Landscape and Urban Planning 236 (2023) 104764

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Four decades of urban land cover change in Philadelphia

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HIGHLIGHTS

- Urban tree canopy (UTC) change studies are currently limited.
- Short temporal extents, few time steps, & low categorical resolution hamper inference.
- Land cover change sequence tabulation, multinomial regression, & clustering were used.
- Increasing homeownership, income, & educational attainment predicted tree persistence.
- Opportunities for tree preservation and planting are discussed.

ARTICLE INFO

Keywords:
Land canopy change
Sequence analysis
Post-industrial city
Urban forest
Urban tree canopy
Spatiotemporal analysis

ABSTRACT

Given ambitious tree canopy goals, land cover change analyses in cities are imperative. Urban tree canopy change analyses have been hindered by data with low categorical resolution (e.g., canopy vs. not canopy), over relatively short time horizons (5–10 years), representing only two points in time, and scarce linkages to other temporal datasets (e.g., historical socioeconomic data). In this study, using a land cover change data set with five cover classes spanning 40 years (1970–2010) for Philadelphia, PA (US), we asked: which types of land cover changes are most common, and how do those relate to and co-vary with socioeconomic change? Specifically, we tabulated land cover changes (i.e., transition sequences), applied multinomial logistic regression with socioeconomic variables as predictors of land cover change, and used cluster analyses to characterize neighborhood changes associated with land cover change. Land cover stability dominated the transition sequences: the four most common sequences were stable road (e.g. road-road-road-road-road), stable building, tree canopy, and herbaceous vegetation, collectively accounting for 62.57% of all sequences. Multinomial logistic regression identified that increases in homeownership, income, and educational attainment were associated with a higher probability of tree canopy persistence. Cluster analyses via Affinity Propagation showed that some Census tracts have similar land cover change trajectories, and yet different socioeconomic trends. These findings point towards opportunities to focus on tree preservation alongside the importance of establishing new tree canopy through planting. Our study demonstrates the mix of stability and dynamism in multidecadal urban land cover change, and the importance of connecting land cover changes with socioeconomic changes.

1. Introduction

Given ambitious tree canopy goals, land cover change analyses in cities are imperative. Consequently, scholarship on urban tree canopy (UTC) cover has advanced considerably over the past decade (O'Neil-Dunne, MacFaden, & Royar, 2014), with numerous studies that have improved our understandings of UTC cover, inequities in distribution, and legacies of past policies and events (Gerrish & Watkins, 2018; Locke et al., 2021; Roman et al., 2018; Watkins & Gerrish, 2018). Comprehensively understanding UTC change requires long-term analyses spanning many decades, because trees are fundamentally slow-growing organisms that take decades to grow (Roman et al., 2021). Analyses conducted with relatively short time spans (<10 years) and with only one time step find mostly that UTC persists (Chuang et al., 2017; Kaspar

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https://doi.org/10.1016/j.landurbplan.2023.104764
Received 17 November 2022; Received in revised form 14 February 2023; Accepted 1 April 2023
0169-2046/Published by Elsevier B.V.

et al., 2017; Locke et al., 2017; Parmehr et al., 2016), plausibly missing the patterns and processes of how urban forests form. In studies spanning four to six decades, with multiple temporal intervals, UTC is less stable over time due to turnover of tree additions and losses, with variation across urban neighborhoods and greenspaces (Healy et al., 2022; Nix et al., 2022; Roman et al., 2021). Given the widespread policy adoption of UTC goals (Hauer & Peterson, 2016; Kimball et al., 2014; Locke et al., 2017), and ambitious tree planting initiatives to achieve them (Doroski et al., 2020; Eisenman et al., 2021), there is a clear and pressing need to understand multidecadal UTC change.

Furthermore, assessing UTC net change alone (Kaspar et al., 2017; Merry et al., 2014; Parmehr et al., 2016) does not capture the complex spatiotemporal dynamics inherent in UTC change. It is critical to recognize that UTC change does not occur in isolation from other phenomena shaping urban landscapes and communities (Healy et al., 2022; Roman et al., 2021); tree canopy is often operationalized as just one form of land cover. Most fundamentally, future tree canopy cover is created from current tree canopy cover, plus the canopy increase from surviving trees' expanding crowns, and new canopy from tree planting or natural emergence, minus canopy loss from tree death, maintenance, or removals by people and/or disturbance events (Luley & Bond, 2002). To understand how UTC changes over time, it is therefore critical to assess the transitions between trees and *other* land cover classes, and across neighborhoods with varying socioeconomic trajectories. Presence versus absence of tree canopy at two points in time are insufficient to understand spatiotemporal trends and to speculate about drivers of land cover change. By understanding the long term trends of tree canopy cover can help determine the factors that promote canopy persistence and/or gain.

The processes influencing UTC change are complex, with UTC spatiotemporal dynamics linked to local land use planning, urban population changes, and the changing racial and wealth characteristics of cities and neighborhoods (Bonney & He, 2019; Healy et al., 2022; Roman et al., 2021). In the United States (US), local changes in land use and socioeconomic profiles, and their associated relationships with UTC, have been explained by national policies and trends, including redlining, urban renewal, depopulation, and suburbanization (Grove et al., 2018; Healy et al., 2022; Hoffman et al., 2020; Merse et al., 2009; Namin et al., 2020; Roman et al., 2021). For cities in the northeastern and midwestern US, such changes reflect processes of post-industrialization and urban shrinkage (Berland et al., 2020; Haase et al., 2014; Roman et al., 2021). Crucially, for cities that experienced declining populations and are also located within forested biomes, abandoned or unmaintained areas can experience unintentional forest emergence, including vacant lots, abandoned industrial areas, and unmowed areas of parks (Berland et al., 2015; Healy et al., 2022; Nix et al., 2022; Roman et al., 2021).

Most information on UTC temporal trends is based on short-term analyses (<10 years), which can be insightful, albeit limited in the ability to discern broader drivers of change, unless there has been a substantial drop in UTC from an extreme event such as a pest outbreak or earthquake (Hostetler et al., 2013; Morgenroth et al., 2017). For example, several high-resolution UTC change studies show a modest net UTC decline over relatively short time horizons (~5–10 years) in US cities (Chuang et al., 2017; Foster et al., 2022; Hostetler et al., 2013; Locke et al., 2017) and in New Zealand (Morgenroth, 2016; Morgenroth et al., 2017). A unique study of individual tree stem loss showed 13,427 and 15,000 trees were lost in Denver, Colorado and Milwaukee, Wisconsin from 2008 to 2013, and 2010 to 2015, respectively (Ossola & Hopton, 2018). Point-based sampling has also shown a small net decline in 17 out of 20 US cities examined from the early- to mid-2000′s (Nowak & Greenfield, 2012b), and national estimates indicate declining UTC and increasing impervious surface (Nowak & Greenfield, 2018).

Connections between socioeconomic variables and UTC change over a few years are also becoming apparent. Prior research from Los Angeles (CA), Baltimore (MD), and Washington, D.C. has suggested that areas with higher incomes lose less UTC (Locke et al. 2017) and lower-income areas lose more (Chuang et al., 2017). In Philadelphia (PA) from 2008 to 2018, racialized groups (Black / African American, Hispanic / Latino, and Asian) were significant negative predictors of tree canopy change on single family residential lands (Foster et al., 2022). However, less is known about multidecadal UTC changes in the context of several land cover classes.

Historical socioeconomic variables reliably predict present-day UTC distribution (Boone et al., 2010; Locke et al., 2021; Locke & Baine, 2014) because trees take time to grow. For example, renter-occupied housing in 1980 is a stronger, negative predictor of year 2008 tree canopy cover than renter-occupied housing in either years 1990 or 2000 in New Haven (CT) (Locke & Baine, 2014). Elucidating how tree canopy changes co-occur with socioeconomic changes remains an important scholarly gap to address, particularly as municipal and non-profit plans and programs seek to address distributional inequities in UTC by prioritizing low-income neighborhoods and BIPOC (Black, Indigenous, and People Of Color) communities for tree planting initiatives (Grant et al., 2022; Riedman et al., 2022).

Despite the advances and empirical findings described above, UTC change analyses have been hindered by data with low categorical resolution (e.g., canopy vs. not canopy), over relatively short time horizons (5–10 years), representing only two points in time, and scarce linkages to other temporal datasets (e.g., historical socioeconomic data). In this study, we assessed 40 years of land cover change (1970–2010) in Philadelphia, PA, a post-industrial city in the northeastern US. Focusing on changes in the developed (i.e., non-park) areas of the city, we asked: First, out of all possible land cover transitions, which specific sequences (i.e., the ordering of land cover transitions across time) occurred most often? The most frequent transition sequences were tabulated to describe the overall types of land cover changes in this city. Second, which socioeconomic variables predict UTC transitions? Socioeconomic changes were used to predict tree/shrub canopy change sequences via multinomial logistic regression. Third, to what extent are there trajectories of changing neighborhoods (in term of shifting socioeconomic characteristics) that have consistent and corresponding land cover change sequences? A cluster analysis called affinity propagation was used to define neighborhood types and then land cover changes were visualized for each cluster. When considered collectively, these three perspectives provide a balanced understanding of long-term UTC change.

2. Methods

2.1. Study area

In 2010, Philadelphia was the fifth-largest US city by population, home to 1.5 million residents, down from a peak of 2 million in 1950 (Philadelphia City Planning Commission (PCPC), 2011). We use 2010 as a reference to coincide with the end of our study period. The city had in 2010 a plurality non-Hispanic Black population (~43%) with a substantial Hispanic minority (~12%; Logan et al., 2014), and it is also has the highest poverty rate of the 10 most populous cities in the US (Bryant, 2017). Philadelphia has approximately 40,000 vacant parcels for which the Philadelphia Water Department has shut off water service, of which an estimated 37,000 are vacant lots, resulting from mid-20th century and early-21st century urban renewal and demolition policies (Econsult Corporation, 2010), with 5% of all land vacant, but substantially more in some neighborhoods (Philadelphia City Planning Commission (PCPC), 2011). The vacant lots are most common and concentrated in the South, West, North, Lower North, Upper North and River Wards planning districts (Fig. 1). Our study period begins in the midst of Philadelphia's post-industrial challenges (1970). Notably, although large parts of Philadelphia's outer neighborhoods were agricultural until the mid-20th century, nearly the entirety of the city's neighborhoods were developed by 1970, albeit with some pseudo-suburban subdevelopments constructed in the Far Northeast and Far Northwest areas in the 1970s to

Fig. 1. Land cover map of Philadelphia, Pennsylvania and its planning districts. Land cover types derived from 2008 high resolution LiDAR and 2008 Orthophotography (O'Neil-Dunne, MacFaden, & Royar, 2014). Districts from (City of Philadelphia, 2022).

early 1980s, and ongoing redevelopment in many neighborhoods (Roman et al., 2021).

Philadelphia was a predominantly temperate deciduous forest prior to European colonization, and the city is near the northern boundary of the human subtropical climate zone in the US (Dyer, 2006; Kottek et al., 2006). In 2018, a high-resolution, high-accuracy, LiDAR-derived land cover assessment (O'Neil-Dunne, 2019) determined that citywide UTC cover was 21% in year 2008 and 20% in year 2018 (Fig. 1), and municipal leaders have sought to increase UTC to 30% in every neighborhood (City of Philadelphia, 2019), which would have public health benefits (Kondo et al., 2020). Municipal leaders will soon release an urban forest strategic plan based on input from stakeholder groups including residents, with the plan centered around environmental justice and equity, including enhancing tree cover and stewardship in neighborhoods that are predominantly communities of color, low-income, and low-canopy (Schmidt, 2021).

2.2. Data sources and processing

2.2.1. Land cover change sequences

To assess historical land cover change, we used visual interpretation of aerial imagery, an approach widespread in urban forestry and landscape ecology (Hilbert et al., 2019; Morgan et al., 2010). Visual interpretation involves a human viewing the imagery and assigning a land cover class. While high resolution ($\leq 1m^2$) land cover is becoming increasingly available in cities and used in UTC analyses (MacFaden et al., 2012; O'Neil-Dunne, MacFaden, & Royar, 2014; O'Neil-Dunne, MacFaden, Royar, et al., 2014; Pallai & Wesson, 2017), such data is fairly recent and reflects current and recent conditions. To assess multidecadal UTC change, historical aerial photos present an opportunity to study UTC during past periods of change (Healy et al., 2022; Roman et al., 2021). Specifically, we used an existing dataset of point-based land cover interpreted from aerial imagery spanning four decades and five images: 1970, 1980, 1990, 2000, and 2010 (Roman et al., 2021, 2023).

This existing unique dataset is suitable to the current analysis because of it has a relatively long temporal reach that spans a diversity of changing neighborhood socioeconomic conditions. The 10,000 points from the original dataset were spatially randomly distributed throughout the city, including both residential lands and parks. This number of points is considerably higher than other studies relying on point-based photointerpretation of historical aerial imagery (generally 500–1000, e.g., (Hilbert et al., 2019; Nowak & Greenfield, 2012a), which limits inferences about variation within a city. All 10,000 points were interpreted by the same individual interpreter, which removed inter-interpreter variation (Berland, 2012). A 5% subsample of the original points were compared to an independent second interpreter, with 91.5% agreement about tree/shrub cover status across all years, and better agreement in more recent images, comparable to other studies (Hilbert et al., 2019; Nowak & Greenfield, 2012a; Roman et al., 2021). The 2010 point interpretations were also compared against 2008 LiDAR-derived UTC, with 93.4% agreement, and areas of disagreement largely explained by different meanings of "tree" (i.e., tree/shrub interpretation for aerials vs. 2.4 m minimum tree height for LiDAR UTC analysis).

The five land cover classes are: tree and shrub (these were not differentiated due to impracticalities of distinguishing them in historical aerial photos), herbaceous vegetation (e.g., lawn, turf), other pervious (e.g., bare soil, water, hereafter referred to as "soil"), building, and other impervious (e.g., roads, parking lots, walkways, etc.). Notably, these land cover classes represent a top-down photointerpretation method, such that tree/shrub cover can be over other land cover classes. Each point therefore has five land cover classes, one for each decade, and we call that set of ordered categories a land cover change sequence, or sequence for short. From previous analysis of this land cover change dataset, it is known that in developed areas of the city, tree/shrub cover increased from 14% in 1970 to 17% in 2010, with substantial increases in both depopulating urban cores and outer neighborhoods with relatively lower housing density (Roman et al., 2021).

We focused on points that were not located in protected open space (i.e., municipal, state, federal, and nonprofit park spaces), that were not permanent water (i.e., water in all five images), and that were interpretable across all years of imagery, which yielded 8,691 points to address research questions 1 (which land cover change sequences are most common) and 2 (which sociodemographic changes predict those land cover changes). Park areas were excluded given the interest in socioeconomic changes alongside land cover changes. When focusing on land cover transitions from 1980 to 2010 that start or end as tree/shrub cover (research question 3), a subset of 1,690 points were retained (and these points are the units of analysis); we did not use 1970 for that analysis because US Census data (described next) from 1970 is not comparable due to changing definitions of racial and ethnic groups. Notably, consistent with Healy and colleagues (2022), we refer to a cover class that remains present at two consecutive points in time as persistence, and reserve the term stability for a cover class that remains the same at more than two points in time. In our analysis, we specifically discuss stability across all five images (and 40 years) of the study.

2.2.2. Socioeconomic and housing data

Research question 3 was addressed at the level of US Census tracts (n = 372). The US Census Bureau splits, merges, and otherwise changes geographic units over time, which complicates spatially-explicit time-series analyses of socioeconomic trends. Therefore, Census data from the Longitudinal Tract Data Base (LTDB) was used, which was designed to rectify these problems using crosswalks of blocks via spatial allocation into their containing tracts over time with proportional coverage-weighting (Logan et al., 2014). The LTDB recasts the tabular data into 2010 polygons, taking into account the tract consolidation, splits, and other spatial misalignments. Tabular data for each decade were joined to the 2010 tract polygons. A comparable spatially-rectified, time-series product for the smaller Census block groups is not available. Census data from 1970 was not used in this analysis because race and ethnic group definitions were not comparable. Downloaded data were transformed to create values that could be readily compared across time and geographies of varying sizes. For example, total population was divided by area to create population density (population per hectare), vacant housing units were divided by total housing units and multiplied by 100 to create percent vacant, and values measured in dollars were inflation-adjusted to year 2010 US dollars. The result of these transformations was socioeconomic and housing (hereafter "Census") variables in five thematic groups: population density (population per hectare), education (% adults, those aged 25 years and older, with at least a high school diploma or GED, and % adults completing at least some college), housing (% vacant and % homeownership), economic status (% unemployed, median household income, and per capita income), and race / ethnicity (% non-Hispanic white, % non-Hispanic Black, and % Hispanic of population irrespective of race). For context in the interpretation of our results, we note here that the citywide portion of non-Hispanic white residents declined from 1980 to 2010 (57.1% to 36.9%), while the portion of non-Hispanic Black residents and Hispanic residents increased from 37.5% to 43.4% and 3.8% to 12.3%, respectively (Logan et al., 2014).

2.3. Land cover change and statistical analyses

Land cover and UTC change were assessed in three primary ways, by 1) providing descriptive statistics and visualizations of land cover change sequences, 2) identifying factors that predict tree/shrub change between 1980 and 2010, and 3) using the same predictor variables to better understand the types of neighborhoods (or "neighborhood clusters") associated with the land cover changes. For the visualizations, we used sequence index plots (Fasang & Liao, 2014) and Sankey diagrams (Cuba, 2015), which can both be used to depict changes in categories or types over time.

Only points that started as tree/shrub canopy in 1980, became tree/shrub canopy in 2010, or both were used in the regression for research question 3 (n = 1,690). We also dropped points transitioning to and from the soil class due to infrequency (Table 2). All predictors were converted into measures of change by subtracting 1980 values from 2010 so that positive values indicate increases, and negative values indicate declines. In order to reduce multicollinearity among predictors, each of the eleven predictor variables were individually regressed against the 1980 to 2010 land cover transition using multinomial logistic regression, excluding the intervening years for simplicity. Predictors within the aforementioned thematic groups population density (composed of population per hectare), education (% adults, those aged 25 years and older, with at least a high school diploma or GED, and % adults completing at least some college), housing (% vacant and % homeownership), economic status (% unemployed, median household income, and per capita income), and race / ethnicity (% non-Hispanic white, % non-Hispanic Black, and % Hispanic of population irrespective of race) were evaluated as potentially redundant. The variable with the lowest Bayesian Information Criterion (BIC) per thematic group was used in multivariate multinomial logistic regression, so that five predicting variables were entered into the final model. The five predictors approximated a normal distribution and outliers were not a concern. The correlations between those five predictors were low (<0.48) and some were not significantly correlated ($p > 0.01$), indicating that multicollinearity was not a problem. The receiver operating characteristic curve – a diagnostic plot depicting the true positive rate versus the false positive rate – was calculated so that the area under the curve (AUC) per outcome class could be computed to evaluate overall and class-specific predictive accuracy.

The significant predictors used in the multinomial logistic regression were then used to cluster tracts into categories. Note that the clusters are not necessarily spatial clusters. Instead, neighborhood characteristics were included in an a-spatial cluster analysis called affinity propagation to categorize neighborhoods. Neighborhoods of the same category may or may not be spatial neighbors. The purpose of this analysis was to classify changing areas into types based on changing socioeconomic and housing conditions, and then to visualize the complex five-class land cover change sequence across all four decades within each type of changing neighborhood. Classifying neighborhoods based on socioeconomic data via clustering techniques has a long history (Charlton et al., 1985; Shevky & Bell, 1955). Tree canopy (Bigsby et al., 2014; Grove et al., 2006, 2014; Troy et al., 2007), tree canopy change (Chuang et al., 2017), and participation in urban tree giveaways (Locke & Grove, 2016; Nguyen et al., 2017) have all been shown to vary by types of neighborhoods created using various clustering techniques. Present-day urban vegetation more broadly (Hoffman et al., 2020; Namin et al., 2020) and tree canopy specifically (Locke et al., 2020) have been shown to vary by historical neighborhood classification systems as well. Classifying neighborhoods over time has been used to show persistence and change in socioeconomic and housing conditions along multiple dimensions simultaneously (Delmelle, 2015, 2016).

Affinity propagation (Bodenhofer et al., 2011; Frey & Dueck, 2007) was chosen as the clustering method. Although K-means clustering is often used in similar types of work, affinity propagation has properties that, compared to k-means that make it better suited for this analysis. K-means clustering can find means in data space that do not represent the actual input data; cluster centers are means but not necessarily actual observations. K-means and K-medoids use random starts in data space to start identifying clusters. These methods therefore produce different results when a different random seed is chosen; their results are sensitive to a particular random start. Finally, both K-means and K-medoids require that the user specify the number of clusters to create. Affinity propagation starts with a similarity matrix, and then pairs of data points are iteratively compared for relative attractiveness until clusters emerge (Frey & Dueck, 2007). The user does not specify the number of clusters a priori, instead the algorithm identifies the appropriate number in the data. Additionally, affinity propagation identifies archetypes (the most representative observations per cluster), is deterministic (finds the same clusters and cluster membership each time), and finds the number of clusters in the data (Frey & Dueck, 2007). Refinements allow the user to increase or decrease the number of clusters to improve interpretability (Bodenhofer et al., 2011), this last step can be thought of as tuning the number of clusters. Affinity propagation does not require the user to specify the number of clusters, is not dependent upon random starts, and identifies actual exemplars in the data (instead of unobserved means), and was therefore selected as the appropriate clustering method.

The significant predictors in the regression analyses were used to cluster neighborhoods to better understand how types of neighborhoods correspond to types of land cover changes. A diagnostic heatmap of cluster membership and pairwise similarity was used to tune the resulting clustering and provide more interpretable clusters by setting $q = 0.01$. That setting reduced the number of clusters from the uninterpretably high 30 to just 7.

All analyses were conducted using R version 4.1.2. (R Core Team, 2021). Data and reproducible code are available via Roman et al., 2023.

3. Results

3.1. Sequences

Each point has five values, one for each decade, which we call a sequence. The unique sequences were tallied as counts and as a percentage of all observed frequencies (Table 1). Only 369 (11.81%) of the 3,125 possible sequences were observed. The distribution of sequence frequency is highly dominated by stability (Fig. 2, Table 1). The top four most common sequences were stable other impervious, building, tree/shrub, and herbaceous vegetation, meaning there was no change in that cover class across the 40-year study period. These four stable cover classes account for 62.57% of all observed sequences (Table 1). Stable soil was the 7th most common sequence. Tree/shrub cover gains often occurred through herbaceous to tree/shrub transitions (Figs. 2 and 3), and three of the ten most common sequences were herbaceous to tree/shrub transitions (accounting for 4.45% of all sequences, Table 1). Out of the 369 observed unique sequences, 174 (47.15%) were observed at only one sample point. Overall, stable points dominate the sequence distribution, followed by numerous unique land cover changes.

3.1.1. Predictors of land cover change

The BIC minimization process used to select among potentially redundant predictors within the five thematic group (population density, education, housing, economic status, and race/ethnicity) indicated that changes in population density, % with some college education, % homeownership, median household income, and % Hispanic provided the best fit within each thematic group. Those variables were used as predictors in the multinomial logistic regression of the probability of transitioning to or from tree/shrub between the 1980 and 2010 observations.

The significant predictors mostly had negative associations which can be interpreted as favoring tree/shrub persistence because tree/shrub persistence was used as the reference category (Fig. 4, Table S1). Increasing education, for example, was associated with lower

Table 1
Frequencies of the ten most common land cover sequences over 40 years and five images, excluding open spaces (total number of sequences = 7,588).

year 1970	year 1980	year 1990	year 2000	year 2010	N	Percent
imperv.	imperv.	imperv.	imperv.	imperv.	1905	25.11
building	building	building	building	building	1463	19.28
herb.	herb.	herb.	herb.	herb.	830	10.94
tree/shrub	tree/shrub	tree/shrub	tree/shrub	tree/shrub	550	7.25
herb.	herb.	tree/shrub	tree/shrub	tree/shrub	138	1.82
herb.	imperv.	imperv.	imperv.	imperv.	138	1.82
pervious	pervious	pervious	pervious	pervious	117	1.54
herb.	tree/shrub	tree/shrub	tree/shrub	tree/shrub	109	1.44
herb.	herb.	imperv.	imperv.	imperv.	98	1.29
herb.	herb.	herb.	tree/shrub	tree/shrub	90	1.19

Table 2
Land cover sequences that involve tree/shrub canopy from 1980 to 2010 (excluding the intervening years, n = 1,690), tabulated by frequency and tract-level demographic changes. Transitions involving soil were dropped due to rarity.

Land Cover Transition, 1980–2010	N	Percent
tree/shrub to tree/shrub	734	43.43
herb. to tree/shrub	273	16.15
tree/shrub to herb.	224	13.25
tree/shrub to other impervious	210	12.43
other impervious to tree/shrub	158	9.35
building to tree/shrub	49	2.9
tree/shrub to building	42	2.49
Demographic changes, 1980–2000	**Mean**	**s.d.**
Population Density (people / hectare)	−5.07	13.49
Adults w some College Education, %	−11.85	10.51
Owner-Occupied Housing Units, %	−4.79	12.16
Median Household Income (year 2010 USD$)	−0.27	14.76
Hispanic Population, %	5.24	7.86

probability of tree/shrub-to-building (Odds Ratio 0.95 95% CI [0.91 to 0.98]) and tree/shrub-to-herbaceous vegetation (OR 0.98 95% CI [0.96 to 0.99]). Increasing population density was also negatively associated with building-to-tree/shrub (OR = 0.96), other impervious-to-tree/shrub (OR = 0.98), and tree/shrub-to-other impervious (OR = 0.98) transitions. Increases in homeownership were associated with lower probabilities of herbaceous vegetation-to-tree/shrub (OR = 0.98), and tree/shrub-to-other impervious (OR = 0.98). The only positive coefficients were for the increasing Hispanic population and the other impervious-to-tree/shrub class (OR = 1.04) and tree/shrub-to-other impervious (OR = 1.03). Overall, the accuracy was low to moderate, class-specific AUC ranged from 0.54 (herbaceous vegetation-to-tree/shrub) to 0.71 (building-to-tree/shrub, Table 3). Macro-average was calculated by averaging all group results, and micro-average was calculated by stacking all groups together and reducing the multi-class classification into a binary classification.

3.1.2. Land cover change in neighborhood clusters

Below, the characteristics of each cluster are summarized (Fig. 5, Figure S1). We refer to areas of the city following the Philadelphia City Planning Commission's planning districts (Fig. 1) (City of Philadelphia, 2011).

Cluster 1 is predominantly found in Center City and the nearby University City area of West Philadelphia. This cluster experienced the largest increases in population density and homeownership of any cluster, and the second largest increase in educational attainment. There were very small increases in household income and in the Hispanic population (Figure 6). Impervious surface and building cover dominate, and modest tree/shrub cover and herbaceous cover are stable.

Cluster 2 is largely found in West Philadelphia, and scattered tracts in the Lower North, North, Upper North, and South areas. Tracts in this cluster experienced large declines in population density, modest increases in educational attainment, modest declines in homeownership and median household income, and little change in the Hispanic population. Land cover is predominantly impervious surfaces and buildings, with small declines in herbaceous vegetation and general stability.

Cluster 3 is largely found in the Lower North and North areas. This cluster, represented by only 16 tracts, is characterized by the largest declines in population density of any cluster. There was also modest loss of homeownership, small growth in educational attainment and Hispanic population, and little change in income. Tree/shrub cover and herbaceous vegetation increased as building cover declined.

Cluster 4 is primarily found in Upper and Lower Northwest Philadelphia, along with areas immediately adjacent to the central business district in Center City, South, and Lower North. This cluster witnessed the largest increase in educational attainment and income, modest declines in population density and increases in homeownership, and little change in the Hispanic population. This cluster is characterized by high and increasing tree/shrub cover and building cover at the expense of herbaceous vegetation.

Cluster 5 is the smallest cluster with 13 tracts. This cluster is geographically less dispersed compared to other clusters and is found only in a small area of North Philadelphia and the River Wards neighborhoods. This cluster had the largest increase in the Hispanic population as well as the largest decreases in homeownership and income. There was a modest increase in population density and little change in educational attainment. This cluster is nearly all building and impervious cover, and has very low tree/shrub cover (the lowest of all clusters in each year), with little change.

Cluster 6 is mostly found in Lower and Central Northeast Philadelphia, as well as nearby areas of North Delaware, River Wards, North, and Upper North. This cluster is characterized by a large decline in homeownership and income, and the second-highest increase in the Hispanic population. There were also very small increases in population density and educational attainment. Tree/shrub cover has grown over time, but most of this cluster is building and impervious surface.

Cluster 7 is the largest cluster, with 124 tracts located in many parts

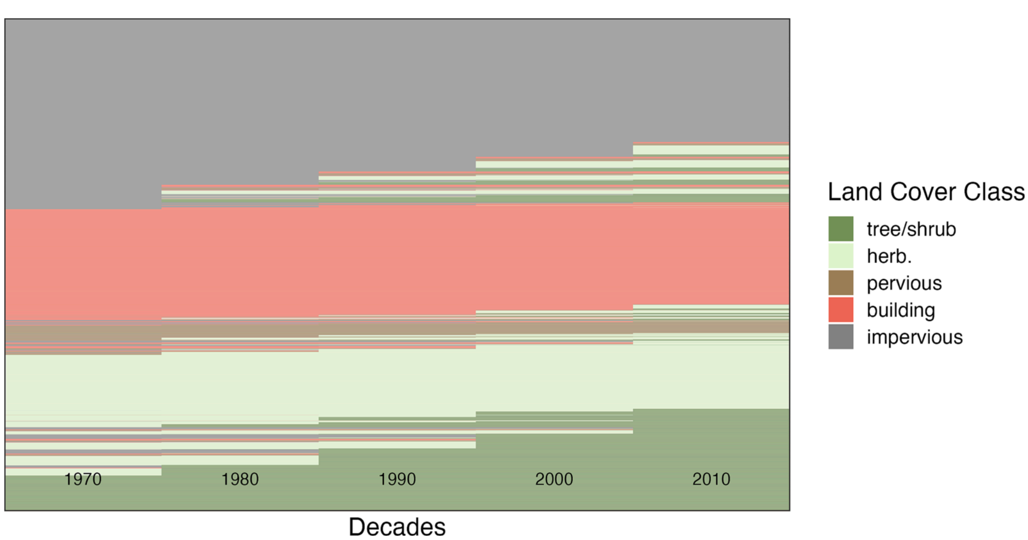


Fig. 2. Sequence index plot for land cover change. Each horizontal line represents a single observed sequence (n = 7,588) of land cover classes across five aerial images spanning 40 years. Solid colors from left to right represent 40-year stability for that land cover class at that point.

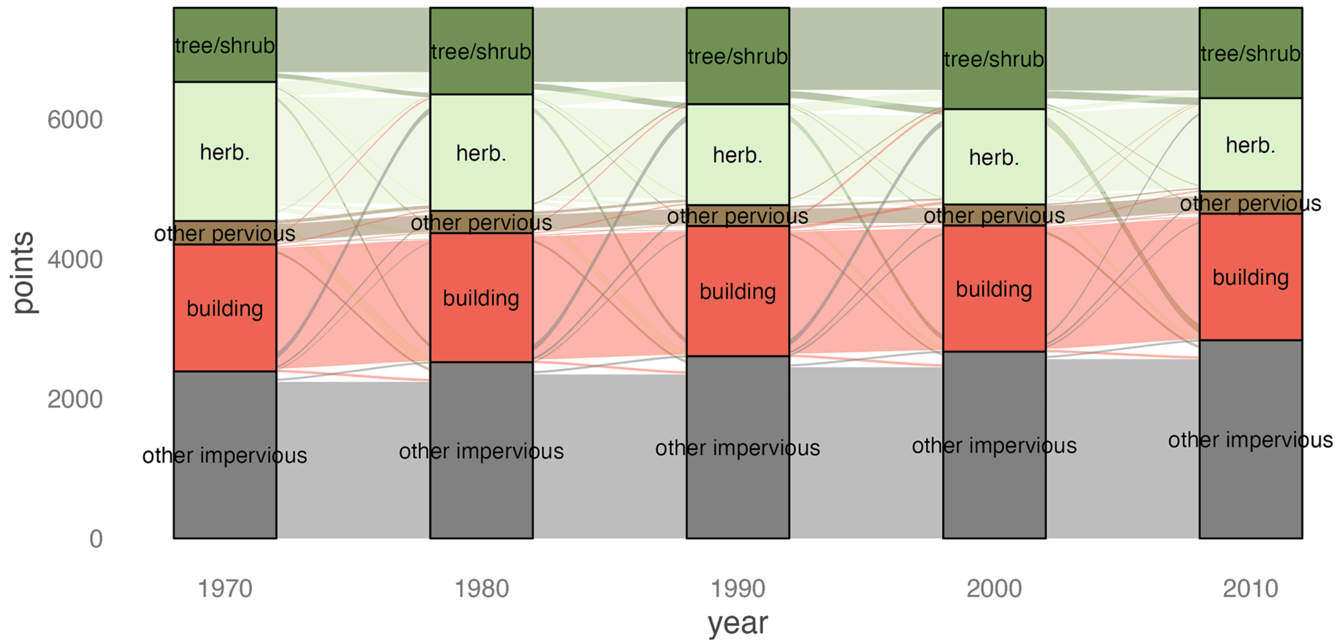


Fig. 3. Sankey diagram for land cover change for five aerial images spanning 40 years. Curved lines between years represent points beginning as one class and ending as another class during that decade; line thickness is proportional to points in that transition.

of the city, including most of the Far Northeast, and parts of the River Wards, Lower and Upper Northwest, and West, Southwest, and South areas. This cluster is characterized by large increases in educational attainment, as well as modest decreases in homeownership and income, and modest increases in the Hispanic population. There was very little change in population density. This cluster witnessed an increase in tree/shrub cover from 1970 to 2000, and then a decline in canopy from 2000 to 2010. Like several other clusters, herbaceous cover also declined over time.

4. Discussion

The analyses of four decades of land cover change in Philadelphia showed that most land cover stayed the same. About two-thirds (64.12%) of all points were stable throughout the 40-year study period, but the long-tailed distribution for sequence frequency showed many unique change trajectories, with nearly half of the land cover change sequences occurring only at a single observation point. For example, building-building-bare soil-other impervious-bare soil occurs only once; there were another 173 one of a kind observed sequences. Stable other impervious (comprised of roads, parking lots, and other impervious covers) was the most common sequence with one-quarter of all observed points falling into this category. Stable tree/shrub represented only 7.25% of points in Philadelphia over the 40-year period (Table 1), and approximately half of the points which began as tree/shrub in 1970 remained tree/shrub throughout all subsequent images (Fig. 2). Without multiple time points it would not have been known that vast majority of land cover sequences are stable while the remaining sequences are unique. This frequency distribution contrasts with the very high persistence across two points in time for UTC change studies using point-based sampling spanning 5–10 years (Nowak & Greenfield, 2012b, 2018), or object-based image analysis (Locke et al., 2017).

Many previous multidecadal analyses of UTC change focused on net change (Berland, 2012; Doick et al., 2020; Merry et al., 2014), not persistence or stability, making comparisons to our study challenging. However, a recent study using manually digitized polygons of tree canopy across 62 years of UTC change (and four years of imagery) in two mid-sized post-industrial cities, Holyoke and Chelsea, Massachusetts, showed extremely low stability (Healy et al., 2022). Only 5.13% and 0.87% of the cities' study areas, respectively, were consistently covered by tree; these numbers included both developed areas and parks in those cities. Our 7% tree/shrub stability finding is broadly consistent with the trend from Healy and colleagues (2022), given that we have a shorter time period (four decades not six). Furthermore, both Healy et al. (2022) and Nix et al. (2022) found that tree stability across an entire six-decade period was lower than persistence at shorter time intervals. Future UTC change studies may consider incorporating persistence and stability metrics to improve interpretation of UTC dynamism.

The regression analyses revealed that tracts with increases in homeownership, income, and educational attainment were associated with a higher probability of tree/shrub canopy persistence, aligning with past research. Looking over a shorter time horizon (2008 to 2018) and only at single family residential land, Foster and colleagues (2022) found that areas with a greater proportion of white residents in Philadelphia were more likely to have tree canopy in 2018 and were more likely to have increases in tree canopy cover. Foster et al (2022) concluded that environmental injustices could be increasing over time, as the gap in tree canopy cover widens between high-income and low-income areas. In the District of Columbia, persistently low-income areas had the largest losses in tree canopy (Chuang et al., 2017). In Los Angeles, CA neighborhoods with relatively higher income were associated with more tree canopy, more persistent canopy, and less loss over a 5-year period (Locke et al., 2017). It has been well-documented that higher income areas (Gerrish & Watkins, 2018), and predominantly white areas (Watkins & Gerrish, 2018) tend to have more UTC. But it remains less-clear how changing neighborhood socioeconomic composition tracks with changing land cover changes, or not. Future research may consider additional analyses of neighborhood change and land cover change jointly.

Philadelphia's increasing Hispanic population was associated with the largest odds ratio of any predictor in the regression analyses. The growing Hispanic population was associated with an increased probability of other impervious-to-tree/shrub, relative to the baseline category of tree/shrub-to-tree/shrub. Since the street grid changed very little with respect to spatial location during our study period, much of the other impervious-to-tree/shrub transitions may be interpreted as the grow-out of street trees, street-adjacent yard trees, and trees and shrubs on vacant lots that overhang what used to be viewed as roads in the

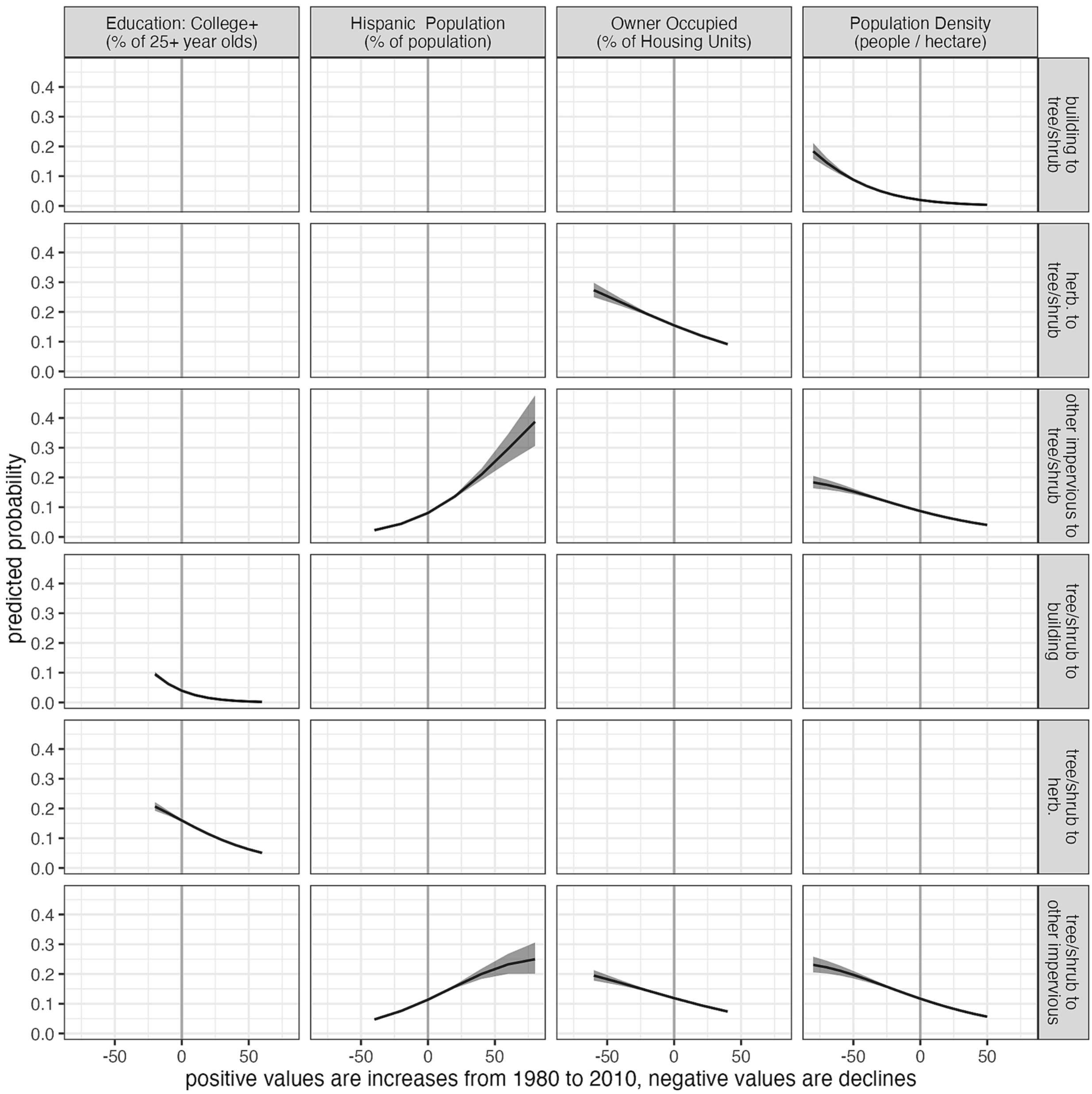
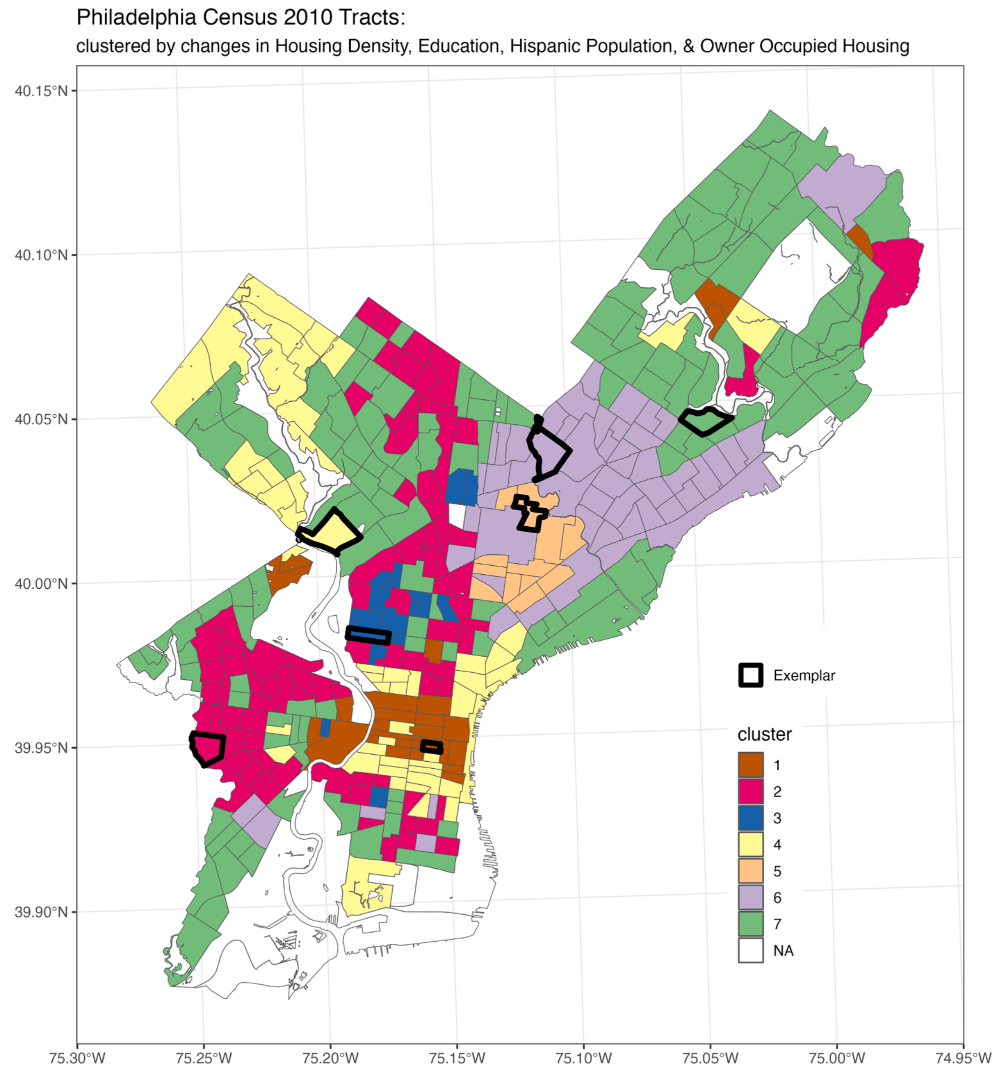


Fig. 4. The association between demographic change and land cover transitions from 1980 to 2010 (excluding the intervening years, n = 1,690). Only significant predictors' relationships are shown.

Table 3
The area under the curve (AUC), indicating probability that the model correctly classified the land cover transition. 1 is perfect classification.

Land Cover Transition	AUC
tree/shrub-to-tree/shrub	0.59
building-to-tree/shrub	0.69
herb.-to-tree/shrub	0.54
other impervious-to-tree/shrub	0.60
tree/shrub-to-building	0.63
tree/shrub-to-herb.	0.58
tree/shrub-to-other impervious	0.58
macro	0.60
micro	0.77

aerial imagery. The growing Hispanic population was also associated with an increased probability of tree/shrub-to-other impervious, which we interpret as representing street, yard, and vacant lot trees which used to overhang roads, and later died or were removed. While this is a seemingly contradictory finding, these kinds of coefficients are common with multinomial logistic regression models because they are effectively a set of binary logistic regressions, and the coefficients are relative to the reference case of tree/shrub-to-tree/shrub here. Our modeling flexibly handles these other impervious/tree/shrub transitions that have been described as "churn" (Kaspar et al., 2017), and are entirely masked by reporting net change in tree/shrub canopy change (Kaspar et al., 2017; Merry et al., 2014; Parmehr et al., 2016), even though these land cover transitions and their spatial arrangement may be of great interest to urban foresters and cognate managers. Churn denotes that while individual points have changed from or to tree/shrub cover, overall, there is no net change because the spatial allocation has changed. Net reporting is akin to stating that a restaurant is on average at 95% capacity from 5 pm to 9 pm. That says nothing about the total number of guests served during that period, the composition of guests, or their distribution across tables of different sizes or configurations. Net reporting therefore seems to occlude some of the most important information about tree/shrub



cluster	counts per cluster	Population Density (people / hectare)	Education: College+ (% of 25+ year olds)	Owner Occupied (% of Housing Units)	Median Houshold Income (inflation-adjusted)	Hispanic Population (% of population)
1	28	28.43	20.09	8.89	4.81	2.05
2	87	-28.14	8.18	-8.86	-8.69	1.18
3	16	-63.66	2.44	-9.34	-1.84	2.11
4	50	-5.69	34.50	2.89	21.99	1.41
5	13	5.64	-1.38	-24.58	-12.44	54.62
6	54	3.23	3.42	-17.15	-10.05	21.01
7	124	-1.00	10.11	-6.48	-8.96	4.83

Fig. 5. Philadelphia's Census tracts were clustered based on changes in population density, education, owner occupied housing, and % Hispanic from 1980 to 2010 (i.e., the variables found to be significantly predictors of land cover change). The most exemplary tract from each cluster is highlighted in black (top) and the demographic and housing characteristics of those exemplars indicate how a typical tract of that cluster type changed over time. The table (bottom) provides the percentage point change in socioeconomic variables for these exemplar tracts.

canopy and/or land cover change.

The neighborhoods with increasing concentrations of Hispanic residents experienced drastic change in the mid-to-late 20th century. Although Philadelphia's Hispanic population grew overall during our study period, from 3.8% in 1980 to 12.3% 2010, these gains were mostly concentrated in neighborhoods in and around the North, Lower Northeast, and River Wards planning districts (see Fig. 1), as seen in clusters 5, 6, and 7. In particular, clusters 5 and 6 also have some of the lowest tree/shrub canopy cover as a proportion of the random points interpreted (5.4% and 11.6%, respectively), and they make up a relatively small portion of the city's overall area (2.32% and 13.8%, respectively, Figures 5 and 6). These neighborhoods have relatively small lots, with minimal yard space, limiting the amount of plantable land, and restricting most tree cover to street trees and small patches of greenspace such as vacant lots and community gardens. A separate study using this same dataset found that neighborhoods subject to urban renewal policies, like North Philadelphia, experienced building demolition and depopulation in the 1950 s-60 s, and later tree plantings from nonprofits and redevelopment projects, as well as trees that emerged unintentionally on vacant, unmaintained lots (Roman et al., 2021). Notably, the cities of Holyoke and Chelsea similarly experienced large increases in Hispanic population in the late 20th century, and likewise

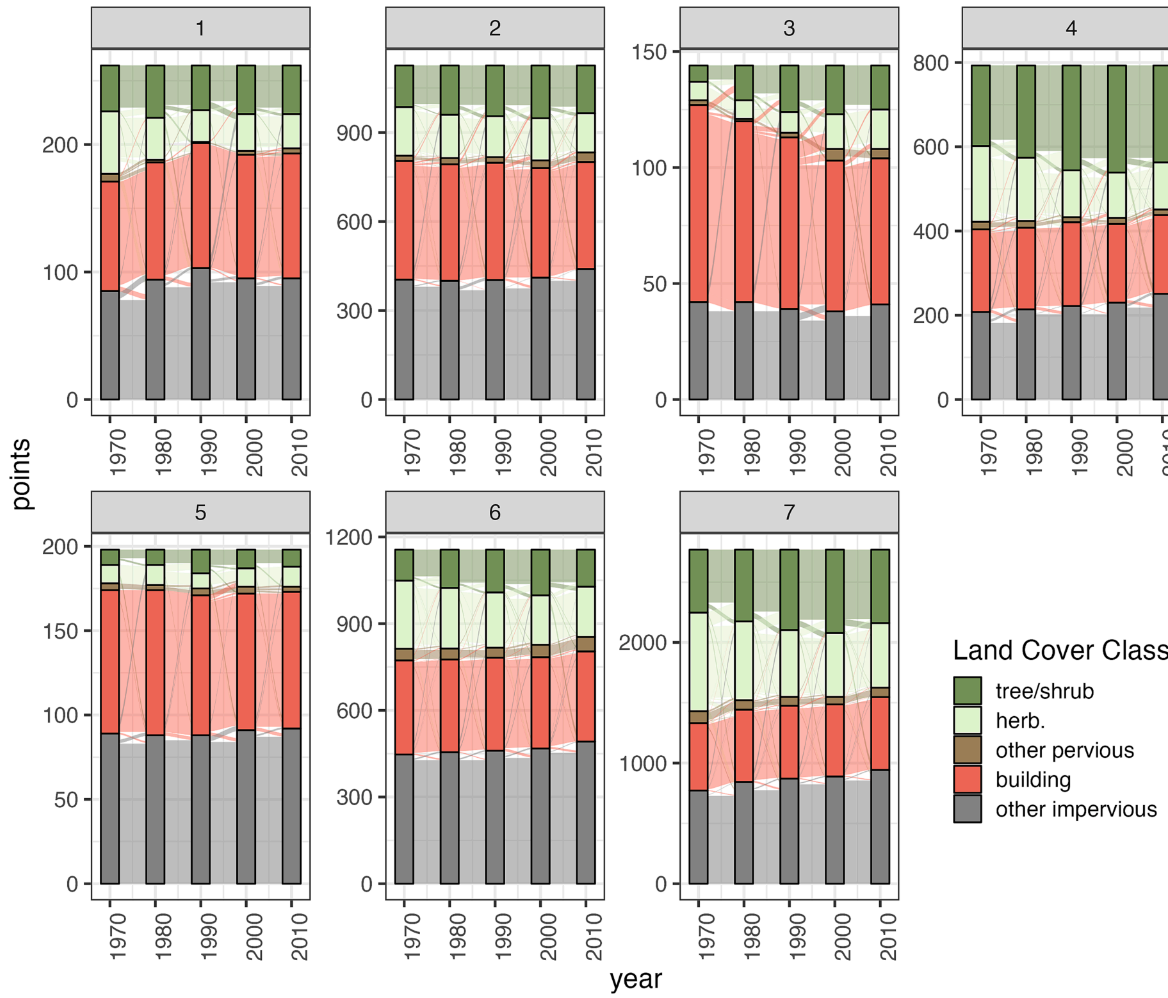


Fig. 6. Sankey diagram depicting land cover change for four decades across 5 images in Philadelphia, PA for the seven clusters. Note the different vertical axes. Cluster numbers correspond to Figure 4

had relatively low canopy stability (Healy et al., 2022). Collectively, the findings from our analysis and others suggest that "churn" in canopy change (Kaspar et al., 2017; Nowak & Greenfield, 2012b, 2018) may reflect large swings in neighborhood sociodemographics, such as the depopulation-repopulation trajectories in some post-industrial cities and neighborhoods (Healy et al., 2022; Roman et al., 2021). It is therefore important to map socioeconomic changes alongside land cover changes, including the non-tree/shrub cover classes, to more holistically understand UTC change.

The regression and cluster analyses revealed joint trends in land cover and neighborhood change. For example, the regression analyses showed that the probability of herbaceous cover to tree/shrub canopy is lower with increasing homeownership and increasing educational attainment, relative to tree/shrub persistence. In other words, points interpreted as tree/shrub were more likely to remain tree/shrub in places with increasing homeownership and educational attainment, like clusters 1 and 4. We infer that the net gains in UTC levels for these clusters resulted not only from the addition of new trees, but also from the retention of existing trees. In recognition of the importance of retaining trees to achieve UTC goals, Philadelphia's urban forest strategic plan calls for enhanced municipal policies around tree preservation during development (Roman et al., 2022). Future research could examine variation in tree preservation and UTC stability across socioeconomic gradients in different cities.

5. Conclusions

In comparison to past UTC change scholarship, our study adds greater categorical resolution (five land cover classes instead of canopy vs. not canopy), a longer time horizon (40 years) with more points in time (five images), and linkages to historical US Census data. While our findings are largely confirmatory of shorter-time period studies, that might not have been the case. What was previously ignored or assumed from shorter time period studies with fewer time steps has been empirically demonstrated here. We demonstrated the mix of stability and dynamism in multidecadal urban land cover change and used visualization techniques which are new to UTC analyses. Without a long temporal extent and without several time steps, it would not have been known that most points were stable, and the changes that do occur are often unique. Simultaneously, some neighborhoods experience substantial churn in land cover, which is predicted by large changes in sociodemographic characteristics. By adding socioeconomic change, we identified that increases in homeownership, income, and educational attainment were associated with a higher probability of tree/shrub cover persistence. The results add to the small but growing literature that jointly analyze land cover change and neighborhood change. These trends raise distributional environmental justice concerns, particularly in light of the equity focus of Philadelphia's forthcoming urban forest plan (Schmidt, 2021). Cluster analyses showed that some Census tracts have similar land cover change trajectories, but different socioeconomic trends, which may help inform tree preservation and planting strategies.

Declaration of Competing Interest

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

Data availability

Data and reproducible code are available via Roman et al., 2023 https://doi.org/10.2737/RDS-2021-0033-2.

Acknowledgements

The findings and conclusions in this paper are those of the authors and should not be construed to represent any official USDA or US Government determination or policy. We thank Indigo Catton for producing the land cover data and Eric Greenfield for advising on aerial image interpretation. Mike Treglia and Miranda Mockrin provided thoughtful comments on an earlier version that helped clarify and strengthen the paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104764. Underlying code and reproducible *.Rmd script can be accessed via Roman et al., 2023.

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