.e., buildings and homes) that might be considered improvements to the property or might be considered manufacturing or commercial facilities (Ficek et al., 1980). Parking lots, swimming pools, sidewalks, and other hardscape features were also grouped into the developed area class, and often these interpretation calls required utilizing the time series of imagery (and associated changes in tone and color) along with evidence of pattern and shape. Discerning the difference between grasses often required a broader perspective to associate these features with other surrounding features. For example, residential grass was located next to homes, while athletic grass was found in schoolyards and parks. Further challenges encountered involved using expert knowledge, evidence of

shadows, and the Google Earth Pro *street view* to distinguish, for example, the tree class from the shrub class.

### 2.3. Statistical methods

For each city, the proportion of each cover class ( $p$ ) was estimated by dividing the number of sample points ( $x$ ) classified as a particular land cover class and the total number of interpretable sample points ( $n$ ) within each city ( $p = x/n$ ). Subsequently, the standard error of the estimate ( $SE$ ) was calculated (Lindgren and McElrath, 1959). This method has been used to assess canopy cover in other studies (e.g., Nowak et al., 1996; Nowak and Greenfield, 2010; Nowak and Greenfield, 2012). The McNemar test was used to assess statistical significance in changes in the proportion of a land cover class (McNemar, 1947; Bradley, 1968; Foody, 2004). Here, the test was employed to determine whether a statistical significance in the gain or loss of land cover classes over time was observed. In this study, the test was used to determine whether a net change of  $y\%$  in the developed area class between 2007 and 2018 was different than zero using an assumed alpha (significance) level. Other studies (e.g., Nowak and Greenfield, 2012; Nowak and Greenfield, 2020; Momeni et al., 2016; Yan et al., 2006) have also used the McNemar test for similar purposes.

In addition, using R Statistical Software (version 1.2.5001, RStudio, Inc., Boston, MA, USA), point pattern analysis was conducted on points that were classified as not developed in 2007 and developed in 2018 to determine the spatial pattern of cover class change. The  $L(r)$  function, normalized version of Ripley's  $K$  function, was applied given its wide use in point pattern analyses (Law et al., 2009; Gadow et al., 2012). To plot the result, the  $L(r)$  function was subtracted from the  $r$  (bandwidth) using the equations below:

$$K(r) \text{ function : } K(r) = \frac{A}{n^2} \sum_{i=1}^n \sum_{j=1}^n w_{ij}^{-1} I_r(u_{ij}) \quad (1)$$

$$L(r) \text{ function : } L(r) = \sqrt{\frac{K(r)}{\pi}} \quad (2)$$

$$\text{The normalized version of } L(r) \text{ function : } \hat{L}(r) = \sqrt{\frac{K(r)}{\pi}} - r \quad (3)$$

where  $A$  is the study area,  $n$  is the number of individuals,  $I_r(u_{ij})$  is an indicator function (which is either 1 when  $u_{ij} < r$  or 0 when  $u_{ij} > r$ ), and  $w_{ij}$  is a weight value for edge correction. Since the study site did not guarantee a homogeneous density of points across their areas, the Heterogeneous Poisson process (HP) model was preferred as the null model

**Table 5.** Changes of land cover classes in time series from 2007 to 2018 in Denver.

Land cover classes	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	Net change (2018-2007)	Average change per year
Grass	-0.43	-0.04	-0.61	0.61	-1.00	-1.22	-0.26	0.87	0.13	-0.22	-0.13	-2.30***	-0.21
Developed	-0.04	0.22	0.22	0.09	0.17	0.35	-0.09	0.04	0.39	0.22	0.26	1.83***	0.17
Transportation	-	0.04	0.13	0.04	0.04	0.09	0.13	-0.04	0.09	0.13	-	0.65*	0.06
Bare ground	0.09	-0.57	-0.35	-0.09	0.39	-0.13	0.04	0.22	-0.09	0.39	0.30	0.22	0.02
Shrub	0.43	0.09	0.52	-0.61	0.74	1.13	0.13	-0.91	-0.39	-0.04	-0.30	0.78	0.07
Tree	-	-	-0.04	-0.04	-0.09	-	-	-	-0.17	-0.26	-	-0.57*	-0.05
Crop/Pasture	-0.13	0.13	0.04	-0.04	-0.17	-0.17	0.09	-0.22	0.04	-0.09	-0.04	-0.57	-0.05
Nursery/Orchard	-	-	0.04	-	-	-	-	-	-	-	-	0.04	-
Water	0.04	0.04	-	-	-	0.09	-	-	-	0.04	-0.04	0.17	0.02
Marsh	-	-	-	-	-	-	-	-	-	-	-	-	-
Other	0.04	0.09	-	0.04	-0.09	-0.13	-0.04	0.04	-	-0.17	-0.04	-0.26	-0.02

\*Changes significantly different from zero as  $p < 0.05$ .

\*\*Changes significantly different from zero as  $p < 0.01$ .

\*\*\*Changes significantly different from zero as  $p < 0.001$ .

rather than the complete randomness process (CSR) which assumes homogeneity across the study site (Wiegand and Moloney, 2013). Monte Carlo simulation (200 permutations) was applied to produce the envelop covering the 95% confidence level range of the null model. When the observed values were located outside the envelop, the pattern of land use change was suggested to be statistically significantly different than the null model. Further, a negative value was indicative of a dispersed pattern, while a positive value was indicative of a clustered pattern (Wiegand and Moloney, 2013).

### 3. Results

In San Diego, during 2007, the shrub land cover classification type occupied the largest percentage of the city (35.6%), followed by developed areas (24.9%), grasses (11.8%), transportation (11.1%), and trees (6.9%) (Table 2). In 2018, the developed, transportation, shrub, and marsh classes increased their cover by +2.0%, +0.3%, +0.1%, +0.1%, respectively (Table 3). In contrast, a decrease in grass (-0.4%), bare ground (-1.1%), tree (-0.4%), and crop/pasture (-0.4%) cover classes occurred between 2007 and 2018. As a result, the land cover classification types that occupied the largest percentages in 2018 was the shrub with 35.7% followed by the developed area with 26.9%. Both transportation and grass cover types occurred at the same proportion (11.4%) in 2018 (Table 2). Significant changes were observed for the developed ( $p < 0.001$ ), bare ground ( $p = 0.0015$ ), and crop/pasture ( $p = 0.0265$ ) classes (Table 3). In addition, the most prominent San Diego land cover class transitions between 2007 and 2018 occurred as follows: grass to developed areas (1.0%), bare ground to developed areas (0.7%), bare ground to grass (0.6%), bare ground to shrub (0.5%), grass to shrub (0.4%) (Table 2).

In Denver, the greatest amount of land cover in 2007 was grass (31.4%) followed by developed areas (27.0%), transportation (14.6%), crop/pasture (11.1%), and trees (9.2%) (Table 4). In 2018, we estimated a decrease in grasses (-2.3%) and trees (-0.6%), as well as crop/pasture (-0.6%) and the "other" (-0.3%) land cover class (Table 5). In contrast, developed areas (+1.8%), transportation (+0.7%), bare ground (+0.2%), shrub (+0.8%), nursery/orchard (+0.04%), and water (+0.2%) classes increased their proportion of land cover by 2018 (Table 5). The results of the McNemar test showed that there were significant decreases in the grass ( $p < 0.001$ ) and tree ( $p = 0.026$ ) land cover classes. Otherwise, significant increases were observed in the developed ( $p < 0.001$ ) and transportation ( $p = 0.012$ ) classes (Table 5). The most pronounced land cover transitions between 2007 and 2018 occurred from grass to developed areas (1.2%), grass to bare ground (1.2%), grass to shrub (1.1%), bare ground to grass (1.0%), tree to grass (0.6%), grass to transportation (0.6%), and shrub to grass (0.4%). Denver showed the highest percentage of crop/pasture lands of the three cities (Table 4).

Finally, in Buffalo, the developed (38.7%), grass (23.8%), tree (16.2%), transportation (14.1%), and shrub (2.4%) land cover classes had the highest percentages of the sampled land cover in 2007 (Table 6). By 2018, land cover proportion increased for the developed areas (+0.5%), transportation (+0.1%), shrub (+0.6%), and water (+0.04%) classes. In contrast, a decrease in land cover classes grass (-0.04%), bare ground (-0.3%), trees (-0.9%) and marsh (-0.04%) was observed (Table 7). Significant differences in land cover changes were only observed in the tree and shrub land cover classes with  $p$ -values of 0.001 and 0.026, respectively (Table 7). Of the percentage of land cover change between 2007 and 2018, bare ground transitioned to grass (0.6%), tree to grass (0.6%), grass to developed areas (0.6%), grass to shrub (0.5%), developed areas to grass (0.5%) and grass to bare ground (0.3%) (Table 6).

In general, we observed that between 2007 and 2018 grass and tree land cover classes decreased while the developed, transportation, and shrub classes increased in coverage in all three cities (Figures 3, 4, and 5). The bare ground class only increased in Denver (Figure 3) and the crop/pasture class remained stable only in Buffalo (Figure 4) where it was of minor significance. No statistically significant changes were observed for

**Table 6.** Percent change of land cover classes between 2007 and 2018 in Buffalo.

		2018											2007	
	Land class	Grass	Developed	Transportation	Bare ground	Shrub	Tree	Crop/Pasture	Nursery/Orchard	Water	Marsh	Other	Total	SE
2007	Grass	21.91	0.61	0.22	0.30	0.52	0.22	-	-	-	-	-	23.78	0.009
	Developed	0.48	38.04	-	0.09	0.09	0.04	-	-	-	-	-	38.74	0.010
	Transportation	0.09	0.04	14.00	-	-	-	-	-	-	-	-	14.13	0.007
	Bare ground	0.61	0.22	-	0.74	0.13	0.04	-	-	-	-	-	1.74	0.003
	Shrub	0.04	0.09	-	0.22	2.09	-	-	-	-	-	-	2.43	0.003
	Tree	0.61	0.26	0.04	0.09	0.17	15.00	-	-	-	-	-	16.17	0.008
	Crop/Pasture	-	-	-	-	-	-	0.09	-	-	-	-	0.09	0.001
	Nursery/Orchard	-	-	-	-	-	-	-	-	-	-	-	-	-
	Water	-	-	-	-	-	-	-	-	2.35	-	-	2.35	0.003
	Marsh	-	-	-	-	-	-	-	-	0.04	0.30	-	0.35	0.001
	Other	-	-	-	-	-	-	-	-	-	-	0.22	0.22	0.001
2018	Total	23.74	39.26	14.26	1.43	3.00	15.30	0.09	-	2.39	0.30	0.22		
	SE	0.009	0.010	0.007	0.002	0.004	0.008	0.001	-	0.003	0.001	0.001		

**Table 7.** Changes of land cover classes in time series from 2007 to 2018 in Buffalo.

Land cover classes	2007–2008	2008–2009	2009–2010	2010–2011	2011–2012	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	2017–2018	Net change (2018–2007)	Average change per year
Grass	-0.04	0.09	-0.13	-0.04	0.04	0.13	0.04	-0.13	0.17	-0.13	-0.04	-0.04	-
Developed	-0.04	0.04	-	0.13	0.22	-0.22	0.04	-	-0.04	0.22	0.17	0.52	0.05
Transportation	-	-	0.09	-0.09	0.04	-	0.04	-0.09	0.04	-	0.09	0.13	0.01
Bare ground	0.13	-0.04	-0.13	-0.09	-0.26	0.09	0.17	0.35	-0.17	-0.26	-0.09	-0.30	-0.03
Shrub	-	-0.09	0.22	0.13	0.09	-0.04	-0.09	-0.04	0.13	0.17	0.09	0.57*	0.05
Tree	-0.04	-0.04	-0.04	-0.04	-0.13	0.04	-0.17	-0.09	-0.17	-	-0.17	-0.87**	-0.08
Crop/Pasture	-	-	-	-	-	-	-	-	-	-	-	-	-
Nursery/Orchard	-	-	-	-	-	-	-	-	-	-	-	-	-
Water	-	-	-	-	-	0.04	-	-	-	-	-	0.04	-
Marsh	-	-	-	-	-	-0.04	-	-	-	-	-	-0.04	-
Other	-	0.04	-	-	-	-	-0.04	-	0.04	-	-0.04	-	-

\*Changes significantly different from zero as  $p < 0.05$ .

\*\*Changes significantly different from zero as  $p < 0.01$ .

\*\*\*Changes significantly different from zero as  $p < 0.001$ .

the water, marsh, and nursery/orchard land cover classes in any of the three cities (Figures 3, 4, and 5).

Lastly, as a result of applying the  $\hat{L}(r)$  functions to investigate patterns of the points that changed from not developed to developed between 2007 and 2018 (Figure 6), we observed some trends. Specifically, some of the locations of those points that converted to the developed land cover in 2018 exhibited a clustered pattern at a smaller scale, while others exhibited a dispersed pattern at a larger scale (Figure 7). A statistically discernible clustered pattern was observed in San Diego at the range of 2.5 km, while a statistically discernible dispersed pattern was observed in Denver at larger than 5 km of range (Figure 7). This suggests that development activities during the study period were concentrated in local areas throughout these two cities, and not randomly dispersed. There was no evidence of a clustered or dispersed spatial pattern in the places that had become developed in Buffalo over the 2007–2018 time period.

#### 4. Discussion

As of 2019, there were an estimated 7.7 billion people worldwide. Although the increase in the world's population is slowing, it has been

projected that the global population could reach 8.5 billion in 2030 and 9.7 billion in 2050 (United Nations, 2019a). In the United States, about 327 million people (82% of the population) lived in urban areas in 2018 and the percentage is likely to increase above 90% by 2050 (United Nations, 2019b). Continued urbanization of cities implies a higher demand for land development which in turn creates land cover changes. Certainly, several factors (both natural and human) may influence the general structure and condition of land cover of a particular place (Sanders, 1984). Examples of potential temporal changes in land cover after a recessionary economic period are presented in this study. For instance, Denver, San Diego, and Buffalo all showed a decrease in green areas (e.g., grass and tree land cover classes) during 2007–2018. Although an increase in green areas was observed in the shrub land cover class, transitions to the shrub land cover class mainly came from bare ground (0.5% in San Diego) or grass classes (1.1% in Denver and 0.5% in Buffalo). Here, such green spaces seem to have been mainly replaced with developed land uses including transportation-related surfaces. Otherwise, there were minor transitions from non-green areas to green areas. In addition, even though the majority portion of the bare ground stayed as bare ground, the bare ground stage of land development may be transitory in the long run; thus, the largest percentage of change within

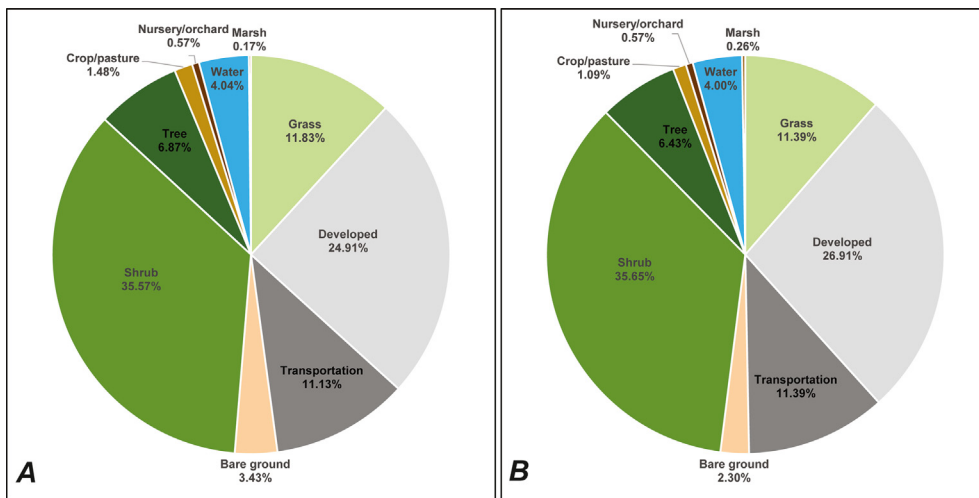


Figure 3. The land cover class composition by percentage in San Diego (A: 2007; B:2018).

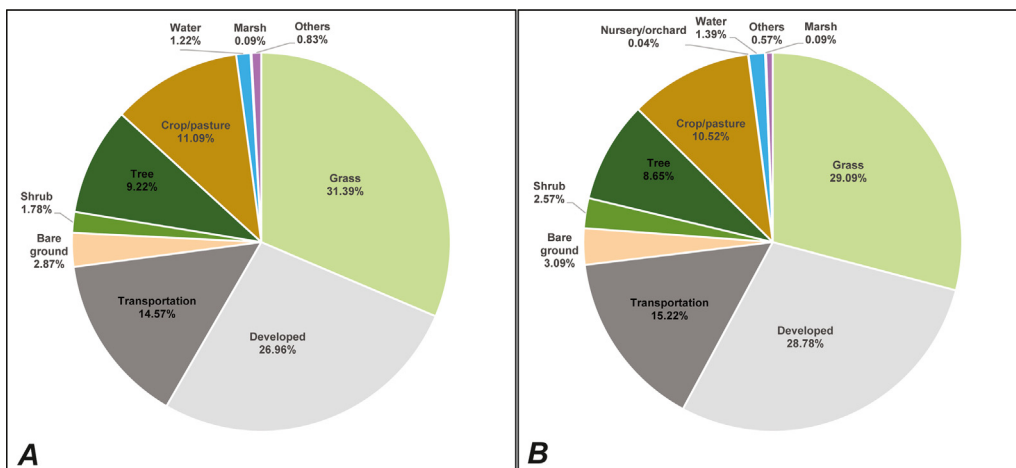


Figure 4. The land cover class composition by percentage in Denver (A: 2007; B:2018).

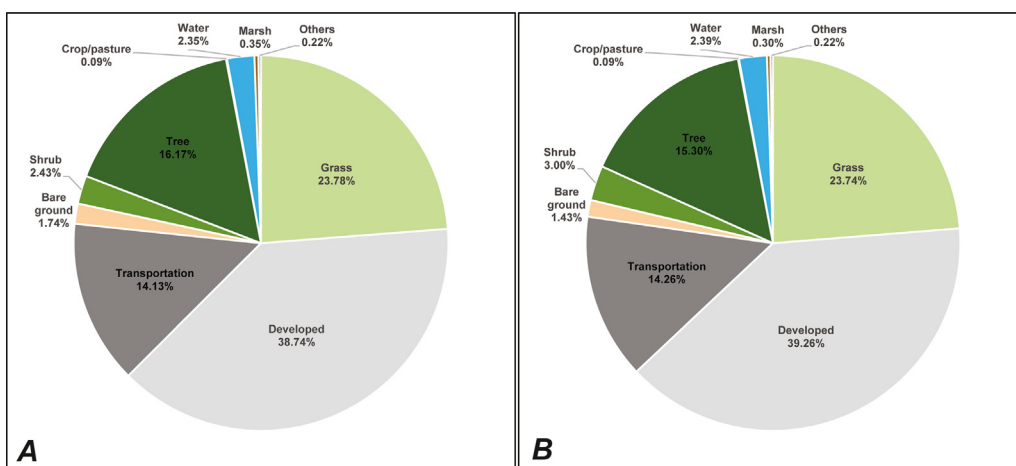


Figure 5. The land cover class composition by percentage in Buffalo (A: 2007; B:2018).

this class was to grass in both Denver and Buffalo while in San Diego it was from bare ground to developed. This result is particularly important if we recall that the studied cities (and many others in the U.S.) have different programs and campaigns to plant or re-plant trees focused on

increasing tree canopy in their urban areas. However, our results suggest that these types of land cover classes have decreased over the last decade which is comparable to findings from Nowak and Greenfield (2012) in other cities in the U.S. Particularly, the results presented here are



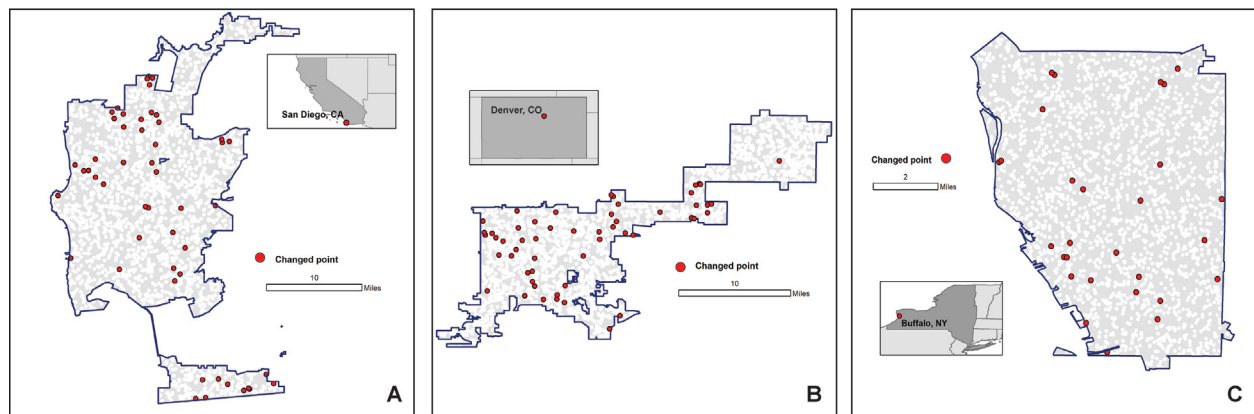


Figure 6. The changed land cover class locations between 2007 and 2018 (A: San Diego; B: Denver; C: Buffalo).

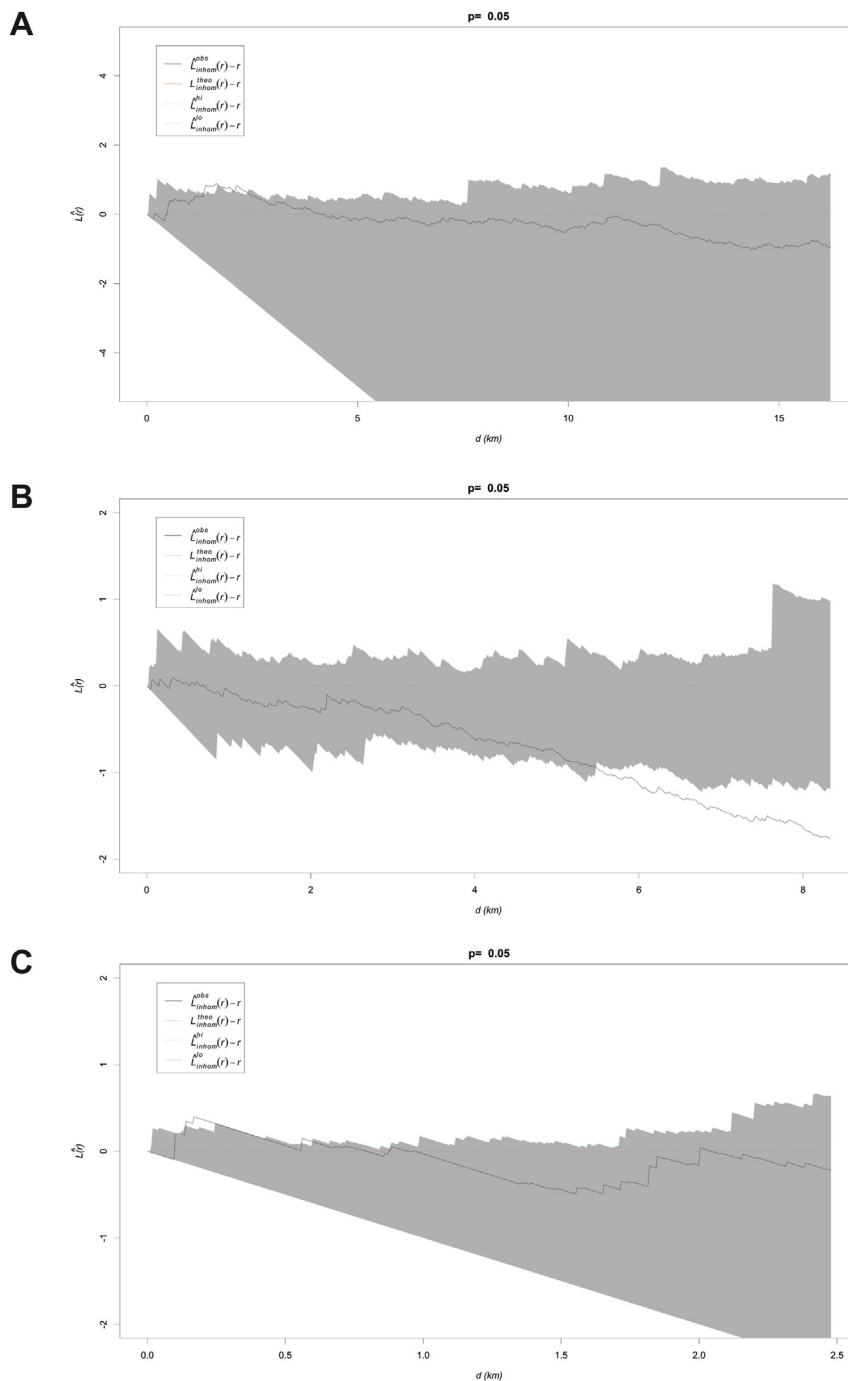
comparable to those of forest cover in Denver (Nowak and Greenfield, 2012) indicating that there has been little permanent change in forest cover since the end year of their analysis (2009) and to global trends of urban tree cover decrease and urban impervious cover increase (Nowak and Greenfield 2020). However, the estimated forest cover in San Diego from this study (6.4%, 2018) is nearly half that of the estimate (13%, 2017) of the City of San Diego (2017) in 2015. Although the estimate of forest cover in the City of San Diego in 2017 was derived utilizing remote sensing technologies (rather than sampling), we believe that the difference in analytical methods had a minor influence on the accuracy of data quality (King and Locke, 2013). The time difference between the two studies might have also been a reason for the difference among estimates. Regarding Buffalo, we are unaware of any forest canopy cover estimates for this city; therefore, no benchmark can be used for direct comparison.

Unlike other studies, we applied spatial pattern analysis to represent how patterns of locations where the land cover class changed look alike using a normalized version of Ripley's  $K$  function. In San Diego, the land cover classes changed in a clustered pattern, while the land cover classes changed in a more dispersed manner in Denver. In Buffalo however, the land cover class change appeared to be randomly distributed across the city. These results can aid the urban planning process as detecting land cover class changes and assessing the connectivity of green areas are essential in urban planning (Bagan and Yamagata 2014; Pirmat and Hladnik, 2018). Anecdotally, through visual assessment, the majority of conversion to development in Denver occurred in the north-northeastern portion of the city and was predominantly new residential and commercial development with most transitions originating from bare ground or grass land cover classes. However, changes to developed land cover were dispersed across other parts of the city and were largely categorized as infill development with limited loss of tree cover. In San Diego, the majority of conversion to the developed land class was located in the northern portion of the city and included some residential and commercial development. Similarly, the majority of these changes originated from bare ground or grass land cover classes, with only one sample point noted as transitioning from trees to developed.

The fact that our observations did not indicate large changes in tree cover had occurred between 2007 and 2018 suggests that the effectiveness of tree planting campaigns and other initiatives to increase urban tree cover might need to be adjusted and should not be viewed as a final solution to addressing perceived low urban tree canopy levels (Nowak and Greenfield, 2012). However, one might also conclude that tree planting campaigns and other initiatives were effective at staving off declines in tree canopy cover in the face of increasing development activities. Interestingly, we observed land class transitions between the green land classes (grass, shrub, tree), but rarely from non-green to green land class. Tree planting strategies need to be well articulated, with policies and programs for planting and evaluation of effects at the local

level, so that a more tangible impact can be achieved. One limitation of this study is the lack of a social analysis component that might support a potential relationship between income and green areas, race and green areas, etc. Locke and Grove (2016) suggested that to increase tree canopy in an urban area it is necessary to increase tree planting or tree preservation on commercial and private residential properties. Others have pointed to open areas within cities (bare land or areas containing grasses or shrubs) as potential places to increase the urban tree canopy (Merry et al., 2013). Additionally, to increase the success of greening programs, it is necessary to understand the ecological and economic characteristics of a city which are drivers of tree canopy distribution (Locke et al., 2017). Such studies, like the one presented here, along with others on urban land cover change, tree health, planning and zoning, and area demographics can serve as stronger tools for managers and policy makers. Therefore, this work can help inform urban planning policies by showing evidence of potential land use and tree cover changes due to a higher demand for development, and due to changes in socio-economic conditions after a recessionary economic period perhaps in response to a growing population.

Without a deeper investigation into the demographics and economic condition of the landowners or the desires of governmental agencies associated with the land use changes, it is difficult to understand why clumped or dispersed patterns of new development occurred. Silverman et al. (2015) suggested that land abandonment and re-development seemed to concentrate in certain areas of Buffalo. In fact, the City of Buffalo officials demolished over 3,000 houses between 2007 and 2012 to stimulate development, perhaps clustered in certain areas of the city (Silverman et al., 2015), yet our analysis did not detect a clustered pattern of development over the study period. The motives of landowners and governmental agencies may also drive development decisions. After the recession, some landowners may have sensed an opportunity to increase their net worth and may have pursued developmental projects. Governmental agencies on the other hand may have allowed development (roads, buildings) to occur on vacant lots for the greater social benefit, through growth management or urban revitalization strategies. Yet without a deeper investigation of each instance of development action, it is impossible to know whether the land use changes were planned over a long period of time (perhaps even before the recession) or were opportunistic and conducted rather quickly. And it would also be difficult to know whether the developmental changes occurred prior to or after a change in ownership among individuals, or similarly after transfer of ownership to a governmental agency due to tax delinquencies or land abandonment, without a thorough analysis of the thousands of land records (deeds) associated with land use changes. These questions pertaining to the spatial aspects of neighborhood decline and economic development remain an open area of work.



**Figure 7.** The  $\hat{L}(r)$  function of the changed land cover class between 2007 and 2018 (A: San Diego; B: Denver; C: Buffalo). The black line represents the observed patterns, while the red dot-line shows the expected value under Heterogeneous Poisson process (HP) and the shaded area represents envelopes for 200 Monte Carlo simulations with 95% of confidence level.

**5. Conclusions**

Land cover change was studied for three cities in the United States, and although the employed statistical tests showed significant changes for some of the classes (particularly increases in the developed class and decreases in the green areas), these seemed to not be very remarkable given the continuous population increase and the demand for developed infrastructure. Notwithstanding, this study provides results that can be complemented further with social and economic analysis to produce richer evidence of relationships between all these factors in connection to land cover change. Some evidence of the clustering of new developmental activities was observed at a relatively small spatial scale in San

Diego. Further, some evidence of the dispersion of new developed activities was noticed at a larger scale in Denver. The similarities (slight increase in developed areas, slight decrease in green areas) and the dissimilarities (the spatial arrangement of changes in land uses) further adds to the land use history story of development in United States cities, and how geography, demographics, and history can contribute to the intriguing futures of these human systems. If decision-makers are concerned about recent trends in the pattern of development, as well as in the relative size and rate of change of land uses, the employment of this analysis can help them coordinate planning policies that focus on the management of urban change, urban footprints, and urban forests. The methods employed to estimate transitions in land use over time, and to

estimate whether development activities are statistically clustered, can easily be applied to other urban areas of the world. There are no place-specific limitations with regard to the sampling and analysis protocols, other than certain land uses may be less relevant in other parts of the world, and other land uses not recognized here may be more relevant in other parts of the world.

## Declarations

### Author contribution statement

Krista Merry & Pete Bettinger: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Taeyoon Lee: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Alba Rocio Gutierrez Garzon: Analyzed and interpreted the data; Wrote the paper.

Volkan Bektas: Analyzed and interpreted the data; Wrote the paper.

Jennifer Cruise-Palmer: Conceived and designed the experiments; Performed the experiments.

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### Data availability statement

Data associated with this study has been deposited at Dryad under <https://doi.org/10.5061/dryad.h18931znt>.

### Declaration of interests statement

The authors declare no conflict of interest.

### Additional information

No additional information is available for this paper.

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