COMPARING FREQUENCY-BASED MEASURES OF SPECTRAL AND MORHPOLOGICAL DIVERSITY WITH SOCIODEMOGRAPHIC CHARACTERISTICS IN AN URBAN AREA

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ABSTRACT:

Remotely-sensed imagery has a demonstrated connection to urban demographic variables. In a previous study, frequency-based contextual counts of cover type classes have been related to census housing variables. A different, frequency-based contextual color type measure is introduced. This spectral metric, applied to a SPOT image, shows a high correlation with both housing characteristics and crime data compiled by census tract. The two-dimensional regression analysis of urban variation is then extended to include three dimensional measures of form and variation. Both spectral and morphometric measures show a strong connection to demographic variables, indicating a latent connection between human objectives and the spatial patterns visible in the remotely sensed urban landscape.

1. INTRODUCTION

From the earliest days of remote sensing, the discipline has played a critical role in observing and documenting mankind's effects on the landscape. Cities, with their intricate transportation networks and mixed cover types, have always presented a challenge to researchers. Yet as humanity shifts from a majority rural to majority urban population, understanding the social and spatial dynamics of urban systems becomes ever more essential to developing a comprehensive understanding of the human condition.

Though often chaotic in appearance to the casual observer, cities are constructed with purpose and intent. To be more exact, the urban mosaic is an aggregate composition of the competing intentions of a multitude of actors, both individuals and groups. As such, it is not unreasonable to imagine that the observable features of urban neighborhoods and districts are indicative of underlying economic and social characteristics.

Urban remote sensing has, to date, been largely focused on cover-type identification and feature extraction. Increasing spatial and spectral resolutions, coupled with advanced processing techniques, have delivered ever more accurate instantaneous representations of cities. Yet rarely have practitioners moved beyond identifying what is on the ground to examining why it is there. If the sensible characteristics of place are connected with underlying social structures and patterns, the inherent spatiality of imagery provides a useful tool for understanding this more human dimension of cities.

In pioneering work, Forster (1980; 1983) demonstrated that both housing density and value measures exhibited strong correlation with multispectral satellite data. Lo (1986) found that various housing characteristics related to brightness values in aerial photography. Welch (1980) took a novel approach, connecting remotely sensed measurements of nighttime urban illumination with patterns of energy usage. Lo and Faber (1997) found that a suite of metrics derived from satellite imagery could be compared with census demographics to extract a Quality of Life index for a medium-sized city. Wharton (1982) first suggested the use of a frequency-based contextual classification procedure for the discrimination of land cover classes. Eyton (1993) extended this technique to the urban environment, exploring cover frequency counts by census tract, and discovered strong relationships between these measures and housing value as well as age and type of dwelling.

The purpose of the present paper is to replicate and expand on Eyton's previous study. Initially, the same per-census-tract frequency-based contextual classification procedure used successfully in Edmonton, Alberta was utilized to explore correlation with housing characteristics for the Austin, Texas area. Rather than using cover-type frequency analysis, the method was modified to a related quantitative "color-type" frequency concept which was drawn from experience with human visual interpretation models. In addition to housing variables alone, crime data (available on the same census tract basis) was also compared with color-type frequencies. Finally, recognizing that urban geometry has a third dimension, the regression model was extended to include an analysis of lidar-derived morphometric frequencies as well.

First, the paper will lay the groundwork for the "color-type" frequency concept, followed by examinations of the relationships between this metric and housing characteristics as well as crime variables. Next, a new morphometric measure will be introduced, bringing a third dimension into the assessment. This morphometric model will once again be compared with housing measures. Finally, the significance of the results and future avenues of research will be examined.

2. METHODS AND RESULTS

2.1 Color Frequencies

As previously established by Forster (1980; 1983), Lo (1986) and Eyton (1993), the measured reflectance of remotely-sensed imagery in the visible/near-visible portion of the spectrum is highly correlated with housing values and other demographic characteristics. Yet this is only quantitative confirmation of a fact long-recognized. Colwell (1970) pioneered both early multispectral remote sensing techniques and the visual interpretation of color composites. Image interpreters have recognized that certain urban features demonstrate characteristic color signatures in composite form. In color infrared composites, for instance, newer neighborhoods tend to exhibit an overall bright cyan coloration, indicative of their newly paved surfaces and lack of vegetation. Older residential areas, on the contrary, tend to demonstrate more of a dark cyan appearance from years of surface deterioration mixed with pinks and reds of overhanging vegetation growth.

Yet if this information is visual to the naked eye in composite form, the same data is evident in the digital numbers of the three bands employed. The 16,777,216 possible colors in a 24 bit image composite are actually quite redundant. A level-sliced composite delivers much the same tonal rendition while employing only 27 individual colors. A SPOT multispectral image of Austin was converted to such a level-sliced composite (Figure 1). The frequency of occurrence for each of these new color type values was counted by census tract. This allowed a regression analysis to be performed comparing these color types with socio-demographic characteristics.

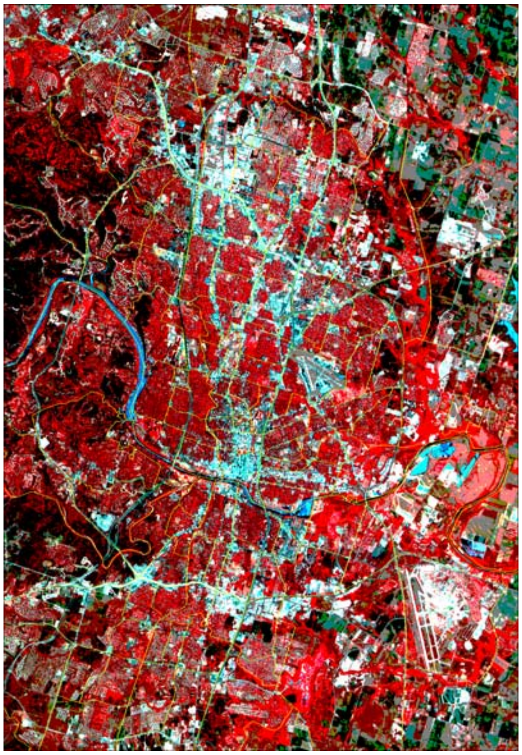

Figure 1. Level-sliced composite with tract boundaries

What are the advantages of using color-type frequencies over cover-type frequencies? Such a measure removes one level of abstraction from the data, as quantitative analysis is performed on a derivative of the original image values rather than a classification product subject to ambiguities and vagaries of human intervention. Additionally, the regression results are attached directly to an image product, allowing human interpretation to be employed at a later step in conjunction with analysis. And finally, the level-sliced composite represents a familiar product with tones that hold intuitive meaning to experienced image interpreters.

2.2 Housing Characteristics and Color Frequencies

Color frequencies may then be compared to the spatial distribution of housing variables. The frequency count of the level-sliced image showed that six of the twenty-seven simplified colors did not occur in the image; six colors were therefore excluded. Linear regression was performed, matching the remaining 21 class counts (raw and percentage) as independent variables against four different census housing attributes, one at a time (Table 1).

Census Variable	Raw Count		Percent Count	
	n=82	*n=104*	*n=82*	*n=104*
Age of Home	0.65	0.56	0.67	0.67
Home Value	0.64	0.52	0.70	0.60
Number Homes	0.71	0.69	0.48	0.40
Number Rooms	0.65	0.58	0.66	0.63

Table 1. Coefficients of determination (r^2) for color frequencies vs. housing variables

The results were similar to those achieved earlier in the Edmonton, Alberta study. Percentage of census tract covered by each class showed a higher correlation to the age and value of dwelling. In addition, the number of rooms (a new variable indicative of size) was also strongly correlated to percent of tract coverage by class. On the other hand, raw pixel counts per tract were again more related to the total number of individual homes. As stands to reason, the value, age, and to some extent size of homes is likely to be fairly uniform within a given area or district, particularly in modern suburbs. A raw frequency count, on the other hand, is more responsive to the number of homes in a census tract (especially if resolution is fine enough to distinguish individual structures).

Further exploration of the results from this regression, in concert with visual analysis of the image, revealed an interesting fact. The 21 color type frequencies might be further reduced to four dominant and corresponding tone groups (Table 2). Infrared and combination infrared and green reflectors (Group 1) are largely indicative of vegetation. Red, green, and combination red and green reflectors are associated mostly with manmade materials such as concrete, asphalt, and roofing tile (Group 2). Combination infrared and red reflectors (Group 3) consist mostly of soils and dormant vegetation. And finally, neutral color types, showing similar low, medium, or high reflectance in visible and infrared portions of the spectrum, seemed to correspond to shadows, certain recently disturbed soils, very bright concretes and quarries (Group 4).

Group 1. IR and IR+G Reflectors (Growing Vegetation)

CIR Colors	Level-Sliced Reflectance		
	IR	R	G
Red	High	Low	Low
Dark Red	Med	Low	Low
Light Red	High	Med	Med
*Magenta	High	Low	High
Dark Magenta	Med	Low	Med
Light Magenta	High	Med	High
Pink	High	Low	Med
*Purple	Med	Low	High

Group 2. R, G, and R+G Reflectors (Concrete, Rooftops)

CIR Colors	Level-Sliced Reflectance		
	IR	R	G
*Blue	Low	Low	High
Light Blue	Med	Med	High
Dark Blue	Low	Low	Med
*Green	Low	High	Low
Light Green	Med	High	Med
Dark Green	Low	Med	Low
Cyan	Low	High	High
Light Cyan	Med	High	High
Dark Cyan	Low	Med	Med

Group 3. IR+R Reflectors (Soils, Dormant Vegetation)

CIR Colors	Level-Sliced Reflectance		
	IR	R	G
*Yellow	High	High	Low
Light Yellow	High	High	Med
Dark Yellow	Med	Med	Low
*Lime	Med	High	Low
Orange	High	Med	Low

Group 4. IR+R+G Reflectors (Neutrals)

CIR Colors	Level-Sliced Reflectance		
	IR	R	G
White	High	High	High
Gray	Med	Med	Med
Black	Low	Low	Low

*Denotes colors low in frequency in Austin image

Table 2. CIR composite color reflectance groups

This qualitative analysis of the image led to a refinement of the quantitative model. The 21 color type classes used were further reduced to the four groups above. The same 4 dependent variables were compared, again one at a time, with the frequency counts of these four new groups. Following best results from the 21 class analysis, percentage counts were used against age, value, and size while frequency counts were calculated for number of single detached dwellings.

The results show that in each case the variables were highly correlated with a single reflectance group (Table 3). Value and number of single detached dwellings were each strongly correlated with vegetation. People are drawn to green space, be it in their yard or a nearby park. Size, on the other hand, highly correlates with the visible reflector group. Again, this stands to reason. The more area covered by impervious surface, the higher percentage of a census tract's area will show a manmade signature. Finally, age was highly correlated with the final class of neutral objects. The oldest areas have been widely built out. The few remaining houses in these regions may share their neighborhoods with industrial or commercial developments. Additionally, concrete and roofs of these older neighborhoods show a more neutral tone from years of deterioration.

	Age	Value	Number	Size
Group 1 (Veg.)	0.43	0.56	0.43	0.35
Group 2 (Visible)	0.28	0.25	0.16	0.51
Group 3 (IR+R)	0.24	0.14	0.26	0.13
Group 4 (Neutrals)	0.53	0.33	0.35	0.15
All 21 Frequencies	+0.67	+0.70	*0.71	+0.66

* Raw Count (n=82) +Percentage Count (n=82)

Table 3. Coefficients of determination (r^2) for Austin housing characteristics vs. group color frequencies

The original 27 colors, created by the level-slicing process, reduced to 21 classes, and further aggregated into four visually representational reflectance classes account for a great deal of the variation of housing prices in Austin by census tract. A combination of exploratory statistics and visual interpretation was instrumental in refining the model to simplified categories, explained by visual analysis while retaining much in the way of predictive power.

2.3 Crime and Color Frequencies

If the level-sliced frequency classes are highly correlated with housing characteristics and are indicative of neighborhood conditions, it is not unreasonable to expect similar relationships to emerge when compared to other demographic data. To explore this theory, crime data obtained at the census tract level for the year 1995 were regressed against census tract counts of the same color type classes used in the housing study. Thirteen available individual and aggregate crime variables were used, one at a time, as dependent variables in the regression, with the 21 color type classes serving as independent variables.

In all cases, the coefficient of determination showed a reasonable predictability of crime occurrence based on contextual color type frequency counts (Table 4). These determination coefficients ranged from a low of .19 for arson all the way up to .81 for theft. If 81% of the total variation in the theft variable by census tract can be explained by these 21 reflectance classes, then the level-sliced SPOT composite appears to be accentuating some underlying dynamic of urban structure.

Perhaps the most interesting feature of this table is the list of crime types ranked by their coefficients of determination. The seven variables displaying greater than 50% determination in the regression were individual property-associated, or indexed crimes. Determination coefficients dropped off rapidly for the remaining six person-associated crime variables. In other words, location-dependent crimes such as property and auto theft show a much stronger relationship to the metric that the frequency-based contextual color type classifier provides. Indeed this measure, initially derived from qualitative visual interpretation techniques, seems to be delivering a quantitative assessment of neighborhood or regional attributes.

	Crime Statistic	r^2	Adjusted r^2
Against Property	Theft	0.81	0.77
	Property per 1000	0.79	0.74
	Crime Index	0.78	0.73
	Total	0.75	0.69
	National Index	0.71	0.64
	Auto Theft	0.61	0.51
	Robbery	0.58	0.48
Against Person	Aggravated Burglary	0.46	0.33
	Assault	0.41	0.27
	Rape	0.39	0.25
	Armed Robbery	0.35	0.19
	Murder	0.29	0.12
	Arson	0.19	0.00

Table 4. Coefficients of determination for 1995 crime statistics vs. image frequencies

Because theft displayed the highest connection with color type frequency counts for the Austin area, this individual variable was chosen for further regression against the 4 previously derived reflectance groups (Table 5). The analysis provided startling results. A full 77% of the total variation in theft occurrence could be explained by the percentage counts of visible reflectors per census tract. By comparison, all 21 color type classes provided a slightly higher than .81 coefficient of determination. What does this mean? The portion of a census tract covered by human-produced surfaces (concretes, roofs) is highly connected with the amount of property crime experienced. In Austin, at least, the density of development in an area appears to be indicative of the levels of property-crime experienced by local residents.

	r^2
Group 1 (Veg.)	0.13
Group 2 (Visible)	0.77
Group 3 (IR+R)	0.10
Group 4 (Neutrals)	0.07
All 21 Color Frequencies	0.81

Table 5. Coefficients of determination for Austin theft variation vs. group color frequencies

A map of these highly visible (Group 2) reflectance areas overlaid with census tract boundaries (Figure 2) is useful for further analysis of this link. The Group 2 reflectors highlight the central business district, airport, large commercial developments, strip malls, and light industrial areas. All these areas have one significant thing in common—parking lots. These areas also tend to closely parallel primary or secondary transportation arteries. Finally, the densely developed areas tend to cluster near the edges of census tract boundaries. This is not surprising on reflection; the census tract boundaries are often delineated by major roads.

Theft is occurring in areas of dense commercial development. Additionally, areas of dense commercial development fall near major thoroughfares on the boundaries of designated census tracts. This implies two factors at play. First, theft and property crime are occurring at or near the places people congregate, either in commercial developments themselves or in nearby parking lots. Second, property crimes are at some level related to transportation network accessibility. It appears that some portion of the underlying social fabric of urban development may manifest itself in the reflective image records of human constructed and influenced environments.

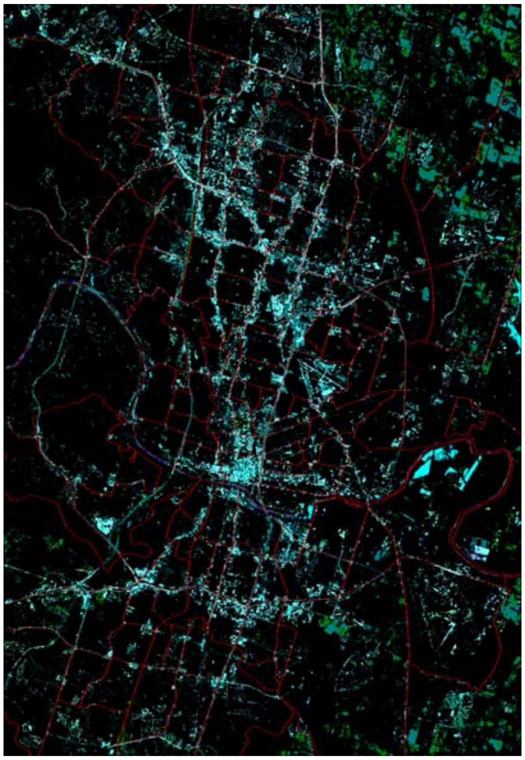

Figure 2. Map of visible reflectors with tract boundaries

2.4 Urban Morphometry

Two dimensional reflectance patterns of cityscapes, then, display a demonstrable relationship to certain demographic measures of housing and crime. Yet the urban environment humans experience exists in three dimensions. Limiting analysis to the x and y dimensions alone, as experienced from vertical satellite imagery, necessarily simplifies the full dimensionality of human city structure. Researchers have often focused on qualitative or descriptive assessments of urban morphology. Yet such assessments are quantitatively lacking. Moore points out that the significance of form and volume in urban structures has largely been ignored (2002). Grimmond and Oke's (1999) aerodynamic research represents one of the few attempts to link detailed three-dimensional models of city form with assessments of underlying spatial distributions and flows.

The growing prevalence of lidar-derived altimetry information makes detailed three dimensional models of urban morphometry increasingly accessible. If the height component of urban features plays a role in demographic distributions, lidar-derived digital elevation models (DEMs) would provide a useful tool for discovering connections between human constructs and the social landscape. A 1.5 meter spaced DEM collected in 2000 and covering a portion of the earlier Austin study area was provided by the Bureau of Economic Geology at the University of Texas. While not covering the full spatial extent of the metropolitan area, this smaller data set still covers a varied portion of the cityscape at much higher resolution. In the interest of consistency, census tract block group level housing statistics, acquired in 2000 and more appropriate to the larger scale of the spatial data, were utilized. Once again age, size, value and number of single detached dwellings were examined for each block group. Unfortunately, matching crime statistics were not publicly available at this greater scale.

Of the 121 block groups covered in this lidar dataset, only 55 were completely contained within the data or had all necessary census statistics. The other 66 were excluded from the study. Local elevation variations were subtracted from the dataset to produce a model of buildings and landscape only, excluding underlying terrain. Separate elevation, slope and curvature datasets were computed from the lidar values. Each of these datasets were classified into 20 equal interval groups. The frequency of occurrence of all 20 classes was then calculated for each of the 55 relevant census tract block groups. A regression analysis was performed using frequency counts of the separate elevation, slope and curvature classes as independent variables and each housing variable as a separate dependent variable.

The concept was to provide a morphological fingerprint for each census tract block group, exhibiting not just characteristics such as elevation or curvature, but a measure of the variation of elevation or curvature within the areal unit. Such an approach allows the regression model to express sensitivity to the texture of structural topography.

2.5 Housing Characteristics and Urban Morphometry

A morhpometric measure permits the comparison of housing characteristics and three-dimensional form. Housing age, value and number of homes each showed a high correlation to frequency counts of elevation, slope, and curvature (Table 6). In general, a third derivative measure of curvature displayed the best results for two of these variables, explaining 75% of the total variation in housing value and some 87% of the total variation in number of dwellings per census tract block group. While highly correlated with all three measures, age showed a slightly higher coefficient of determination when compared to elevation. On the other hand, number of rooms was much more related to raw elevation frequency counts, which explained 71% of the total variation in this demographic.

Census Value	Elevation Frequency Count	Slope Frequency Count	Curvature Frequency Count
Age of Home	0.61 (0.40)	0.69 (0.56)	0.75 (0.65)
Home Value	0.69 (0.51)	0.57 (0.40)	0.61 (0.46)
Number Homes	0.65 (0.45)	0.78 (0.69)	0.87 (0.82)
Number Rooms	0.71 (0.55)	0.41 (0.18)	0.49 (0.28)

(Values in parentheses denote adjusted r^2)

Table 6. Coefficients of determination (r^2) for Austin housing characteristics vs. classed frequencies of elevation, slope and curvature

Analyzing these morphometric results presents a slightly more complicated scenario. Unlike satellite spectral reflectances, form measures have no traditional urban interpretation scheme to draw upon. Careful study of the results, however, yields interesting implications. The number of dwellings, especially at this resolution, is best evidenced in a curvature frequency assessment. The frequency of curvature variations within a block group would obviously be tied to the number of individual shapes or forms it contained. By logical extension, the same argument would hold for home value. Generally speaking, less densely spaced and larger domiciles have a higher value, as evidenced by a map of frequency counts for one illustrative block group (Figure 3). This particularly holds true for Austin, where the priciest suburban homes are perched on steep hills, not allowing for a high planimetric density of dwellings. On the other hand, neighborhoods of more modest means (Figure 4) show a more regular and densely spaced pattern of development. Conversely, age measures respond slightly better to raw elevation counts. One reasonable explanation of this pattern would be that the greater tree canopy cover associated with older neighborhoods displays a greater variation in morphometric form and texture than newer subdivisions with less robust vegetation development.

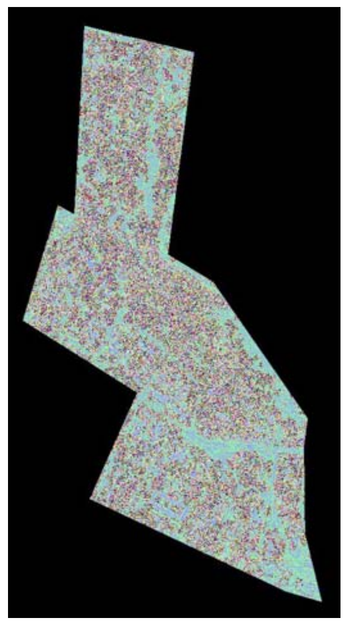

Figure 3. Frequency distribution in a high value block group

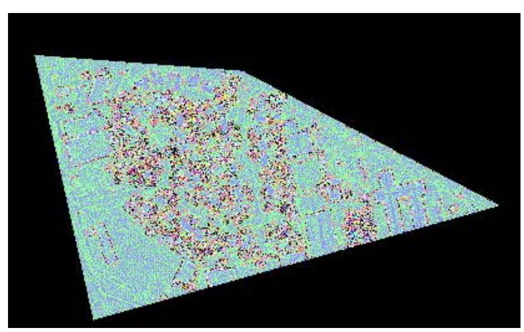

Figure 4. Frequency distribution in a low value block group

Slightly more perplexing is the observation that the surrogate measure of size (average number of rooms) shows a significantly higher amount of variance described by raw elevation rather than either slope or curvature measures. Perhaps the answer is as simple as the fact that taller structures are likely to contain more rooms. Regardless, raw counts of elevation frequency per census tract block group will clearly be a more sensitive measure of enclosed volume than variations in either slope or form. When dealing with size in three dimensional space, volume would certainly be the relevant factor.

While less analytically accessible than spectral reflectance contextual frequency counts, morphometric frequencies add a new level of dimensionality to the remotely sensed assessment of urban spaces. Humans do not interact and live their lives in two dimensions. A comprehensive remote sensing exploration of the physical structure of cityscapes and the social spaces within which populations operate would be incomplete without accounting for volume and measures of texture.

3. CONCLUSIONS

Cities have long been a focus of remote sensing study. Beyond the transformation of imagery to thematic maps and feature delineation, quantitative analysis has demonstrated great promise in spotlighting underlying urban sociodemographic forms. This research seeks to expand these techniques, introducing the concept of contextual color type frequencies derived from traditional qualitative imagery analysis techniques. Color type frequencies derived from level-sliced, color infrared composite SPOT satellite imagery demonstrate a high correlation to several representative housing and crime variables. Additionally, at a larger scale, urban morphometric form measures (as derived from lidar-extracted DEMs) show a strong connection to housing value, size, age, and dwelling counts.

By highlighting the pattern of sociodemographic trends on the mapped urban landscape, measures of spectral or morphometric variance uncover the spatial commonalities between the experienced, social world of humans and the objective, observed physical urban environment. For instance, by discovering a link between land cover and crime such a study might suggest areas to focus law enforcement efforts. More importantly, an understanding of why these particular locations are conducive to criminal activity could be useful in addressing the causes of crime prior to its occurrence. Likewise, discovering a link between housing characteristics and morphometric measures could provide urban planners a useful tool to aid in the mitigation of current problems and the design of more successful cities for the future.

Following from the techniques utilized in this study, several paths for further research present themselves. Because crime appears to have a strong relation to place, comparing crime measures to quantitative morphometric models seems a logical progression of the research. Additionally, given the utility of both reflectance and form measures in explaining the variation in certain sociodemographic variables, combining these separate metrics into an interacting suite could provide a powerful urban analysis tool. By expanding the dimensionality of the data utilized, more robust measures of variance within cityscapes might be achieved. Finally, expanding the study to a larger urban area with more complete lidar coverage (the authors are currently examining Houston, Texas) would subject the methods and models proposed to a more rigorous assessment.

Remote sensing has always been a useful tool for displaying the complexity and heterogeneity of urban patterns. If cities are truly the collaborative compositions of diverse actors, social and economic as well as individual and group in nature, then their palettes of spectral signatures and brush strokes of morphometric form are not just inert swaths on the landscape but expressions of human meaning and intent. Learning to read and appreciate these intricate patterns teaches us not just of specific city structures but of the humans who live there.

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