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. 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 build 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 enviroment in urban lanscscape, 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 has been used to identified 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 strucutre. 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 km^2 of which 350 km^2 are land and the rest, water. Phildelphia 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 is 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 build 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 m^2 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 ‘tgwp’ and ‘tgwpl’.

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**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	0		
tgw	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	**0.02**	0	
tgbp	**0.02**	**0.02**	**0.02**	3.74	**0.02**	4.02	**0.02**	**0.02**	**0.02**	0

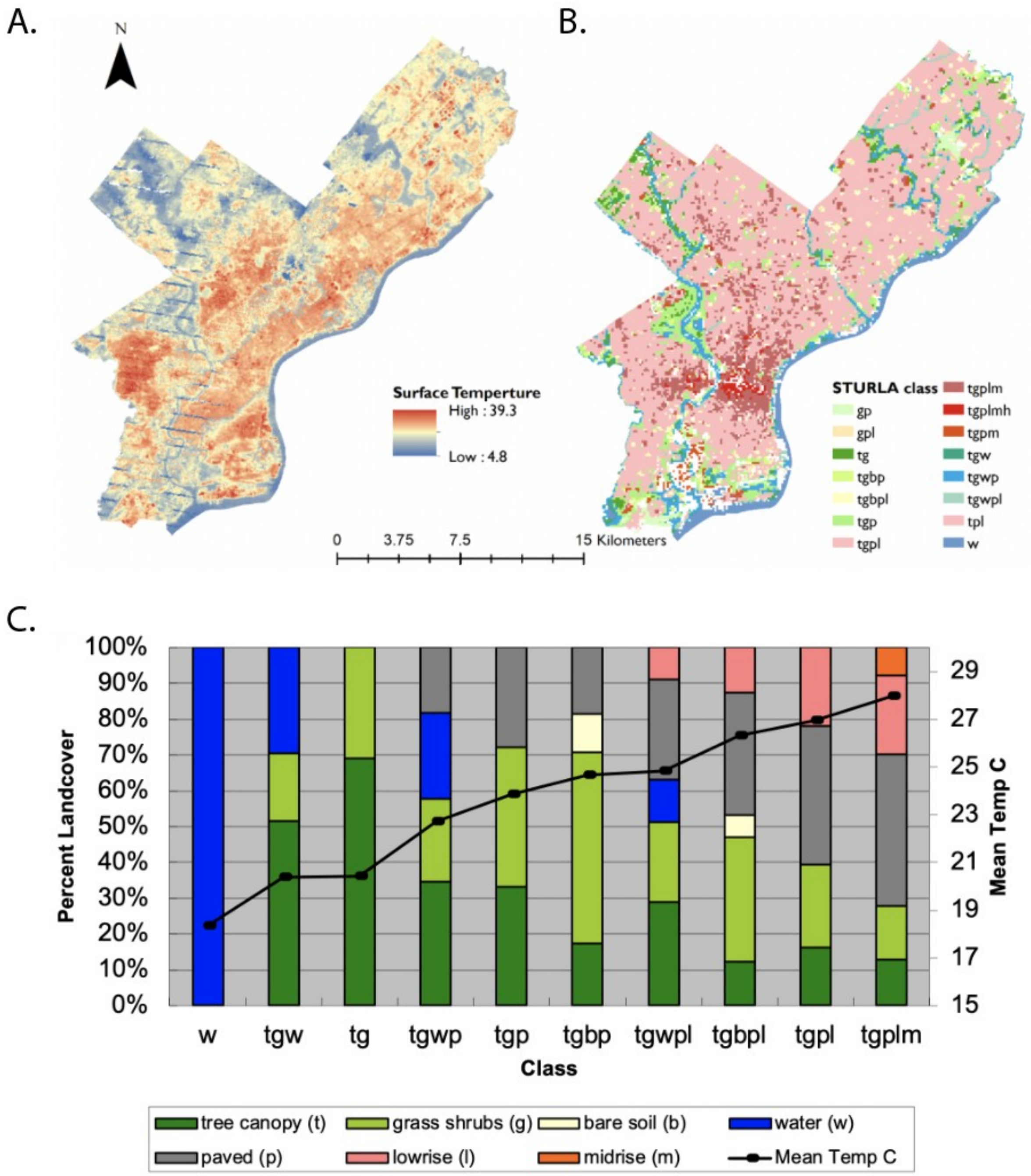

Figure 1. A. Spatial distribution of STURLA classes B. Spatial distribution of ST in Philadelphia. C. STURLA classes, mean % landcover of individual components, and mean ST for Philadelphia. STURLA class codes: t-trees; g-grass; b-bare soil; w-water; p-paved; l-low building; m-medium building

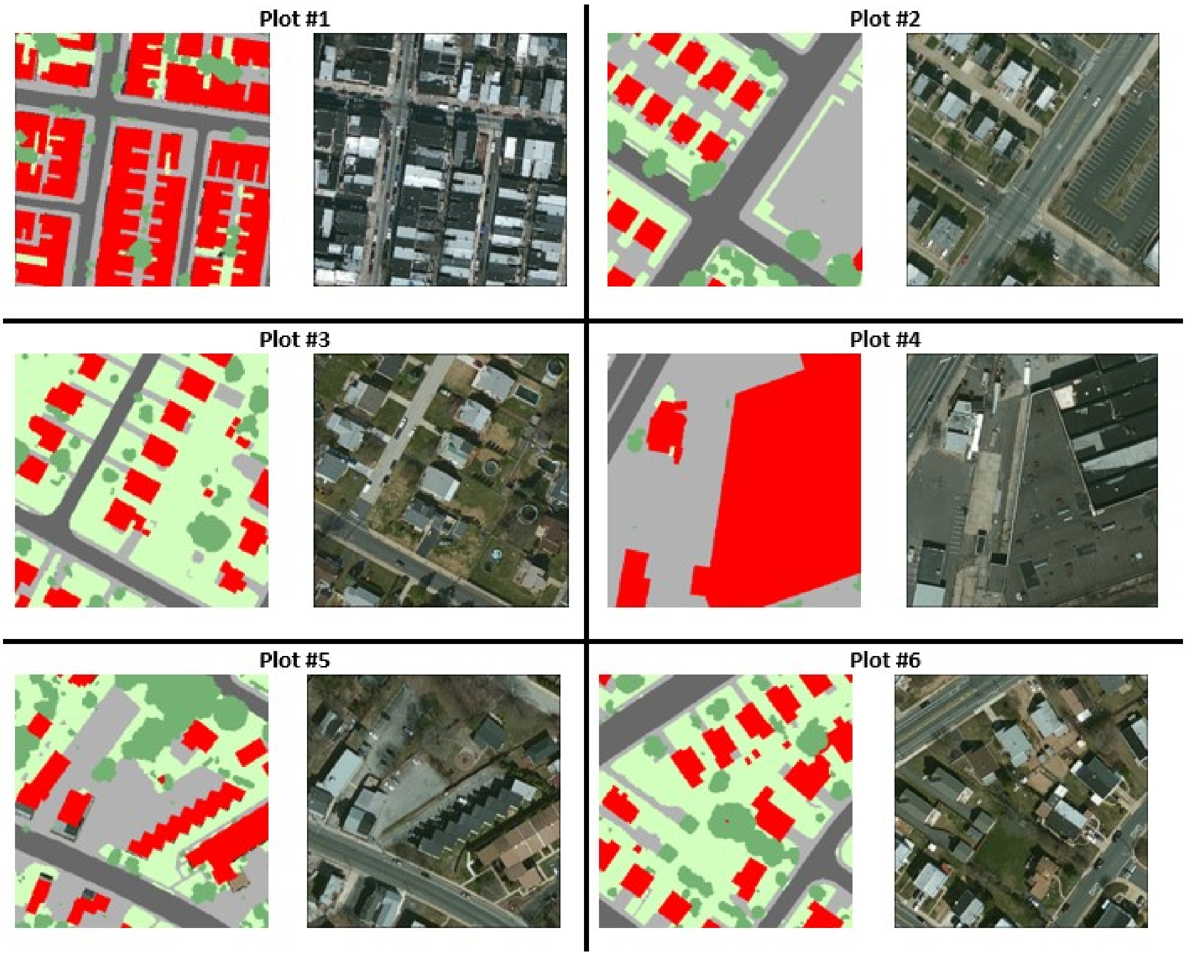

Figure 2: Example of the composition of STURLA grid cells of the most common STURLA class in Philadelphia 'tgpl'. STURLA ‘tpgl’ cells are shown next to corresponding areal imagery.

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