

Structure of Urban Landscape and Surface Temperature: a Case Study in Philadelphia, PA

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Abstract

Discerning the relationship between urban structure and function is crucial for sustainable city planning and requires examination of how components in urban systems are organized in three-dimensional space. The Structure of Urban Landscape (STURLA) classification accounts for the compositional complexity of urban landcover structures including the built and natural environment. Building on previous research, we develop a STURLA classification for Philadelphia, PA and study the relationship between urban structure and land surface temperature. Finally, we evaluate the results in Philadelphia as compared to previous case studies in Berlin, Germany and New York City, USA. In Philadelphia, STURLA classes hosted ST that were unique and significantly different as compared to all other classes. We find a similar distribution of STURLA class composition across the three cities, though NYC and Berlin showed strong correlation with each other but not with Philadelphia. Our research highlights the use of STURLA classification to capture a physical property of the urban landscape.

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Abstract

Discerning the relationship between urban structure and function is crucial for sustainable city planning and requires examination of how components in urban systems are organized in three-dimensional space. The Structure of Urban Landscape (STURLA) classification accounts for the compositional complexity of urban landcover structures including the built and natural environment. Building on previous research, we develop a STURLA classification for Philadelphia, PA and study the relationship between urban structure and land surface temperature. We evaluate the results in Philadelphia as compared to previous case studies in Berlin, Germany and New York City, USA. In Philadelphia, STURLA classes hosted ST that were unique and significantly different as compared to all other classes. We find a similar distribution of STURLA class composition across the three cities, though NYC and Berlin showed strong correlation with each other but not

with Philadelphia. Our research highlights the use of STURLA classification to capture a physical property of the urban landscape.

Key Words

Urban Landscape, Urban surface temperature, STURLA, Urban structure, city comparison

Introduction

Urban spatial structure is important to understanding social and ecological interactions between the built and natural environment and provides a bridge to sustainable development (Zhou et al., 2017). Characteristics including vegetation and other landcover classes influence, and can be used to estimate ecological functions (Bastian et al., 2014; van Oudenhoven et al., 2012) and forecast changes (Dietze, 2019; Dietze et al., 2018) that are crucial under global change scenarios. Identifying patterns and processes of the structure-function relationship in the urban landscape in the context of environmental and ecological processes is challenging due to variable density and patchy spatial patterns (Pickett & Cadenasso, 2008).

While it is well established that urban areas host ecological communities subject to unique stressors (Jones & Harrison, 2004; Joyner et al., 2019; Reese et al., 2016) absent in natural systems (e.g. pollution, high population density), the influence of landscape heterogeneity on the environment is poorly described. Functional classification of urban structure is necessary for understanding the nature of social and ecological relationships in urban areas (Cadenasso et al., 2007; McPhearson et al., 2016; Zhou et al., 2014). Over the last decade, fine-scale landcover classification for urban areas have been developed (MacFaden et al., 2012; Pickard et al., 2015) that allows more nuanced analyses of urban landcover. While some functional classification approaches have been suggested (see for example Cadenasso et al., 2007), major challenges remain in integration of spatial structure and configuration that allows scalable and reproducible analysis of relationships between urban form and process.

A major barrier for understanding the relationship between urban structure and environmental function is the lack of independent measurement of the fine-scale spatial variability of the distribution of environmental and ecological variables. Particularly important is the vertical dimension (e.g. building height) and variation of the three-dimensional landscape that is rarely addressed (Alavipanah et al., 2017) in ecological studies. Where independent measurements exist, such as data from Environmental Protection Agency (EPA) air pollution monitoring stations or United States Geographical Survey (USGS) water monitoring sites, the spatial distribution is not sufficient to allow intra-urban analysis. Surface temperature is one example of a physical property of the urban environment that has been used in research addressing landcover (Zhou et al., 2011), urban heat islands (Rosenzweig et al., 2009; Zhao et al., 2011), and ecosystem services (Schwarz et al., 2011). Likewise, ST structures patterns of taxonomic and functional biodiversity (Scherrer & Körner, 2011; Zogg et al., 1997), hydrology (Reyes et al., 2018), air quality (Li et al., 2018; Sillman & Samson, 1995), and social variables relevant for studies of environmental injustice (Huang & Cadenasso, 2016; Zhang et al., 2017). We employ ST as a proxy for a wide range of potential variables of interest across biotic and abiotic dimensions.

To account for the heterogenous vertical dimension of the built environment in urban landscape, we employ The Structure of Urban Landscapes (STURLA) classification (Hamstead et al., 2016). STURLA is a new classification procedure developed by co-PI Kremer that incorporates the complexity of urban land cover structures, including the vertical dimensions of the built environment. The novelty in the STURLA approach is that it offers a composite functional classification of urban structure, including the vertical dimension, that is automated, and thus can be applied to wide geographic regions systematically. STURLA has been used to identify patterns of microbial biogeography in the atmosphere of Philadelphia (J. Stewart et al., 2020), and ST in NYC (Hamstead et al., 2016) and Berlin (Kremer et al., 2018).

The objectives of this short study are to identify if STURLA could explain the variation of urban structure in a new model city (Philadelphia), and quantify this variation using a physical property of the environment (ST). Results suggest STURLA identifies common urban structure units that encompass the majority of

the variation in the urban landscape structure. Moreover, when correlated to surface temperature, these common urban structure classifications exhibit distinct temperature signatures for different urban structure units with temperature trends dramatically similar between Berlin and NYC. Here, we contribute to the developing literature on the urban structure–function relationship using STURLA in Philadelphia.

Materials and methods

Study area

Philadelphia PA, USA is the sixth largest city in the United States with a city population of 1.6 million inhabitants (U.S. Census Bureau, 2016) and hosts an average population density of 30,297 inhabitants per square kilometer. It is located at the confluence of the Delaware and Schuylkill rivers on the eastern border of Pennsylvania with the Appalachian Mountains to the west and the Atlantic Ocean to the east. The city has a total area of about 370 km² of which 350 km² are land and the rest, water. Philadelphia is one of the poorest cities in the US, with 26 percent of its population living in poverty (PEW, 2017). Philadelphia is also one of the most segregated cities in the US, with African American and Asian populations concentrated in neighborhoods in West and North Philadelphia respectively (The Brookings Institution, 2003). The city’s population peaked in 1950 with over 2 million people, and was declining until 2010 when it started growing again. Recently, Philadelphia is experiencing strong, yet uneven economic resurgence reflected in job growth and rising housing prices (PEW, 2017).

Philadelphia’s urban structure emerged through the evolution of its original plan, laid out by William Penn in 1643. It has a gridded layout with mostly low and mid-rise residential buildings. A long time “gentleman’s agreement” kept Penn’s statue on top of city hall as the highest building in the city, preventing high-rise development for decades until the 1980s. The most common residential structures in the city are rowhouses. Rowhouses commonly occupy a narrow street frontage and are attached to other homes on both sides (Simmons Schade et al., 2008). Aside from the built environment, green space in the city includes 19% tree cover and 24% grass-shrub cover that are distributed unevenly across the city with some neighborhoods densely vegetated and others with little to no green space (O’Neil-Dunne, 2011). Part of the city’s sustainability plan, Greenworks Philadelphia, includes a goal of tree canopy cover of 30% in all city neighborhoods by 2025 (City of Philadelphia, 2015a). However, until recently, the only publicly available data for a comprehensive analysis of the city’s green space has been the National Landuse-Landcover (NLCD) datasets that do not have the spatial resolution and functional categories required to identify small and fragmented patches of landscape elements within the city. In 2011, a fine scale dataset of Philadelphia landcover was released (City of Philadelphia, 2011) that is used here as the basis for the STURLA classification system. Empirical evidence from two cities, Berlin and New York City (NYC), were compared (Larondelle et al., 2014) and more detailed analysis of within class and neighborhood effects were performed in a Berlin case study (Kremer et al., 2018).

Pre-processing urban landscape structure data

To construct the urban structure dataset, we used a 2008 1.0-meter resolution land cover dataset (City of Philadelphia, 2011), the Property Assessment dataset from the Philadelphia Office of Property Assessment (City of Philadelphia, 2015b) indicating number of floors in buildings for each tax lot in the city in tabular format, and the Philadelphia Department of Water parcels dataset. We joined the property assessment tabular data to the parcels dataset using unique parcel IDs and created a 1.0-meter resolution raster dataset from the “Number of Floors” field in the Property Assessment dataset. Number of floors was classified into three categories: lowrise (1–3 stories), midrise (4–9 stories) and highrise (>9 stories) (Larondelle et al., 2014; I. D. Stewart & Oke, 2012). We then combined it with the land cover raster dataset, by replacing all building land cover pixels with a value representing building height category to create our basic urban structure dataset.

Constructing the STURLA classification

We constructed a 120.0 m² cellular grid aligned to the Landsat surface temperature dataset and derived

STURLA classes as the presence of all land cover and building height types that fell within each grid cell. Following Hamstead et al. (2016) a zonal statistics tabulate area operation to compute the area of each land cover or building height category within each cell was conducted. Finally, we generated and assigned a STURLA class variable for each grid cell (e.g, “tgpl”, trees, grass, pavement, lowrise building).

Comparison of STURLA classification results from current and previous studies

Permutational t-tests with Bonferroni correction were used to test for differences between cities in STURLA classes. The permutational t-test selected because we test data representing the population rather than a sample. The null hypothesis of the permutational t-test is that STURLA class composition does not differ between the cities. Permutational Pearson correlations were conducted to determine if the cities distribution of STURLA classes were similar between cities. These tests were conducted in R using the package “RVAideMemoire” (Hervé, 2020).

Surface Temperature Processing

Surface temperature was obtained from Landsat 7 thermal band 6(1). We obtained monthly composite data for the month of July 2010 from the Global Web-enables Landsat Data (WELD) website. Each monthly composite image is normally a composite of two Landsat scenes because LANDSAT returns to any single location every 16 days. Using a composite scene helps address the Landsat 7 scan line corrector error. WELD data is terrain-corrected and radiometrically calibrated Landsat data (Roy et al., 2010). Top-of the -Atmosphere reflectance was converted to surface temperature followed the methodology detailed in Kremer et al. (2018) in processing surface temperature.

Analysis of class surface temperature

We computed the mean, min, max and standard deviation of surface temperature pixels that fell within each cell of the STURLA grid using zonal statistics (Table 1) and joined these results with the STURLA class variable. Averaging was necessary because Landsat 7 thermal bands are resampled to 30 meters for distribution (Roy et al., 2010) while the STURLA grid is 120 m. Thus, we averaged sixteen 30 m pixels that fell within each 120 m cell. Similar to Hamstead et al. (2016) and Larondelle et al. (2014) we focused the class temperature analysis on the most frequently occurring classes, which cumulatively comprise 90% of the city’s land area. As done with comparison of STURLA classes between cities, permutational t-tests with Bonferroni correction were employed to test significance. Likewise, the null hypothesis of the permutational t-test is that ST does not differ between the STURLA classes.

Results

The most prevalent composite class in Philadelphia contains trees, grass, paved surfaces, and low rise buildings (‘tgpl’) (Table 1). The ‘tgpl’ class accounts for about 57% of total city area and can be found in all parts of the city and was largely homogenous in spatial distribution (Figure 1A). The second largest class, ‘tgplm’ at 8.5% of the area, which is similar to ‘tgpl’ except it includes midrise buildings, is concentrated in the center of the city and along a few main corridors to the North and West. STURLA classes were able to identify the role of urban structure influencing ST (Figure 1B). Classes generally hosted ST that were unique (Figure 1B) and significantly different (Table 2) compared to all other classes with the exception of ‘tgbp’ with similar ST values to ‘tgpw’ and ‘tgpwl’.

The prevalence and distribution of the STURLA classes in Philadelphia differs from what we found in previous studies of urban structure NYC and Berlin (Figure 2). In Berlin and NYC, ~1/3 of the landscape can be explained by one highly composite STURLA class. Another difference between the results in Philadelphia and previous studies is the number of classes that cumulatively explain 90% of the area of the city. Ten classes covered 90% of the area of Philadelphia while the same number of classes only covered 79% of the area of New York City and 68% of the area in Berlin. Despite these differences, pairwise comparison of each city revealed that STURLA class proportions were not significantly different between the cities (all $p > 0.05$) Still, Berlin and NYC were highly correlated ($r^2 = 0.952$, $p < 0.05$) while Philadelphia’s distribution of urban structure remained uncorrelated to the other cities ($p > 0.05$).

Due to the compositional nature of a STURLA cell where the relative proportions of all elements sum to one Figure 2 provides an example of compositional variability within the most common class in Philadelphia ‘tgpl’ using six grid cells taken from a larger city-wide random sample. The different grid cells and corresponding satellite imagery show the different types of buildings and proportion of each element of the class, trees, grass, paved surfaces, and lowrise buildings, can vary greatly from one another but still fall into the class. Most grid cells from the ‘tgpl’ class show row houses or single-family detached houses since they fall within the size parameters of lowrise buildings (1-3 stories).

Discussion:

STURLA captured urban structure and characterized the physical property of ST in Philadelphia as previously done in NYC (Hamstead et al., 2016) and Berlin (Kremer et al., 2018), despite variation in size, demography, and historical planning. This suggests that urban areas may be subject to similar processes that result in between city-redundant spatial organizations (Votsis & Haavisto, 2019). Likewise, STURLA may be suited for understanding urban biogeography, environmental justice, and city planning for a sustainable future. Global analyses of cities may also identify clusters of urban areas that would benefit from similar management practices. Likewise, STURLA offers a computationally inexpensive alternative to network analyses of urban structure (Zhong et al., 2014).

One of the main limitations of STURLA classification is the binary nature of class assignment. If the STURLA grid were shifted it would change the relative proportions of the within class elements (e.g. trees decrease and other elements increase). Despite this variation, STURLA classes are a discrete countable number and have a Poisson distribution. Thus, the ranked order abundances of different STURLA classes should not vary in the most frequent classes. For example, since ‘tgpl’ is common in Philadelphia, a reduction in a large number of ‘tgpl’ classes in the city would be relatively less influential than additions/reductions of less common class.

Conclusion

In this paper we demonstrate the application of STURLA classification to quantify the relationship between urban structure and surface temperature in Philadelphia. We show it can be applied to cities with different historical patterns of growth in a reproducible manner. Furthermore, patterns in class abundance and composition can be used to determine the surface temperature signature of a composite landscape. Additional research is needed to compare cities of vastly different urban structure and identify patterns in the relationship between urban structure with social and ecological properties of the environment. Understanding general urban structure-environmental function relationships will help build tools for effective urban planning and management under global change scenarios.

Table 1: 10 most common STURLA classes in Philadelphia and their ST statistics. STURLA class codes: t-trees; g-grass; b-bare soil; w-water; p-paved; l-low building; m-medium building

Class	% of total	% cumulative	Mean ST C	Min ST C	Max ST C
tgpl	57.44	57.44	26.95	25.01	28.79
tgplm	8.55	65.99	27.95	25.89	29.93
tgp	7.39	73.37	23.86	22.10	25.75
tgwp	4.36	77.73	22.72	20.77	24.75
w	2.92	80.65	18.34	17.85	19.03
tgwpl	2.57	83.22	24.83	22.41	27.29
tgbpl	2.46	85.69	26.31	24.16	28.60
tg	1.94	87.63	20.42	19.37	21.62
tgw	1.42	89.05	20.37	19.16	21.69
tgbp	1.29	90.34	24.68	22.81	26.64

Table 2. P-values with Bonferroni correction from pairwise permutational t-tests (n=999) of ST values for

the top ten STURLA classes. Bold values indicate statistical significance ($p < 0.05$).

Class	tgpl	tgplm	tgp	tgwp	w	tgwpl	tgbpl	tg	tgw	tgbp
tgpl	0									
tgplm	0.02	0								
tgp	0.02	0.02	0							
tgwp	0.02	0.02	0.02	0						
w	0.02	0.02	0.02	0.02	0					
tgwpl	0.02	0.02	0.02	0.02	0.02	0				
tgbpl	0.02	0.02	0.02	0.02	0.02	0.02	0			
tg	0.02	0								
tgw	0.02	0								
tgbp	0.02	0.02	0.02	3.74	0.02	4.02	0.02	0.02	0.02	0

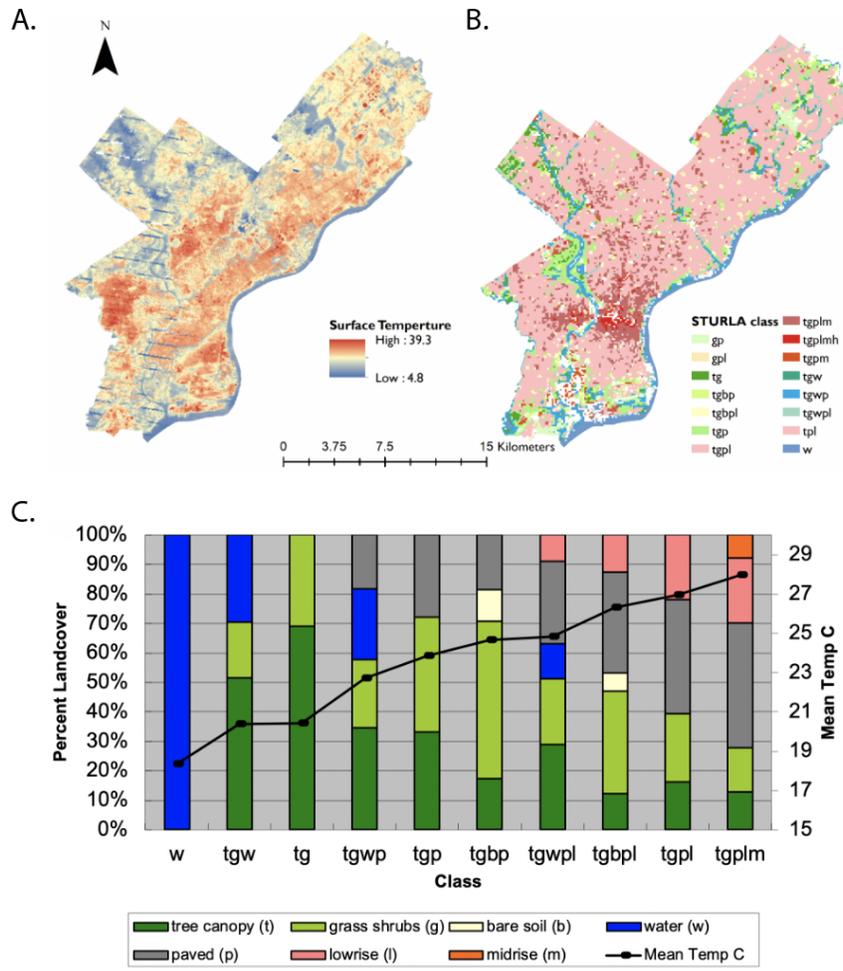


Figure 1. A. Spatial distribution of STURLA classes B. Spatial distribution of ST in Philadelphia. C. STURLA classes, mean % landcover of individual components, and mean ST for Philadelphia. STURLA

class codes: t-trees; g-grass; b-bare soil; w-water; p-paved; l-low building; m-medium building



Figure 2: Example of the composition of STURLA grid cells of the most common STURLA class in Philadelphia 'tgp1'. STURLA 'tgp1' cells are shown next to corresponding areal imagery.

References

- Alavipanah, S., Haase, D., Lakes, T., & Qureshi, S. (2017). Integrating the third dimension into the concept of urban ecosystem services: A review. In *Ecological Indicators* (Vol. 72, pp. 374–398). <https://doi.org/10.1016/j.ecolind.2016.08.010>
- Bastian, O., Grunewald, K., Syrbe, R.-U., Walz, U., & Wende, W. (2014). Landscape services: the concept and its practical relevance. *Landscape Ecology*, 29 (9), 1463–1479. <https://doi.org/10.1007/s10980-014-0064-5>
- Cadenasso, M. L., Pickett, S. T. A., & Schwarz, K. (2007). Spatial heterogeneity in urban ecosystems: reconceptualizing land cover and a framework for classification. *Frontiers in Ecology and the Environment*, 5 (2), 80–88. [https://doi.org/10.1890/1540-9295\(2007\)5](https://doi.org/10.1890/1540-9295(2007)5)
- City of Philadelphia. (2011). *Philadelphia Land Cover Raster*. OpenDataPhilly.
- City of Philadelphia. (2015a). *Greenworks Philadelphia: 2015 Progress Report*.
- City of Philadelphia. (2015b). *Property Assessment Data*.
- Dietze, M. C. (2019). Ecological Forecasting. In *Ecological Forecasting*. <https://doi.org/10.2307/j.ctvc7796h>
- Dietze, M. C., Fox, A., Beck-Johnson, L. M., Betancourt, J. L., Hooten, M. B., Jarnevich, C. S., Keitt, T. H., Kenney, M. A., Laney, C. M., Larsen, L. G., Loescher, H. W., Lunch, C. K., Pijanowski, B. C., Randerson, J. T., Read, E. K., Tredennick, A. T., Vargas, R., Weathers, K. C., & White, E. P. (2018). Iterative near-term ecological forecasting: Needs, opportunities, and challenges. *Proceedings of the National Academy of Sciences of the United States of America*. <https://doi.org/10.1073/pnas.1710231115>

- Hamstead, Z. A., Kremer, P., Larondelle, N., McPhearson, T., & Haase, D. (2016). Classification of the heterogeneous structure of urban landscapes (STURLA) as an indicator of landscape function applied to surface temperature in New York City. *Ecol. Indic.* , 70 , 574–585. <https://doi.org/10.1016/j.ecolind.2015.10.014>
- Hervé, M. (2020). *Package ‘RVAideMemoire.’*
- Huang, G., & Cadenasso, M. L. (2016). People, landscape, and urban heat island: dynamics among neighborhood social conditions, land cover and surface temperatures. *Landscape Ecology* . <https://doi.org/10.1007/s10980-016-0437-z>
- Jones, A. M., & Harrison, R. M. (2004). The effects of meteorological factors on atmospheric bioaerosol concentrations—a review. *Sci. Total Environ.* , 326 (1), 151–180. <https://doi.org/10.1016/j.scitotenv.2003.11.021>
- Joyner, J. L., Kerwin, J., Deeb, M., Lozefski, G., Prithiviraj, B., Paltseva, A., McLaughlin, J., Groffman, P., Cheng, Z., & Muth, T. R. (2019). Green Infrastructure Design Influences Communities of Urban Soil Bacteria. In *Frontiers in Microbiology* (Vol. 10). <https://doi.org/10.3389/fmicb.2019.00982>
- Kremer, P., Larondelle, N., Zhang, Y., Pasles, E., & Haase, D. (2018). Within-Class and Neighborhood Effects on the Relationship between Composite Urban Classes and Surface Temperature. *Sustainability* ,10 (3), 645. <https://doi.org/10.3390/su10030645>
- Larondelle, N., Hamstead, Z. A., Kremer, P., Haase, D., & McPhearson, T. (2014). Applying a novel urban structure classification to compare the relationships of urban structure and surface temperature in Berlin and New York City. *Appl. Geogr.* , 53 , 427–437. <https://doi.org/10.1016/j.apgeog.2014.07.004>
- Li, H., Meier, F., Lee, X., Chakraborty, T., Liu, J., Schaap, M., & Sodoudi, S. (2018). Interaction between urban heat island and urban pollution island during summer in Berlin. *Science of the Total Environment* . <https://doi.org/10.1016/j.scitotenv.2018.04.254>
- MacFaden, S. W., O’Neil-Dunne, J. P. M., Royar, A. R., Lu, J. W. T., & Rundle, A. G. (2012). High-resolution tree canopy mapping for New York City using LIDAR and object-based image analysis. *Journal of Applied Remote Sensing* , 6 (1), 063567. <https://doi.org/10.1117/1.JRS.6.063567>
- McPhearson, T., Pickett, S. T. A. A., Grimm, N. B., Niemelä, J., Alberti, M., Elmqvist, T., Weber, C., Haase, D., Breuste, J., & Qureshi, S. (2016). Advancing Urban Ecology toward a Science of Cities. *BioScience* , biw002. <https://doi.org/10.1093/biosci/biw002>
- O’Neil-Dunne, J. (2011). *A Report on the City of Philadelphia’s Existing and Possible Tree Canopy* .
- PEW. (2017). *Philadelphia 2017: The State of the City* .
- Pickard, B. R., Daniel, J., Mehaffey, M., Jackson, L. E., & Neale, A. (2015). EnviroAtlas: A new geospatial tool to foster ecosystem services science and resource management. *Ecosystem Services* , 14 , 45–55. <https://doi.org/10.1016/j.ecoser.2015.04.005>
- Pickett, S. T. A., & Cadenasso, M. L. (2008). Linking ecological and built components of urban mosaics: an open cycle of ecological design. *Journal of Ecology* , 96 , 8–12. <https://doi.org/10.1111/j.1365-2745.2007.01310.x>
- Reese, A. T., Savage, A., Youngsteadt, E., McGuire, K. L., Koling, A., Watkins, O., Frank, S. D., & Dunn, R. R. (2016). Urban stress is associated with variation in microbial species composition—but not richness—in Manhattan. *ISME J.* , 10 (3), 751–760. <https://doi.org/10.1038/ismej.2015.152>
- Reyes, B., Hogue, T., & Maxwell, R. (2018). Urban irrigation suppresses land surface temperature and changes the hydrologic regime in semi-arid regions. *Water (Switzerland)* . <https://doi.org/10.3390/w10111563>
- Rosenzweig, C., Solecki, W. D., Cox, J., Hodges, S., Parshall, L., Lynn, B., Goldberg, R., Gaffin, S., Slosberg, R. B., Savio, P., Watson, M., & Dunstan, F. (2009). Mitigating New York City’s Heat Island: Integrating

Stakeholder Perspectives and Scientific Evaluation. *Bulletin of the American Meteorological Society* , 90 (9), 1297–1312. <https://doi.org/doi:10.1175/2009BAMS2308.1>

Roy, D. P., Ju, J., Kline, K., Scaramuzza, P. L., Kovalsky, V., Hansen, M., Loveland, T. R., Vermote, E., & Zhang, C. (2010). Web-enabled Landsat Data (WELD): Landsat ETM+ composited mosaics of the conterminous United States. *Remote Sensing of Environment* , 114 (1), 35–49. <https://doi.org/10.1016/j.rse.2009.08.011>

Scherrer, D., & Körner, C. (2011). Topographically controlled thermal-habitat differentiation buffers alpine plant diversity against climate warming. *Journal of Biogeography* . <https://doi.org/10.1111/j.1365-2699.2010.02407.x>

Schwarz, N., Bauer, A., & Haase, D. (2011). Assessing climate impacts of planning policies—An estimation for the urban region of Leipzig (Germany). *Environmental Impact Assessment Review* , 31 (2), 97–111. <https://doi.org/10.1016/j.eiar.2010.02.002>

Sillman, S., & Samson, P. J. (1995). Impact of temperature on oxidant photochemistry in urban polluted rural and remote environments. *Journal of Geophysical Research* . <https://doi.org/10.1029/94jd02146>

Simmons Schade, R., Architects, B., Spina, L. M., Farnham, J., Fine, A., Gallery, J. A., Gladstein, E., Gregorski, M., Hauck, P., Jastrzab, G., Koksuz, B., Michel, L., Nikolic, T., Placke, C., Sauer, R., Schaaf, D., Urek, A., Wilds, S., & Wilson, D. (2008). *Philadelphia Rowhouse Manual A PRACTICAL GUIDE FOR HOMEOWNERS SPECIAL THANKS TO Steering Committee* .

Stewart, I. D., & Oke, T. R. (2012). Local Climate Zones for Urban Temperature Studies. *Bulletin of the American Meteorological Society* , 93 (12), 1879–1900. <https://doi.org/doi:10.1175/BAMS-D-11-00019.1>

Stewart, J., Kremer, P., Shakya, K. M., Conway, M., & Saad, A. (2020). Outdoor Atmospheric Microbial Diversity is Associated with Three-Dimensional Urban Landscape Structure and Differs from Indoor-Transit Systems. *BioRxiv* . <https://doi.org/10.1101/2020.06.17.157651>

The Brookings Institution. (2003). *Philadelphia in Focus: A Profile from Census 2000* . The Brookings Institution.

U.S. Census Bureau. (2016). *State and County Quick Facts* .

van Oudenhoven, A. P. E., Petz, K., Alkemade, R., Hein, L., & de Groot, R. S. (2012). Framework for systematic indicator selection to assess effects of land management on ecosystem services. *Ecological Indicators* , 21 , 110–122. <https://doi.org/10.1016/j.ecolind.2012.01.012>

Votsis, A., & Haavisto, R. (2019). Urban DNA and Sustainable Cities: A Multi-City Comparison. *Frontiers in Environmental Science* , 7 (JAN), 4. <https://doi.org/10.3389/fenvs.2019.00004>

Zhang, X., Estoque, R. C., & Murayama, Y. (2017). An urban heat island study in Nanchang City, China based on land surface temperature and social-ecological variables. *Sustainable Cities and Society* . <https://doi.org/10.1016/j.scs.2017.05.005>

Zhao, C., Fu, G., Liu, X., & Fu, F. (2011). Urban planning indicators, morphology and climate indicators: A case study for a north-south transect of Beijing, China. *Building and Environment* , 46 (5), 1174–1183. <https://doi.org/10.1016/j.buildenv.2010.12.009>

Zhong, C., Arisona, S. M., Huang, X., Batty, M., & Schmitt, G. (2014). Detecting the dynamics of urban structure through spatial network analysis. *International Journal of Geographical Information Science* . <https://doi.org/10.1080/13658816.2014.914521>

Zhou, W., Cadenasso, M., Schwarz, K., & Pickett, S. (2014). Quantifying Spatial Heterogeneity in Urban Landscapes: Integrating Visual Interpretation and Object-Based Classification. *Remote Sensing* , 6 (4), 3369–3386. <https://doi.org/10.3390/rs6043369>

Zhou, W., Huang, G., & Cadenasso, M. L. (2011). Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes. *Landscape and Urban Planning* , 102 (1), 54–63. <https://doi.org/10.1016/j.landurbplan.2011.03.009>

Zhou, W., Pickett, S. T. A., & Cadenasso, M. L. (2017). Shifting concepts of urban spatial heterogeneity and their implications for sustainability. *Landscape Ecology* , 32 (1), 15–30. <https://doi.org/10.1007/s10980-016-0432-4>

Zogg, G. P., Zak, D. R., Ringelberg, D. B., White, D. C., MacDonald, N. W., & Pregitzer, K. S. (1997). Compositional and Functional Shifts in Microbial Communities Due to Soil Warming. *Soil Sci. Soc. Am. J.* ,61 , 475–481. <https://doi.org/10.2136/sssaj1997.03615995006100020015x>

1 **Structure of Urban Landscape and Surface Temperature: a Case Study in Philadelphia,**
2 **PA**
3

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13

14 **Abstract**

15 Discerning the relationship between urban structure and function is crucial for
16 sustainable city planning and requires examination of how components in urban systems are
17 organized in three-dimensional space. The Structure of Urban Landscape (STURLA)
18 classification accounts for the compositional complexity of urban landcover structures
19 including the built and natural environment. Building on previous research, we develop a
20 STURLA classification for Philadelphia, PA and study the relationship between urban
21 structure and land surface temperature. We evaluate the results in Philadelphia as compared
22 to previous case studies in Berlin, Germany and New York City, USA. In Philadelphia,
23 STURLA classes hosted ST that were unique and significantly different as compared to all
24 other classes. We find a similar distribution of STURLA class composition across the three
25 cities, though NYC and Berlin showed strong correlation with each other but not with

26 Philadelphia. Our research highlights the use of STURLA classification to capture a physical
27 property of the urban landscape.

28

29 **Key Words**

30 Urban Landscape, Urban surface temperature, STURLA, Urban structure, city comparison

31

32 **Introduction**

33

34 Urban spatial structure is important to understanding social and ecological interactions
35 between the built and natural environment and provides a bridge to sustainable development
36 (Zhou et al., 2017). Characteristics including vegetation and other landcover classes
37 influence, and can be used to estimate ecological functions (Bastian et al., 2014; van
38 Oudenhoven et al., 2012) and forecast changes (Dietze, 2019; Dietze et al., 2018) that are
39 crucial under global change scenarios. Identifying patterns and processes of the structure-
40 function relationship in the urban landscape in the context of environmental and ecological
41 processes is challenging due to variable density and patchy spatial patterns (Pickett &
42 Cadenasso, 2008).

43 While it is well established that urban areas host ecological communities subject to
44 unique stressors (Jones & Harrison, 2004; Joyner et al., 2019; Reese et al., 2016) absent in
45 natural systems (e.g pollution, high population density), the influence of landscape
46 heterogeneity on the environment is poorly described. Functional classification of urban
47 structure is necessary for understanding the nature of social and ecological relationships in
48 urban areas (Cadenasso et al., 2007; McPhearson et al., 2016; Zhou et al., 2014). Over the
49 last decade, fine-scale landcover classification for urban areas have been developed
50 (MacFaden et al., 2012; Pickard et al., 2015) that allows more nuanced analyses of urban

51 landcover. While some functional classification approaches have been suggested (see for
52 example Cadenasso et al., 2007), major challenges remain in integration of spatial structure
53 and configuration that allows scalable and reproducible analysis of relationships between
54 urban form and process.

55 A major barrier for understanding the relationship between urban structure and
56 environmental function is the lack of independent measurement of the fine-scale spatial
57 variability of the distribution of environmental and ecological variables. Particularly
58 important is the vertical dimension (e.g. building height) and variation of the three-
59 dimensional landscape that is rarely addressed (Alavipanah et al., 2017) in ecological studies.
60 Where independent measurements exist, such as data from Environmental Protection Agency
61 (EPA) air pollution monitoring stations or United States Geographical Survey (USGS) water
62 monitoring sites, the spatial distribution is not sufficient to allow intra-urban analysis. Surface
63 temperature is one example of a physical property of the urban environment that has been
64 used in research addressing landcover (Zhou et al., 2011), urban heat islands (Rosenzweig et
65 al., 2009; Zhao et al., 2011), and ecosystem services (Schwarz et al., 2011). Likewise, ST
66 structures patterns of taxonomic and functional biodiversity (Scherrer & Körner, 2011; Zogg
67 et al., 1997), hydrology (Reyes et al., 2018), air quality (Li et al., 2018; Sillman & Samson,
68 1995), and social variables relevant for studies of environmental injustice (Huang &
69 Cadenasso, 2016; Zhang et al., 2017). We employ ST as a proxy for a wide range of potential
70 variables of interest across biotic and abiotic dimensions.

71 To account for the heterogenous vertical dimension of the built environment in urban
72 landscape, we employ The Structure of Urban Landscapes (STURLA) classification
73 (Hamstead et al., 2016). STURLA is a new classification procedure developed by co-PI
74 Kremer that incorporates the complexity of urban land cover structures, including the vertical
75 dimensions of the built environment. The novelty in the STURLA approach is that it offers a

76 composite functional classification of urban structure, including the vertical dimension, that
77 is automated, and thus can be applied to wide geographic regions systematically. STURLA
78 has has been used to identified patterns of microbial biogeography in the atmosphere of
79 Philadelphia (J. Stewart et al., 2020), and ST in NYC (Hamstead et al., 2016) and Berlin
80 (Kremer et al., 2018).

81 The objectives of this short study are to identify if STURLA could explain the
82 variation of urban structure in a new model city (Philadelphia), and quantify this variation
83 using a physical property of the environment (ST). Results suggest STURLA identifies
84 common urban structure units that encompass the majority of the variation in the urban
85 landscape strucutre. Moreover, when correlated to surface temperature, these common urban
86 structure classifications exhibit distinct temperature signatures for different urban structure
87 units with temperature trends dramatically similar between Berlin and NYC. Here, we
88 contribute to the developing literature on the urban structure-function relationship using
89 STURLA in Philadelphia.

90

91 **Materials and methods**

92 *Study area*

93 Philadelphia PA, USA is the sixth largest city in the United States with a city
94 population of 1.6 million inhabitants (U.S. Census Bureau, 2016) and hosts an average
95 population density of 30,297 inhabitants per square kilometer. It is located at the confluence
96 of the Delaware and Schuylkill rivers on the eastern border of Pennsylvania with the
97 Appalachian Mountains to the west and the Atlantic Ocean to the east. The city has a total
98 area of about 370 km² of which 350 km² are land and the rest, water. Phildelphia is one of the
99 poorest cities in the US, with 26 percent of its population living in poverty (PEW, 2017).
100 Philadelphia is also one of the most segregated cities in the US, with African American and

101 Asian populations concentrated in neighborhoods in West and North Philadelphia
102 respectively (The Brookings Institution, 2003). The city's population peaked in 1950 with
103 over 2 million people, and was declining until 2010 when it started growing again. Recently,
104 Philadelphia is experiencing strong, yet uneven economic resurgence reflected in job growth
105 and rising housing prices (PEW, 2017).

106 Philadelphia's urban structure emerged through the evolution of its original plan, laid
107 out by William Penn in 1643. It has a gridded layout with mostly low and mid-rise residential
108 buildings. A long time "gentleman's agreement" kept Penn's statue on top of city hall as the
109 highest building in the city, preventing high-rise development for decades until the 1980s.
110 The most common residential structures in the city are rowhouses. Rowhouses commonly
111 occupy a narrow street frontage and are attached to other homes on both sides (Simmons
112 Schade et al., 2008). Aside from the built environment, green space in the city includes 19%
113 tree cover and 24% grass-shrub cover that are distributed unevenly across the city with some
114 neighborhoods densely vegetated and others with little to no green space (O'Neil-Dunne,
115 2011). Part of the city's sustainability plan, Greenworks Philadelphia, includes a goal of tree
116 canopy cover of 30% in all city neighborhoods by 2025 (City of Philadelphia, 2015a).
117 However, until recently, the only publicly available data for a comprehensive analysis of the
118 city's green space has been the National Landuse-Landcover (NLCD) datasets that do not
119 have the spatial resolution and functional categories required to identify small and
120 fragmented patches of landscape elements within the city. In 2011, a fine scale dataset of
121 Philadelphia landcover was released (City of Philadelphia, 2011) that is used here as the basis
122 for the STURLA classification system. Empirical evidence from two cities, Berlin and New
123 York City (NYC), were compared (Larondelle et al., 2014) and more detailed analysis of
124 within class and neighborhood effects were performed in a Berlin case study (Kremer et al.,
125 2018).

126 *Pre-processing urban landscape structure data*

127 To construct the urban structure dataset, we used a 2008 1.0-meter resolution land
128 cover dataset (City of Philadelphia, 2011), the Property Assessment dataset from the
129 Philadelphia Office of Property Assessment (City of Philadelphia, 2015b) indicating number
130 of floors in buildings for each tax lot in the city in tabular format, and the Philadelphia
131 Department of Water parcels dataset. We joined the property assessment tabular data to the
132 parcels dataset using unique parcel IDs and created a 1.0-meter resolution raster dataset from
133 the “Number of Floors” field in the Property Assessment dataset. Number of floors was
134 classified into three categories: lowrise (1–3 stories), midrise (4–9 stories) and highrise (>9
135 stories) (Larondelle et al., 2014; I. D. Stewart & Oke, 2012). We then combined it with the
136 land cover raster dataset, by replacing all building land cover pixels with a value representing
137 building height category to create our basic urban structure dataset.

138

139 *Constructing the STURLA classification*

140 We constructed a 120.0 m² cellular grid aligned to the Landsat surface temperature
141 dataset and derived STURLA classes as the presence of all land cover and building height
142 types that fell within each grid cell. Following Hamstead et al. (2016) a zonal statistics
143 tabulate area operation to compute the area of each land cover or building height category
144 within each cell was conducted. Finally, we generated and assigned a STURLA class variable
145 for each grid cell (e.g, “tgpl”, trees, grass, pavement, lowrise building).

146

147 *Comparison of STURLA classification results from current and previous studies*

148 Permutational t-tests with Bonferroni correction were used to test for differences
149 between cities in STURLA classes. The permutational t-test selected because we test data
150 representing the population rather than a sample. The null hypothesis of the permutational t-

151 test is that STURLA class composition does not differ between the cities. Permutational
152 Pearson correlations were conducted to determine if the cities distribution of STURLA
153 classes were similar between cities. These tests were conducted in R using the package
154 “RVAideMemoire” (Hervé, 2020).

155 *Surface Temperature Processing*

156 Surface temperature was obtained from Landsat 7 thermal band 6(1). We obtained
157 monthly composite data for the month of July 2010 from the Global Web-enables Landsat
158 Data (WELD) website. Each monthly composite image is normally a composite of two
159 Landsat scenes because LANDSAT returns to any single location every 16 days. Using a
160 composite scene helps address the Landsat 7 scan line corrector error. WELD data is terrain-
161 corrected and radiometrically calibrated Landsat data (Roy et al., 2010). Top-of the -
162 Atmosphere reflectance was converted to surface temperature followed the methodology
163 detailed in Kremer et al. (2018) in processing surface temperature.

164

165 *Analysis of class surface temperature*

166 We computed the mean, min, max and standard deviation of surface temperature
167 pixels that fell within each cell of the STURLA grid using zonal statistics (Table 1) and
168 joined these results with the STURLA class variable. Averaging was necessary because
169 Landsat 7 thermal bands are resampled to 30 meters for distribution (Roy et al., 2010) while
170 the STURLA grid is 120 m. Thus, we averaged sixteen 30 m pixels that fell within each 120
171 m cell. Similar to Hamstead et al. (2016) and Larondelle et al. (2014) we focused the class
172 temperature analysis on the most frequently occurring classes, which cumulatively comprise
173 90% of the city’s land area. As done with comparison of STURLA classes between cities,
174 permutational t-tests with Bonferroni correction were employed to test significance.

175 Likewise, the null hypothesis of the permutational t-test is that ST does not differ between the
176 STURLA classes.

177

178 **Results**

179

180 The most prevalent composite class in Philadelphia contains trees, grass, paved
181 surfaces, and low rise buildings ('tgpl') (Table 1). The 'tgpl' class accounts for about 57% of
182 total city area and can be found in all parts of the city and was largely homogenous in spatial
183 distribution (Figure 1A). The second largest class, 'tgplm' at 8.5% of the area, which is
184 similar to 'tgpl' except it includes midrise buildings, is concentrated in the center of the city
185 and along a few main corridors to the North and West. STURLA classes were able to identify
186 the role of urban structure influencing ST (Figure 1B). Classes generally hosted ST that were
187 unique (Figure 1B) and significantly different (Table 2) compared to all other classes with the
188 exception of 'tgbp' with similar ST values to 'tgwp' and 'tgwpl'.

189 The prevalence and distribution of the STURLA classes in Philadelphia differs from
190 what we found in previous studies of urban structure NYC and Berlin (Figure 2). In Berlin
191 and NYC, $\sim 1/3$ of the landscape can be explained by one highly composite STURLA class.
192 Another difference between the results in Philadelphia and previous studies is the number of
193 classes that cumulatively explain 90% of the area of the city. Ten classes covered 90% of the
194 area of Philadelphia while the same number of classes only covered 79% of the area of New
195 York City and 68% of the area in Berlin. Despite these differences, pairwise comparison of
196 each city revealed that STURLA class proportions were not significantly different between
197 the cities (all $p > 0.05$). Still, Berlin and NYC were highly correlated ($r^2 = 0.952$, $p < 0.05$) while
198 Philadelphia's distribution of urban structure remained uncorrelated to the other cities
199 ($p > 0.05$).

200 Due to the compositional nature of a STURLA cell where the relative proportions of
201 all elements sum to one Figure 2 provides an example of compositional variability within the
202 most common class in Philadelphia ‘tgpl’ using six grid cells taken from a larger city-wide
203 random sample. The different grid cells and corresponding satellite imagery show the
204 different types of buildings and proportion of each element of the class, trees, grass, paved
205 surfaces, and lowrise buildings, can vary greatly from one another but still fall into the class.
206 Most grid cells from the ‘tgpl’ class show row houses or single-family detached houses since
207 they fall within the size parameters of lowrise buildings (1-3 stories).

208

209 **Discussion:**

210

211 STURLA captured urban structure and characterized the physical property of ST in
212 Philadelphia as previously done in NYC (Hamstead et al., 2016) and Berlin (Kremer et al.,
213 2018), despite variation in size, demography, and historical planning. This suggests that
214 urban areas may be subject to similar processes that result in between city-redundant spatial
215 organizations (Votsis & Haavisto, 2019). Likewise, STURLA may be suited for
216 understanding urban biogeography, environmental justice, and city planning for a sustainable
217 future. Global analyses of cities may also identify clusters of urban areas that would benefit
218 from similar management practices. Likewise, STURLA offers a computationally
219 inexpensive alternative to network analyses of urban structure (Zhong et al., 2014).

220 One of the main limitations of STURLA classification is the binary nature of class
221 assignment. If the STURLA grid were shifted it would change the relative proportions of the
222 within class elements (e.g. trees decrease and other elements increase). Despite this variation,
223 STURLA classes are a discrete countable number and have a Poisson distribution. Thus, the
224 ranked order abundances of different STURLA classes should not vary in the most frequent

225 classes. For example, since ‘tgpl’ is common in Philadelphia, a reduction in a large number
 226 of ‘tgpl’ classes in the city would be relatively less influential than additions/reductions of
 227 less common class.

228

229 **Conclusion**

230 In this paper we demonstrate the application of STURLA classification to quantify the
 231 relationship between urban structure and surface temperature in Philadelphia. We show it can
 232 be applied to cities with different historical patterns of growth in a reproducible manner.
 233 Furthermore, patterns in class abundance and composition can be used to determine the
 234 surface temperature signature of a composite landscape. Additional research is needed to
 235 compare cities of vastly different urban structure and identify patterns in the relationship
 236 between urban structure with social and ecological properties of the environment.
 237 Understanding general urban structure-environmental function relationships will help build
 238 tools for effective urban planning and management under global change scenarios.

239

240 Table 1: 10 most common STURLA classes in Philadelphia and their ST statistics. STURLA
 241 class codes: t-trees; g-grass; b-bare soil; w-water; p-paved; l-low building; m-medium
 242 building

<i>Class</i>	<i>% total</i>	<i>of % cumulative</i>	<i>Mean ST C</i>	<i>Min ST C</i>	<i>Max ST C</i>
tgpl	57.44	57.44	26.95	25.01	28.79
tgpl	8.55	65.99	27.95	25.89	29.93
m					
tgp	7.39	73.37	23.86	22.10	25.75

tgwp	4.36	77.73	22.72	20.77	24.75
w	2.92	80.65	18.34	17.85	19.03
tgwp	2.57	83.22	24.83	22.41	27.29
l					
tgbp	2.46	85.69	26.31	24.16	28.60
l					
tg	1.94	87.63	20.42	19.37	21.62
tgw	1.42	89.05	20.37	19.16	21.69
tgbp	1.29	90.34	24.68	22.81	26.64

243

244

245 Table 2. P-values with Bonferroni correction from pairwise permutational t-tests (n=999) of
 246 ST values for the top ten STURLA classes. Bold values indicate statistical significance
 247 (p<0.05).

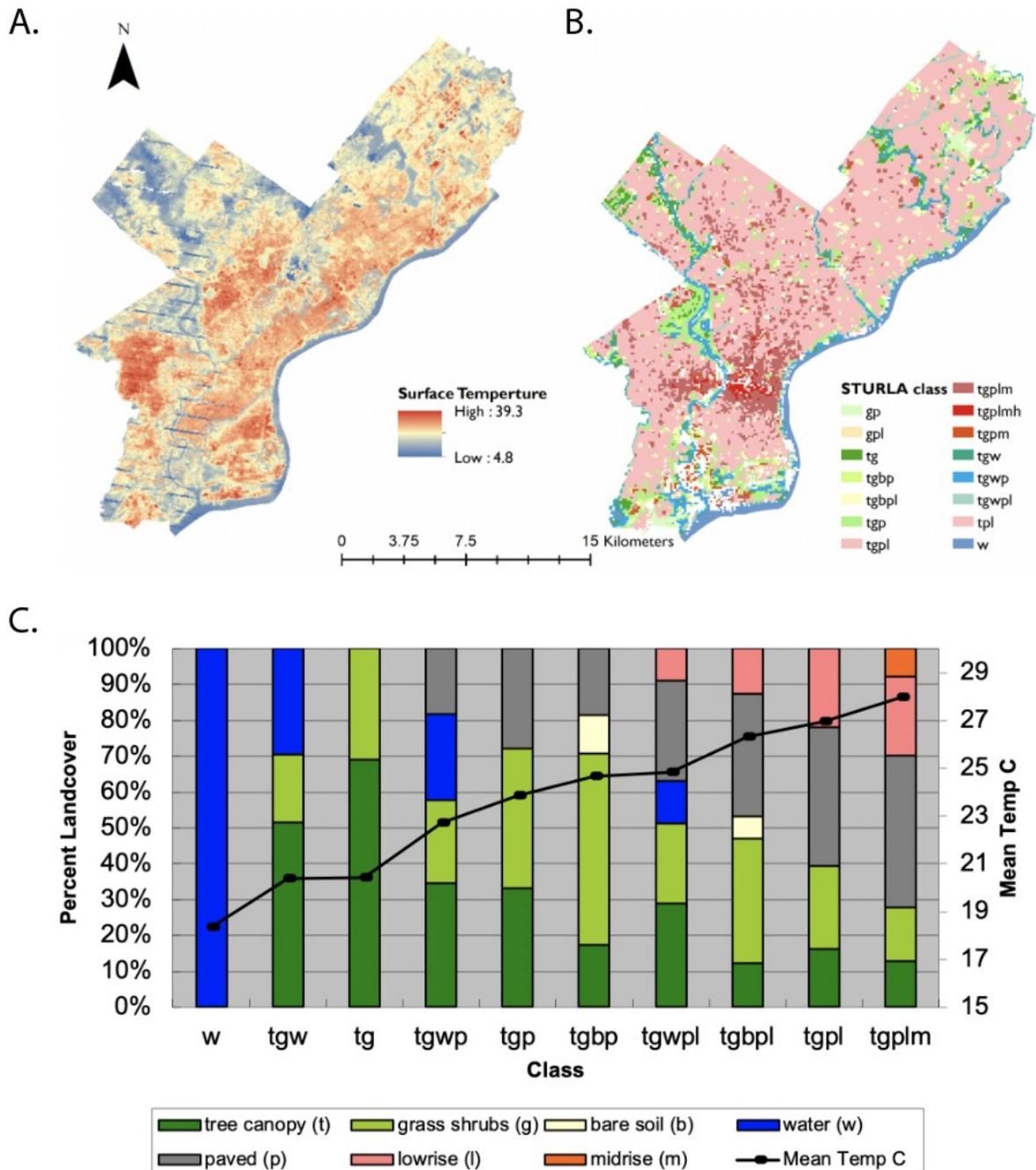
248

Class	tgpl	tgpl	tgpl	tgw	w	tgw	tgbp	tg	tgw	tgb
		m		p		pl	l		p	
tgpl	0									
tgpl	0.02	0								
m										
tgpl	0.02	0.02	0							
tgwp	0.02	0.02	0.02	0						
w	0.02	0.02	0.02	0.02	0					

tgwp	0.02	0.02	0.02	0.02	0.02	0				
l										
tgbp	0.02	0								
l										
tg	0.02	0								
tgw	0.02	0								
tgbp	0.02	0.02	0.02	3.74	0.02	4.02	0.02	0.02	0.02	0

249

250



251

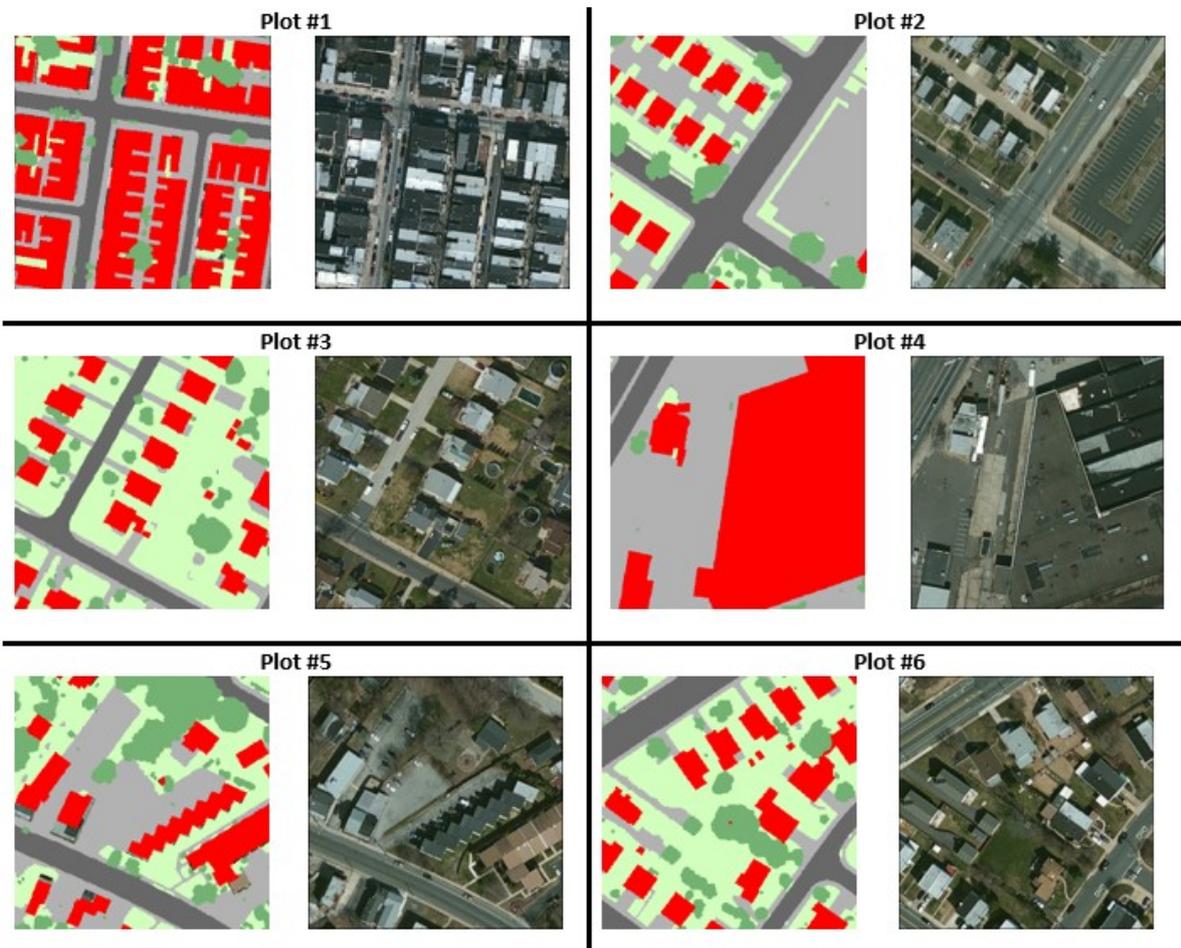
252 Figure 1. A. Spatial distribution of STURLA classes B. Spatial distribution of ST in

253 Philadelphia. C. STURLA classes, mean % landcover of individual components, and mean

254 ST for Philadelphia. STURLA class codes: t-trees; g-grass; b-bare soil; w-water; p-paved; l-

255 low building; m-medium building

256



258

259 Figure 2: Example of the composition of STURLA grid cells of the most common STURLA
 260 class in Philadelphia 'tgp1'. STURLA 'tgp1' cells are shown next to corresponding areal
 261 imagery.

262

263 References

264 Alavipanah, S., Haase, D., Lakes, T., & Qureshi, S. (2017). Integrating the third dimension
 265 into the concept of urban ecosystem services: A review. In *Ecological Indicators* (Vol.
 266 72, pp. 374–398). <https://doi.org/10.1016/j.ecolind.2016.08.010>

267 Bastian, O., Grunewald, K., Syrbe, R.-U., Walz, U., & Wende, W. (2014). Landscape
 268 services: the concept and its practical relevance. *Landscape Ecology*, 29(9), 1463–1479.

269 <https://doi.org/10.1007/s10980-014-0064-5>

270 Cadenasso, M. L., Pickett, S. T. A., & Schwarz, K. (2007). Spatial heterogeneity in urban
271 ecosystems: reconceptualizing land cover and a framework for classification. *Frontiers*
272 *in Ecology and the Environment*, 5(2), 80–88. [https://doi.org/10.1890/1540-9295\(2007\)5](https://doi.org/10.1890/1540-9295(2007)5)

273 City of Philadelphia. (2011). *Philadelphia Land Cover Raster*. OpenDataPhilly.

274 City of Philadelphia. (2015a). *Greenworks Philadelphia: 2015 Progress Report*.

275 City of Philadelphia. (2015b). *Property Assessment Data*.

276 Dietze, M. C. (2019). Ecological Forecasting. In *Ecological Forecasting*.
277 <https://doi.org/10.2307/j.ctvc7796h>

278 Dietze, M. C., Fox, A., Beck-Johnson, L. M., Betancourt, J. L., Hooten, M. B., Jarnevich, C.
279 S., Keitt, T. H., Kenney, M. A., Laney, C. M., Larsen, L. G., Loescher, H. W., Lunch, C.
280 K., Pijanowski, B. C., Randerson, J. T., Read, E. K., Tredennick, A. T., Vargas, R.,
281 Weathers, K. C., & White, E. P. (2018). Iterative near-term ecological forecasting:
282 Needs, opportunities, and challenges. *Proceedings of the National Academy of Sciences*
283 *of the United States of America*. <https://doi.org/10.1073/pnas.1710231115>

284 Hamstead, Z. A., Kremer, P., Larondelle, N., McPhearson, T., & Haase, D. (2016).
285 Classification of the heterogeneous structure of urban landscapes (STURLA) as an
286 indicator of landscape function applied to surface temperature in New York City. *Ecol.*
287 *Indic.*, 70, 574–585. <https://doi.org/10.1016/j.ecolind.2015.10.014>

288 Hervé, M. (2020). *Package 'RVAideMemoire.'*

289 Huang, G., & Cadenasso, M. L. (2016). People, landscape, and urban heat island: dynamics
290 among neighborhood social conditions, land cover and surface temperatures. *Landscape*
291 *Ecology*. <https://doi.org/10.1007/s10980-016-0437-z>

292 Jones, A. M., & Harrison, R. M. (2004). The effects of meteorological factors on atmospheric
293 bioaerosol concentrations—a review. *Sci. Total Environ.*, 326(1), 151–180.

294 <https://doi.org/10.1016/j.scitotenv.2003.11.021>

295 Joyner, J. L., Kerwin, J., Deeb, M., Lozefski, G., Prithiviraj, B., Paltseva, A., McLaughlin, J.,
296 Groffman, P., Cheng, Z., & Muth, T. R. (2019). Green Infrastructure Design Influences
297 Communities of Urban Soil Bacteria. In *Frontiers in Microbiology* (Vol. 10).
298 <https://doi.org/10.3389/fmicb.2019.00982>

299 Kremer, P., Larondelle, N., Zhang, Y., Pasles, E., & Haase, D. (2018). Within-Class and
300 Neighborhood Effects on the Relationship between Composite Urban Classes and
301 Surface Temperature. *Sustainability*, 10(3), 645. <https://doi.org/10.3390/su10030645>

302 Larondelle, N., Hamstead, Z. A., Kremer, P., Haase, D., & McPhearson, T. (2014). Applying
303 a novel urban structure classification to compare the relationships of urban structure and
304 surface temperature in Berlin and New York City. *Appl. Geogr.*, 53, 427–437.
305 <https://doi.org/10.1016/j.apgeog.2014.07.004>

306 Li, H., Meier, F., Lee, X., Chakraborty, T., Liu, J., Schaap, M., & Sodoudi, S. (2018).
307 Interaction between urban heat island and urban pollution island during summer in
308 Berlin. *Science of the Total Environment*.
309 <https://doi.org/10.1016/j.scitotenv.2018.04.254>

310 MacFaden, S. W., O’Neil-Dunne, J. P. M., Royar, A. R., Lu, J. W. T., & Rundle, A. G.
311 (2012). High-resolution tree canopy mapping for New York City using LIDAR and
312 object-based image analysis. *Journal of Applied Remote Sensing*, 6(1), 063567.
313 <https://doi.org/10.1117/1.JRS.6.063567>

314 McPhearson, T., Pickett, S. T. A. A., Grimm, N. B., Niemelä, J., Alberti, M., Elmqvist, T.,
315 Weber, C., Haase, D., Breuste, J., & Qureshi, S. (2016). Advancing Urban Ecology
316 toward a Science of Cities. *BioScience*, biw002. <https://doi.org/10.1093/biosci/biw002>

317 O’Neil-Dunne, J. (2011). *A Report on the City of Philadelphia’s Existing and Possible Tree*
318 *Canopy*.

319 PEW. (2017). *Philadelphia 2017: The State of the City*.

320 Pickard, B. R., Daniel, J., Mehaffey, M., Jackson, L. E., & Neale, A. (2015). EnviroAtlas: A
321 new geospatial tool to foster ecosystem services science and resource management.
322 *Ecosystem Services*, *14*, 45–55. <https://doi.org/10.1016/j.ecoser.2015.04.005>

323 Pickett, S. T. A., & Cadenasso, M. L. (2008). Linking ecological and built components of
324 urban mosaics: an open cycle of ecological design. *Journal of Ecology*, *96*, 8–12. [https://](https://doi.org/10.1111/j.1365-2745.2007.01310.x)
325 doi.org/10.1111/j.1365-2745.2007.01310.x

326 Reese, A. T., Savage, A., Youngsteadt, E., McGuire, K. L., Koling, A., Watkins, O., Frank,
327 S. D., & Dunn, R. R. (2016). Urban stress is associated with variation in microbial
328 species composition—but not richness—in Manhattan. *ISME J.*, *10*(3), 751–760. [https://](https://doi.org/10.1038/ismej.2015.152)
329 doi.org/10.1038/ismej.2015.152

330 Reyes, B., Hogue, T., & Maxwell, R. (2018). Urban irrigation suppresses land surface
331 temperature and changes the hydrologic regime in semi-arid regions. *Water*
332 *(Switzerland)*. <https://doi.org/10.3390/w10111563>

333 Rosenzweig, C., Solecki, W. D., Cox, J., Hodges, S., Parshall, L., Lynn, B., Goldberg, R.,
334 Gaffin, S., Slosberg, R. B., Savio, P., Watson, M., & Dunstan, F. (2009). Mitigating
335 New York City’s Heat Island: Integrating Stakeholder Perspectives and Scientific
336 Evaluation. *Bulletin of the American Meteorological Society*, *90*(9), 1297–1312. [https://](https://doi.org/doi:10.1175/2009BAMS2308.1)
337 doi.org/doi:10.1175/2009BAMS2308.1

338 Roy, D. P., Ju, J., Kline, K., Scaramuzza, P. L., Kovalskyy, V., Hansen, M., Loveland, T. R.,
339 Vermote, E., & Zhang, C. (2010). Web-enabled Landsat Data (WELD): Landsat ETM+
340 composited mosaics of the conterminous United States. *Remote Sensing of Environment*,
341 *114*(1), 35–49. <https://doi.org/10.1016/j.rse.2009.08.011>

342 Scherrer, D., & Körner, C. (2011). Topographically controlled thermal-habitat differentiation
343 buffers alpine plant diversity against climate warming. *Journal of Biogeography*. <https://>

344 doi.org/10.1111/j.1365-2699.2010.02407.x

345 Schwarz, N., Bauer, A., & Haase, D. (2011). Assessing climate impacts of planning policies
346 —An estimation for the urban region of Leipzig (Germany). *Environmental Impact*
347 *Assessment Review*, 31(2), 97–111. <https://doi.org/10.1016/j.eiar.2010.02.002>

348 Sillman, S., & Samson, P. J. (1995). Impact of temperature on oxidant photochemistry in
349 urban polluted rural and remote environments. *Journal of Geophysical Research*. [https://](https://doi.org/10.1029/94jd02146)
350 doi.org/10.1029/94jd02146

351 Simmons Schade, R., Architects, B., Spina, L. M., Farnham, J., Fine, A., Gallery, J. A.,
352 Gladstein, E., Gregorski, M., Hauck, P., Jastrzab, G., Koksuz, B., Michel, L., Nikolic,
353 T., Placke, C., Sauer, R., Schaaf, D., Urek, A., Wilds, S., & Wilson, D. (2008).
354 *Philadelphia Rowhouse Manual A PRACTICAL GUIDE FOR HOMEOWNERS*
355 *SPECIAL THANKS TO Steering Committee*.

356 Stewart, I. D., & Oke, T. R. (2012). Local Climate Zones for Urban Temperature Studies.
357 *Bulletin of the American Meteorological Society*, 93(12), 1879–1900.
358 <https://doi.org/doi:10.1175/BAMS-D-11-00019.1>

359 Stewart, J., Kremer, P., Shakya, K. M., Conway, M., & Saad, A. (2020). Outdoor
360 Atmospheric Microbial Diversity is Associated with Three-Dimensional Urban
361 Landscape Structure and Differs from Indoor-Transit Systems. *BioRxiv*.
362 <https://doi.org/10.1101/2020.06.17.157651>

363 The Brookings Institution. (2003). *Philadelphia in Focus: A Profile from Census 2000*. The
364 Brookings Institution.

365 U.S. Census Bureau. (2016). *State and County Quick Facts*.

366 van Oudenhoven, A. P. E., Petz, K., Alkemade, R., Hein, L., & de Groot, R. S. (2012).
367 Framework for systematic indicator selection to assess effects of land management on
368 ecosystem services. *Ecological Indicators*, 21, 110–122.

369 <https://doi.org/10.1016/j.ecolind.2012.01.012>

370 Votsis, A., & Haavisto, R. (2019). Urban DNA and Sustainable Cities: A Multi-City
371 Comparison. *Frontiers in Environmental Science*, 7(JAN), 4.
372 <https://doi.org/10.3389/fenvs.2019.00004>

373 Zhang, X., Estoque, R. C., & Murayama, Y. (2017). An urban heat island study in Nanchang
374 City, China based on land surface temperature and social-ecological variables.
375 *Sustainable Cities and Society*. <https://doi.org/10.1016/j.scs.2017.05.005>

376 Zhao, C., Fu, G., Liu, X., & Fu, F. (2011). Urban planning indicators, morphology and
377 climate indicators: A case study for a north-south transect of Beijing, China. *Building
378 and Environment*, 46(5), 1174–1183. <https://doi.org/10.1016/j.buildenv.2010.12.009>

379 Zhong, C., Arisona, S. M., Huang, X., Batty, M., & Schmitt, G. (2014). Detecting the
380 dynamics of urban structure through spatial network analysis. *International Journal of
381 Geographical Information Science*. <https://doi.org/10.1080/13658816.2014.914521>

382 Zhou, W., Cadenasso, M., Schwarz, K., & Pickett, S. (2014). Quantifying Spatial
383 Heterogeneity in Urban Landscapes: Integrating Visual Interpretation and Object-Based
384 Classification. *Remote Sensing*, 6(4), 3369–3386. <https://doi.org/10.3390/rs6043369>

385 Zhou, W., Huang, G., & Cadenasso, M. L. (2011). Does spatial configuration matter?
386 Understanding the effects of land cover pattern on land surface temperature in urban
387 landscapes. *Landscape and Urban Planning*, 102(1), 54–63.
388 <https://doi.org/10.1016/j.landurbplan.2011.03.009>

389 Zhou, W., Pickett, S. T. A., & Cadenasso, M. L. (2017). Shifting concepts of urban spatial
390 heterogeneity and their implications for sustainability. *Landscape Ecology*, 32(1), 15–
391 30. <https://doi.org/10.1007/s10980-016-0432-4>

392 Zogg, G. P., Zak, D. R., Ringelberg, D. B., White, D. C., MacDonald, N. W., & Pregitzer, K.
393 S. (1997). Compositional and Functional Shifts in Microbial Communities Due to Soil

394 Warming. *Soil Sci. Soc. Am. J.*, 61, 475–481.
395 <https://doi.org/10.2136/sssaj1997.03615995006100020015x>
396