# THE RELATIONSHIPS BETWEEN LIDAR DATA AND SOCIOECONOMIC VARIABLES FOR AUSTIN, TEXAS

THESIS

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# CHAPTER 1

# INTRODUCTION

The spatial examination of the locations, movements and interactions of human societal characteristics is the driving force of cultural geography. Understanding place requires knowledge of not only the physical landscape, but the cultural attributes of the humans occupying that space. Since gathering demographic data can be a costly and time-consuming process, new tools providing alternative techniques for gathering socio-economic information are useful to those seeking an understanding of cultural processes.

Remote sensing is the practice of gathering information about an object or place without being in actual contact with the object or place in question. In practice, the term remote sensing is usually used to refer to satellite or aerial imaging of the Earth's surface by collecting and examining reflectance or emittance in some part of the electromagnetic spectrum. Remote sensing has become a standard tool for studying distributions and monitoring processes in the physical landscape. This technology has also found broad applications in the monitoring and classification of human activities on, and modifications to, this landscape. But relatively little investigation has been conducted regarding the linkages between remote sensing and social factors.

There is, however, a growing recognition that a fundamental relationship exists between the patterns of reflectance manifested in remotely sensed data and the patterns of human behavior. Studies showing some promise have concentrated on examining the relationship between the spectral content of satellite imagery and socio-economic variables such as housing characteristics (Forster 1983; Eyton 1993), energy consumption (Welch 1980), quality of life (Lo and Faber 1997) and crime (Eyton forthcoming).

At large scales, these patterns are evident in the structures humans build and the manner in which they modify their environment. In other words, local urban characteristics are often reflected in the three-dimensional form or the length, width and height of structures that make up a city. Quantitative measures of this form, in terms of heights and such derivatives as slope and curvature, are also representative of this human urban landscape.

It is theorized that **LI**ght **D**etection **A**nd **R**anging (LIDAR) measurements that produce detailed, high-resolution (approximately 1.5 meter) Digital Elevation Models (DEMs) of urban structures may be indicative of human behavior patterns and provide the basis for determining relationships between the morphometrics of an urban landscape and the socio-economic characteristics of the local culture as expressed in the local urban morphometry.

Summaries of the social characteristics of an urban population are of paramount interest to politicians, planners, developers, marketers, and other decision makers. These parties have long relied on census data to evaluate local populations and formulate policy. While the decadal census provides a wealth of information about the state of American society at different scales, the infrequent intervals at which these data are collected presents difficulties for demographers trying to keep pace with the rapid changes occurring in the modern urban environment. Estimated values are derived by the census bureau for intervening years, but an independent, objective source of data could corroborate these projected values. Gathering LIDAR data has a lower cost and requires less time than conducting a census or survey. Additionally, existing LIDAR datasets could be utilized to further minimize expenses. Though such laser altimetry data is currently collected only at irregular intervals for specific projects or purposes, the availability of high resolution data and even repeat coverage is becoming more prevalent. And unlike a survey, the results of aerial surveys do not depend on the timely cooperation of human participants or their willingness to divulge information.

To test the veracity of this theory, a LIDAR data set representing a major portion of the city of Austin, Texas, was registered to block group level census housing data. Multiple regression analysis was performed to determine what correlation exists between the elevation values (heights) and derivatives that describe the city's form and the socioeconomic values that depict the distribution of cultural processes.

Since different types of urban morphology have distinctive forms, LIDAR data and the features quantitatively represented therein should have a demonstrable relationship with the socioeconomic factors. Demographic data, such as housing values tend to cluster spatially on the landscape. The median housing values for a newly developed subdivision at the edge of a city are usually very different from an inner-city neighborhood of fifty-year-old tract housing. Likewise, city centers with densely packed streets and numerous parking lots or garages (see figure 1a), have different housing densities than sprawling suburban neighborhoods (see figure 1b).

If a correlation can be shown to exist between socio-cultural factors and the measurable form of a city, this could enhance understanding of the processes at work, provide an important new supplemental source of objective data to demographers and help to further extend the tools of remote sensing into the realm of cultural geography.

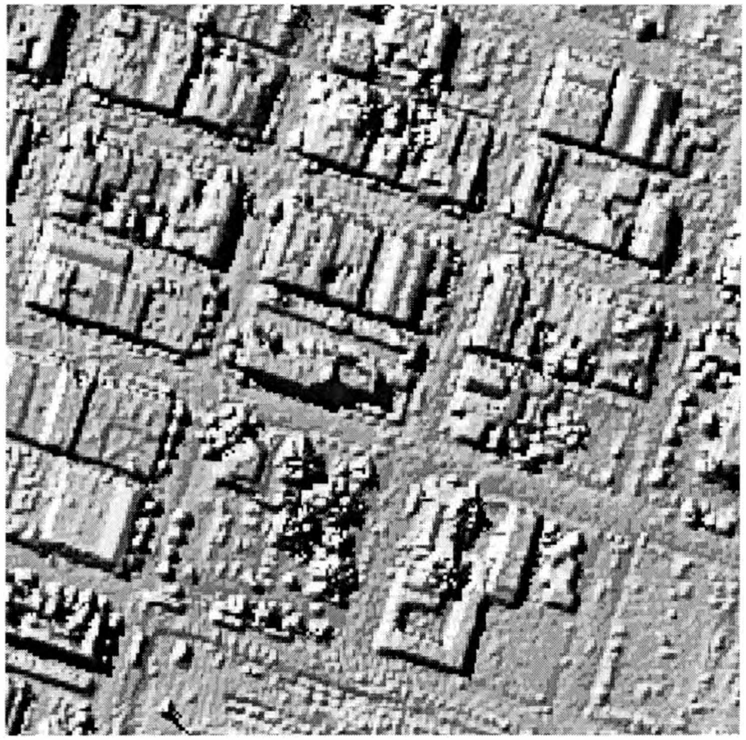

Fig. 1a. Central Austin streets lined with cars (Hillshaded DEM).

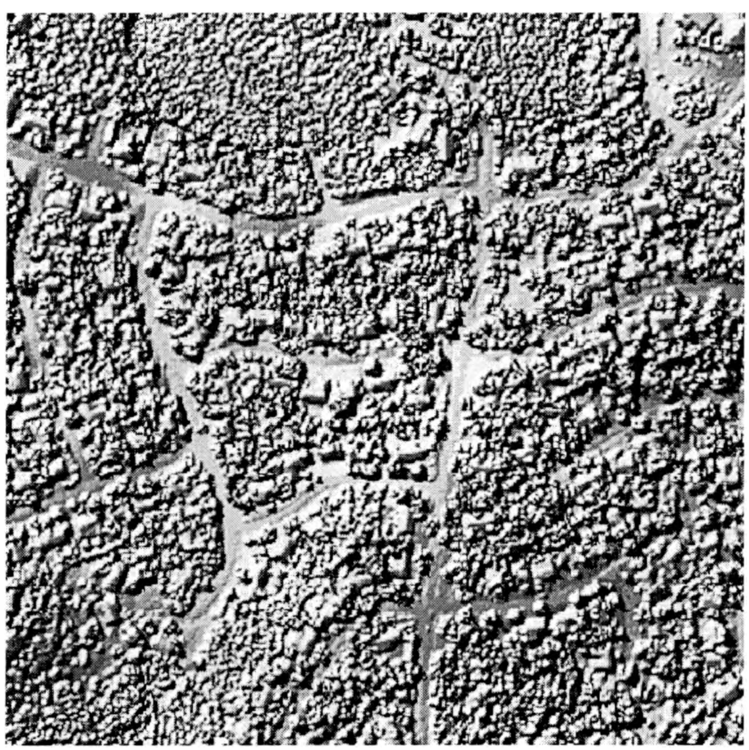

Fig. 1b. Suburban residential development (Hillshaded DEM).

# CHAPTER 2

# BACKGROUND LITERATURE

The social and economic structures of cities have been the focus of intense scrutiny in the geographic realm. Human actions are indelibly linked to the environmental context in which they transpire. This creates complex patterns of form, both structurally and sociologically, within cities. The built environment can be conceived as a manifestation of the attributes of the creators and occupants of urban space. Characterizations, both qualitative and quantitative, of this structural component of urban form have proven useful to urban geographers. Most of these representations have focused on only the two-dimensional components of cities. Three-dimensional, or height, measurements of landforms can provide various derivative measures of shape and volume. While a variety of remotely-collected information has been shown to correlate with the reflectances of urban targets, little research has been done to examine the connections between the morphometry (or measurable form) of an urban landscape and the socioeconomic characteristics of a city's inhabitants.

## Urban Demographics

The cultural patterns of cities are the results of a complicated milieu. Human actions are inherently affected by the spaces they occupy. Thomlinson (1969) notes that despite efforts to change the landscape and overcome spatial barriers, human attitudes and activities "are still closely associated with the spatial characteristics of the areas [they] inhabit" (Thomlinson 1969, 3). These actions, in turn, modify the original landscape creating a complex web of interactions between population attributes and form. Knox (1982) argues that "the built environment is to a large extent a product of the social, economic and technological conditions prevailing at the time of construction" (Knox 1982, 62). In other words, the constructed landscape and the resident population reflect and influence one another over time.

Complex urban demographic patterns result from the dynamic relations between humans and the built environment. At the neighborhood scale, these social factors can vary greatly (Golledge and Stimson 1997). Similarly minded individuals tend to group together, by choice or controlling factors, into communities reflecting their values and status. The unequal distribution of resources and talent lead to a disparity of opportunity within cities. "Patterns of differentiation in the economic and social fortunes of citizens" have emerged (Golledge and Stimson 1997, 72). The characteristics of a residential population will evolve to reflect changing economic and social realities.

## Urban Structure

Cities develop complex and hierarchical internal patterns of organization. Garner (1970) sees a straightforward, systematic approach as the best way for characterizing urban areas. The patterns present, he argues, are best understood in terms of variations in the nature and density of land use. In this approach, the framework of a city may be viewed as "a surface of differing intensity and character of use" (Garner 1970, 6). Such a statistical surface allows for the modeling of density gradients, providing a valuable tool for the analysis of urban structure.

On the other hand, Southwarth and Owens (1993), in their exploratory study of development on the urban fringe of San Francisco, present a more dynamic approach to patterns of city structure in space and time. They examine the shape and direction of development throughout the twentieth century at three nested levels of scale. From the basic "skeletal" structure of streets, down to the size of lots and the presence or absence of roadside landscaping, they assert that neighborhoods reflect the prevailing values and attitudes of their developers and original tenants.

## Urban Morphology

The study of city form was one of the earliest components of urban geography. Qualitative descriptions of building form, or morphology, were the original way of describing cityscapes. "Morphololological studies are concerned, by convention, with variations in style, layout and function of buildings" (Knox 1982, 62). By their nature, such analyses contain a subjective component. Human characterizations such as land use or building function do not correspond to sharply defined classes or variables. Descriptive accounts can help to portray the general pattern of built structure within a city, but do not allow for the accurate modeling of spatial variability.

In contrast, later methods have focused on a more quantitative approach to the representation of city form. Numerical datasets representing building extent, function, and shape are more appropriately employed for statistical analyses. Even so, such techniques have concentrated primarily on the two-dimensional aspect of city form, representing the footprint of structures and the growth of urban areas on a two-dimensional plane. The three-dimensional morphology represented by the form and volume of urban buildings has largely been ignored (Moore, 2002).

Few current studies of urban areas take into account the morphometric texture and volume of structural components. Grimmond and Oke (1999) did make use of detailed three-dimensional models of several North American cities in their study of aerodynamic flows in urban locales. But the focus of this research was the effect of such obstacles on physical processes such as wind patterns. The density, local variability, and volume of city structures was not considered.

## Measures of Form

In raster datasets representing landform, values portraying the third dimension, or height, are traditionally stored in spatially relative rows and columns. These data sets, known as digital elevation models (or DEMs), may be used to extract representative measures of elevation and the derivatives slope and curvature. DEMs can also be used to create three-dimensional perspective views of the landscape. Increasingly, airborne laser altimetry is being used as a tool for the creation of detailed, highly-reliable DEMs (Flood 2002). Unlike traditional DEMs, the original data collected from LIDAR sensors include values for the elevation of above-surface elements of the environment such as vegetative cover or buildings. Standard processing of LIDAR datasets includes procedures to remove such non-ground elements, but this portion of the data set contains accurate, high-resolution measurements of these features. Although this information is a hindrance to the creation of accurate landform surface models, in urban areas the structures and landscaping contained in this layer of data represent a detailed model of the three-dimensional form including the human constructed components such as buildings and landscaping.

## Remotely Sensed Data and Socioeconomic Variables

Past studies have demonstrated a connection between remotely-collected data, representing the structure of cities, and tabular demographic data. Housing characteristics have been shown to relate to the brightness values in aerial photography (Lo 1986). Since the nature of housing often controls certain factors of the outside appearance of the dwelling, such as size or roof geometry, this stands to reason.

In pioneering studies, Forster (1980, 1983) found that housing value and housing density could also be predicted from visible/near-infrared satellite imagery in an urban area, allowing for the convenient simultaneous assessment of large urban expanses. The usefulness of these techniques improves with the resolution of the sensing system. Eyton (1993) found a high correlation between frequency counts of cover types in a classified Landsat image and both the housing value and age of dwelling. He also found that cover type frequency datasets were useful "in multiple regression models to examine the relationships between urban measures and the heterogeneous patterns of urban cover types" (Eyton 1993, 117).

Similarly, Welch (1980) used regression to relate patterns of urban energy consumption to the volume of three-dimensional plots of brightness values derived from nighttime satellite imagery. He found a correlation between energy consumption patterns and image brightness for several urban areas of the United States. Again, this makes sense. The nighttime illumination of urban areas would have a direct relation to the electricity consumption of the population.

Lo and Faber (1997) took a different approach, combining satellite-derived data with census variables to assess a quality of life index for Athens, Georgia. They found the complementary use of these disparate datasets to create a useful measure of lifestyle. This index was highly related to vegetative cover and green spaces.

In his recent study, Alexander Pfaff (1999) explored connections between land cover change in the Brazilian Amazon, as portrayed by satellite imagery derived measures, and demographic and socioeconomic factors of immigrants in determining rates of deforestation. He concluded that the use of demographic "spatially disaggregated information" would provide for the more effective linkages with high-spatial resolution imagery (Pfaff 1999, 41). In other words, smaller groupings of tabular descriptive information are necessary with finer resolutions of imagery.

Eyton (forthcoming) examined the relationships between Landsat satellite data and crime variables. He found a high degree of correlation, reporting $r^2$ values between .75 and .85. He concluded that a demonstrable link may exist between reflected radiation values, as characterized by frequency counts of classified cover type, and crime rates.

And finally, Seto and Kaufmann (2003) attempted to model the controlling forces of urban land use change by comparing features extracted from a series of high spatial resolution images with socioeconomic data for a rapidly urbanizing area of the Pearl River Delta in China. While they found some ambiguity in the causality of relationships between these variables, a statistically significant linkage was present.

# CHAPTER 3

# STUDY AREA AND DATA

The Austin, Texas metropolitan area provides a dynamic environment for exploring the links between urban structure and socioeconomic data. Different neighborhoods throughout the city exhibit a variety of demographic characteristics and morphometric forms. Austin's nature, physically and socioeconomically, presents an interesting test case for exploring correlations between these variables.

## Site Location

Located along the Colorado River at the physiographic boundary of the Texas Hill Country and the Blackland Prairie, Austin is a growing metropolitan area with a population of more than one million. Originally founded as the capital city of the independent Texas Republic, Austin's purpose as a civil and administrative center persisted after statehood. In addition to public administration, the presence of the University of Texas played a central role in the development and expansion of the area. In the past few decades, the city has experienced a dramatic surge of growth related to high-tech research and infrastructure. Austin's position along the Interstate 35 corridor, one of the main arteries connecting the United States and Mexico, plays an increasingly important role in the city's growth.

The late 1990's witnessed a dramatic redevelopment of Austin's central business district and the rapid growth of urban residential properties, accompanied by an influx of residents into the central city. Associated measures of housing value, age, and density provide a robust test case for exploring the intuitive connection between urban form and descriptive social data.

The Austin area also offers a complex mixture of styles, in terms of architecture and layout, from different eras. Neighborhoods included in the study area vary widely. The hills to the west of the city are covered with sprawling, recently-developed upscale housing. Closer in, more established neighborhoods populate the bluff overlooking the central city and the areas bordering the Colorado River immediately adjacent to the Central Business District. North and East of the inner-city are large areas of tract housing from the post-war era. In the central city core itself, apartments and high-rise condominiums predominate.

## Geographic Representation

The primary data utilized in this project was a 1.5 meter resolution raster DEM produced from an airborne LIDAR instrument. This dataset was collected over central Austin, Texas on August 17th and 18th of the year 2000 for the Bureau of Economic Geology at the University of Texas.

An Optech ALTM 1225 laser altimetry system operating from a modified Cessna 206 platform was employed to capture the data points (Smyth et al. 2001). The laser, operating in the near-infrared portion of the electromagnetic spectrum, is capable of a vertical accuracy of 10 to 15 centimeters and horizontal spacing as close as 1 meter. In addition, an inertial measurement unit logged aircraft attitude information while a differential global positioning receiver computed absolute aircraft trajectory. Several characteristics were recorded for each pulse of the device including the timing for multiple returns and the associated intensity of each measurement.

For a given pulse, not all of the energy may return at the same time. Much of the energy might, for instance, encounter and be reflected by tree canopy, returning directly to the sensor. A portion of the light, however, may penetrate the cover and travel further, providing a second strong return signal from the time of reflection from the ground.

This study used "first return" data or elevations calculated from the length of time elapsed between an outgoing pulse and the initial return signal received at the sensor. The Bureau of Economic Geology transformed these irregularly spaced measurements into a gridded DEM using *SURFER* software.

Additionally, a standard 7.5 minute United States Geological Survey DEM of the study area was incorporated into the project to represent the local terrain of Austin. This 30 meter dataset provides a generalized surface of local topography.

Block group level census data for the year 2000 was obtained from the United States Census Bureau for the Austin-San Marcos Metropolitan Statistical Area. Variables were chosen to provide a representative characterization of housing attributes for the study area. The variables used were number of rooms, number of single detached units per structure (or single family homes), year structure was built, and value for specified owner-occupied housing units. These measures are indicative of the size, density, age, and value of residential properties by census tract block group.

Data included in the project serve to characterize the three-dimensional form of the city, the landforms underlying the urban area, and the properties of residential housing by spatial unit. This provides a sociological and morphological snapshot of the city of Austin in the year 2000 for comparison and analysis.

# CHAPTER 4

## METHODOLOGY

A raster dataset of LIDAR elevation values for the study area was imported into *ArcView GIS 3.2* and set to UTM coordinates. A vector overlay of United States Census Bureau census tract block group boundaries was acquired and reprojected into UTM to match. Four United States Geological Survey 7.5 minute quadrangle DEMs covering the Austin metropolitan area were also reprojected to UTM and merged into a single dataset using *ArcView Grid Analyst.*

After all the data had been converted to the same projection, coverages were clipped to match the extent of the LIDAR study area. A hillshaded map showing elevation-derived relative insolation values for the study area overlaid with census tract boundaries and table numbers was created to assist in feature identification (see figure 2).

Tabular census data for the year 2000 corresponding to the 121 census tract block groups in the study area were obtained from the United States Census Bureau. Variables representing the number of rooms per dwelling, number of single-detached dwellings per block group, year of construction and value were acquired and saved in table form. The data for number of single-detached dwellings was used directly. Average year of construction, average number of rooms and median value were calculated using simple mathematical formulae (see table 1).


Fig. 2. Hillshaded full LIDAR dataset with registered census tract block groups.

Table 1. Formulae for Conversion of Census Variables

| |
|---|
| Average value of dwelling (in thousands of dollars) = $(7.5d_1 + 12.5d_2 + 17.5d_3 + 22.5d_4 + 27.5d_5 + 32.5d_6 + 37.5d_7 + 45.0d_8 + 55.0d_9 + 65.0d_{10} + 75.0d_{11} + 85.0d_{12} + 95.0d_{13} + 112.5d_{14} + 137.5d_{15} + 162.5d_{16} + 187.5d_{17} + 225.0d_{18} + 275.0d_{19} + 350.0d_{20} + 450.0d_{21} + 625.0d_{22} + 875.0d_{23} + 1125.0d_{24})/(d_1 + d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_8 + d_9 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{15} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{22} + d_{23} + d_{24})$<br><br>where: $d_1$ = number with value less than \$10,000<br>and $d_2$ = number with value of \$10,000 to \$14,999<br>and $d_3$ = number with value of \$15,000 to \$19,999<br>and $d_4$ = number with value of \$20,000 to \$24,999<br>and $d_5$ = number with value of \$25,000 to \$29,999<br>and $d_6$ = number with value of \$30,000 to \$34,999<br>and $d_7$ = number with value of \$35,000 to \$39,999<br>and $d_8$ = number with value of \$40,000 to \$49,999<br>and $d_9$ = number with value of \$50,000 to \$59,999<br>and $d_{10}$ = number with value of \$60,000 to \$69,999<br>and $d_{11}$ = number with value of \$70,000 to \$79,999<br>and $d_{12}$ = number with value of \$80,000 to \$89,999<br>and $d_{13}$ = number with value of \$90,000 to \$99,999<br>and $d_{14}$ = number with value of \$100,000 to \$124,999<br>and $d_{15}$ = number with value of \$125,000 to \$149,999<br>and $d_{16}$ = number with value of \$150,000 to \$174,999<br>and $d_{17}$ = number with value of \$175,000 to \$199,999<br>and $d_{18}$ = number with value of \$200,000 to \$249,999<br>and $d_{19}$ = number with value of \$250,000 to \$299,999<br>and $d_{20}$ = number with value of \$300,000 to \$399,000<br>and $d_{21}$ = number with value of \$400,000 to \$499,999<br>and $d_{22}$ = number with value of \$500,000 to \$749,999<br>and $d_{23}$ = number with value of \$750,000 to \$999,999<br>and $d_{24}$ = number with value of \$1,000,000 or above |
| Average year home built = $(99.5d_1 + 96.5d_2 + 92.0d_3 + 84.5d_4 + 74.5d_5 + 64.5d_6 + 54.5d_7 + 44.5d_8 + 34.5d_9)/(d_1 + d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_8 + d_9)$<br><br>where: $d_1$ = number of dwellings built 1999 - March 2000<br>and $d_2$ = number of dwellings built 1995 - 1998<br>and $d_3$ = number of dwelling built 1990 - 1994<br>and $d_4$ = number of dwellings built 1980 - 1989<br>and $d_5$ = number of dwellings built 1970 - 1979<br>and $d_6$ = number of dwellings built 1960 - 1969<br>and $d_7$ = number of dwellings built 1950 - 1959<br>and $d_8$ = number of dwellings built 1940 - 1949<br>and $d_9$ = number of dwellings built 1939 or earlier |

Table 1. (continued)

Average number of rooms = $(1.0d_1 + 2.0d_2 + 3.0d_3 + 4.0d_4 + 5.0d_5 + 6.0d_6 + 7.0d_7 + 8.0d_8 + 9.0d_9)/(d_1 + d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_8 + d_9)$

where: $d_1$ = number of dwellings with 1 room
and $d_2$ = number of dwellings with 2 rooms
and $d_3$ = number of dwellings with 3 rooms
and $d_4$ = number of dwellings with 4 rooms
and $d_5$ = number of dwellings with 5 rooms
and $d_6$ = number of dwellings with 6 rooms
and $d_7$ = number of dwellings with 7 rooms
and $d_8$ = number of dwellings with 8 rooms
and $d_9$ = number of dwellings with 9 rooms or more

after Eyton (1993)

The vector census tract boundary file was converted to a grid. This new raster dataset was then exported from Arcview 3.2 as a binary grid file. The grid cells representing the aereal extent of this mask data were set to a unique value for each census tract block group, from 1 to 121. In other words, the grid cells comprising census tract block group 42 would each hold the value 42.

The 7.5 minute DEMs were resampled from 30 meter resolution to 1.5 meter resolution using a cubic convolution technique. This created a generalized surface of topographic features matching the LIDAR dataset in spatial resolution and extent. A discrepancy of vertical datums was noted between the two elevation models. A set of 72 measurements of difference were sampled throughout the dataset for visible ground features which remained constant between the two dates of compilation. These points, referenced to x and y coordinates within the dataset, were used to create an error surface representing the differences in observed measurement. This correction or error surface was generated using multiquadric equations (Hardy 1971).

The individual grid values from this error surface were subtracted from the corresponding 7.5 minute USGS DEM values, effectively registering the two datasets to the same vertical scale. This new DEM, representative of the topography of the Austin area without the addition of above ground features, was then subtracted from the LIDAR DEM. This data processing was intended to essentially flatten the terrain of Austin, leaving only buildings, trees, and other human-influenced factors to be examined in the final operating dataset.

This final model, containing the elevations of city structural elements, was then processed into three further datasets. The first was a simple elevation model, containing only observed heights. The second data set was a model of slope magnitude. Slope can be simply defined as the rate of change in elevation with respect to distance. The third model was a representation of curvature. Curvature is the rate of change of slope over distance. Curvature manifests itself as concavities and convexities on the landscape. A Laplacian measure of curvature was calculated using a bi-directional operator with a 4-point kernel.

Each of the three datasets was broken into twenty equal intervals based on distribution of the data. These categories were used to classify each of the datasets into a new representative raster file in *Terra Firma*. This resulted in three new files, one each for elevation, slope, and curvature, with the grid cells containing a class value from one to twenty. The mask file was then used to count, for the specific census tract block groups, the frequency of occurrence of each class. The measure created serves not only to count the number of occurrences of each class, but does so in the framework of a known aereal unit (i.e. census tract block groups).

This frequency-based contextual classification data was combined in a spreadsheet with the four chosen housing variables for data analysis. Linear regression analysis was conducted using *SPSS* software. For the 121 census tract block groups, each of the four variables in turn was used as the dependent variable in an individual linear regression, with the 20 elevation equal interval class counts acting as independent variables. The same four regression models were run using slope classes and curvature classes as the independent variables. Resulting $r^2$ values (coefficients of determination) and adjusted $r^2$ values were compiled in tabular form for comparison.

Specific census tract block groups representing high, medium, and low examples for median home value and number of single-detached dwellings variables were selected.

The mask file was used to extract the curvature data from these areas. These Laplacian curvature values were then mapped in classed-color form to assist in the visual interpretation and analysis of the data.

# CHAPTER 5

# RESULTS AND ANALYSIS

This study seeks to elucidate the connection between socioeconomic metrics and measurable three-dimensional form of a city. Such a demonstrable link could provide a better understanding of the way in which demographic patterns manifest themselves in the observable urban environment and help to illustrate the dynamic connections between built locational form and the lives of residents. The $r^2$ and adjusted $r^2$ values derived from linear regression analysis of census housing variables versus classed elevation, slope, and curvature data provide a systematic way of assessing the correlation between these seemingly-disparate factors.

Maps of single census tract block groups, representative of high, medium, and low values in the housing data, help to provide a window on patterns of form that are affecting the regression analysis. These close-up views of elevation or derivatives mapped to smaller neighborhoods show that the frequency-based contextual classification process highlights not only the occurrence of different classes, but encompasses relative measures of distribution between classes. The statistics are capturing not just raw numerical counts, but the variability of form (or sometimes the lack thereof) within a spatial unit.

## Measures of Correlation

All four measures of housing showed high degrees of correlation with elevation frequency counts as well as the other elevation derivatives slope and curvature. Average year constructed and average number of room variables showed the best results using simple elevation classes as independent variables. Average housing value and number of single detached dwellings, on the other hand, showed a very high relation to curvature frequency counts. Of 121 census tract block groups falling within the study area, 66 were either missing one or more of the census bureau housing variables or did not fall entirely within the LIDAR dataset. This left 55 valid census tract block groups as a sample.

The coefficient of determination values for regressions performed using elevation class frequency counts as independent variables showed strong results (see table 2). Not only were $r^2$ values high, but adjusted $r^2$ values (which attempt to account for possible over-determination by the use of too many independent variables) were also strong. Using average housing value as the dependent variable, an $r^2$ of .614 was recorded with an adjusted $r^2$ of .398. Average year constructed had an $r^2$ value of .688 and an adjusted $r^2$ of .513. Number of single detached dwellings had an $r^2$ of .646 and an adjusted $r^2$ value of .449. Finally, average number of rooms had an $r^2$ of .709 and an adjusted $r^2$ of .547. In other words, all 4 housing variables had coefficients of determination of .6 or above when regressed against simple classed elevation.

The slope class regression analysis, using 20 equal interval classes as independent variables, produced results differing from the classed elevation analysis. While $r^2$ values for 3 of the 4 independent variables showed only minor variations, average number of rooms differed markedly—showing much less correlation. Average housing value

Table 2. Coefficients of Determination ($r^2$)

| | Elevation Frequency Count | Slope Frequency Count | Curvature Frequency Count |
|---|---|---|---|
| Average Value | .614 (.398) | .685 (.560) | .746 (.645) |
| Average Year Constructed | .688 (.513) | .571 (.401) | .610 (.456) |
| Number of Single Detached Dwellings | .646 (.449) | .781 (.694) | .872 (.821) |
| Average Number of Rooms | .709 (.547) | .412 (.180) | .486 (.284) |

(adjusted $r^2$ in parentheses)

returned an $r^2$ of .685 and a moderately higher adjusted $r^2$ of .560. Average year constructed showed a less robust .571 $r^2$ and an adjusted $r^2$ of .401. Number of single detached dwellings $r^2$ increased to .781 with an adjusted $r^2$ of .694. But average number of rooms showed a much weaker relationship to slope, with an $r^2$ value of .412 and an adjusted $r^2$ of only .180.

Curvature appears to provide the best measure of form. The results obtained using curvature classes as independent variables were high. Average housing value versus curvature class counts showed an $r^2$ of .746 and an adjusted $r^2$ of .645. Average year constructed had an $r^2$ value of .610 (close to the observed elevation correlation) and an adjusted $r^2$ of .456. Number of single detached dwellings had a coefficient of determination of .872 versus classed curvature frequency counts and an adjusted $r^2$ of .821. Average number of rooms again had a lower $r^2$ of .486 and an adjusted $r^2$ of .284. But overall, curvature seems to be an excellent measure of form and a good morphometric representation for correspondence to housing variables.

## Observed Relations of Form and Socioeconomic Variables

The height and form of structures and landscape features, in terms of elevation value and curvature, appear to have an important connection to census-collected measures of housing characteristics. Slope magnitude, although related, plays a lesser role. Elevation values are representative of the height of structures or trees above the local terrain. The frequency count of Laplacian curvature, on the other hand, serves as a measure of an area's variability in human-influenced form and landscaping.

Variability in concavities and convexities over a given distance can be difficult to visualize at this scale. While 1.5 meters is a relatively high spatial resolution for terrain data, only one value of elevation and one value of concavity or convexity will be calculated for each 2.25 square meters. This captures only general trends in height, slope or curvature in an area, not necessarily specific features. An examination of classed Laplacian curvature maps for specific census tract block groups helps to clarify the factors at work.

## Housing Value

Curvature showed a high correlation with average housing value using linear regression. Census tract block group number 97, just west of Central Austin, has the highest average home value in the city, at $537,000. This block group shows high variability in curvature (see figure 3), which stands to reason. This is one of the oldest residential sections of the city, perched on a bluff covered with live-oak and elm. This tree cover shows up in the dataset as an almost constant variation in curvature. Flatter areas visible in the scene, showing less variation, are Enfield Road (running east to west) and portions of Pease Park and Shoal Creek (running north to south along the right border). Even the roofs in this neighborhood show a higher variability in curvature. This also makes sense. The architecture in this area is quite ornate and gabled roofs are common. Additionally, since this area predates planned subdivisions and is built on steep grades, the roads follow undulating paths and don't exhibit geometric patterns. This area of high housing values, then, seems also to demonstrate significant variation in amounts of Laplacian curvature.

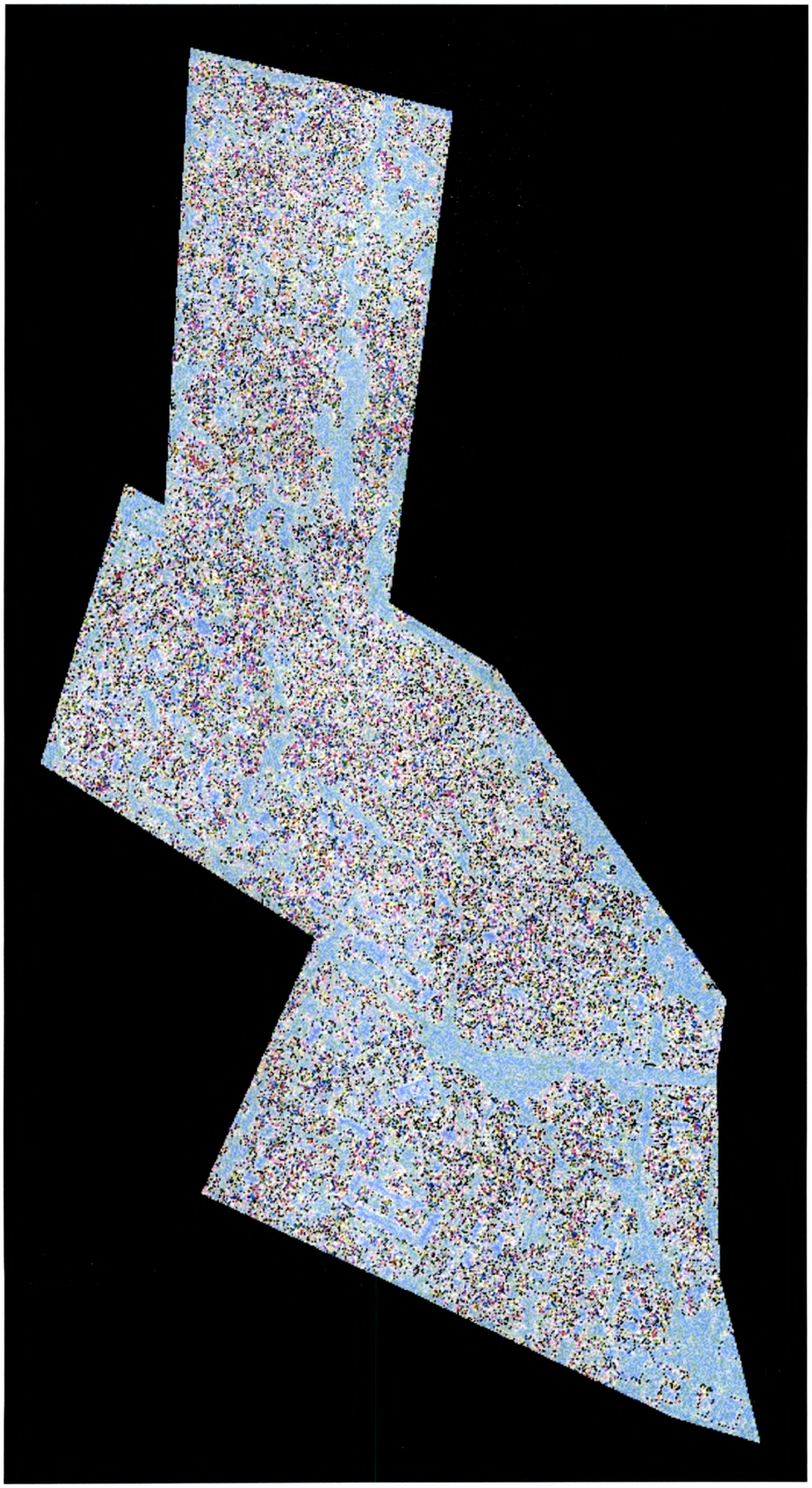

Fig. 3. Census tract block group 97 with high average home value.

Census tract block group number 71, south of the Colorado River in the Barton Skyway area of Austin, is representative of areas of moderate average home value for the city (see figure 4). This is also an older neighborhood, dating from postwar years. Here again the older-growth tree canopy makes for a varied texture. But this neighborhood bears the marks of more systematic planning. A regular pattern of streets can be seen running through the map in a grid pattern. The houses tend to be aligned in direction and similar in shape.

Census tract block group number 6 has a low average housing value. This block group covers a small neighborhood just off Airport Boulevard in East Austin. Again, this is an older neighborhood, in this case consisting of 1950s era tract housing. But curvature in this tract shows much less variability (see figure 5). Airport Boulevard runs down the left-hand side of the map, and the parking lots and roofs associated with the businesses in the area (mainly car rental storage facilities) are relatively flat. This is a trend seen throughout the city. Mixed-use areas generally have lower average housing values than exclusively residential neighborhoods.

Evidently a highly variable mixture of curvature classes, often representative of a thick tree cover, can serve as an indicator of high housing value. The three examples given here all focused on older developments. But there are reasons to believe the same may hold true for newer subdivisions as well. Expensive houses tend to be situated on larger lots, allowing for more landscaping and less disturbance of the vegetation during construction. In Austin, at least, many of the more valuable dwellings built in recent years are in the hills west of town on steep inclines. This makes for less geometric patterns of streets and more open areas (often the ravines between houses are too steep to

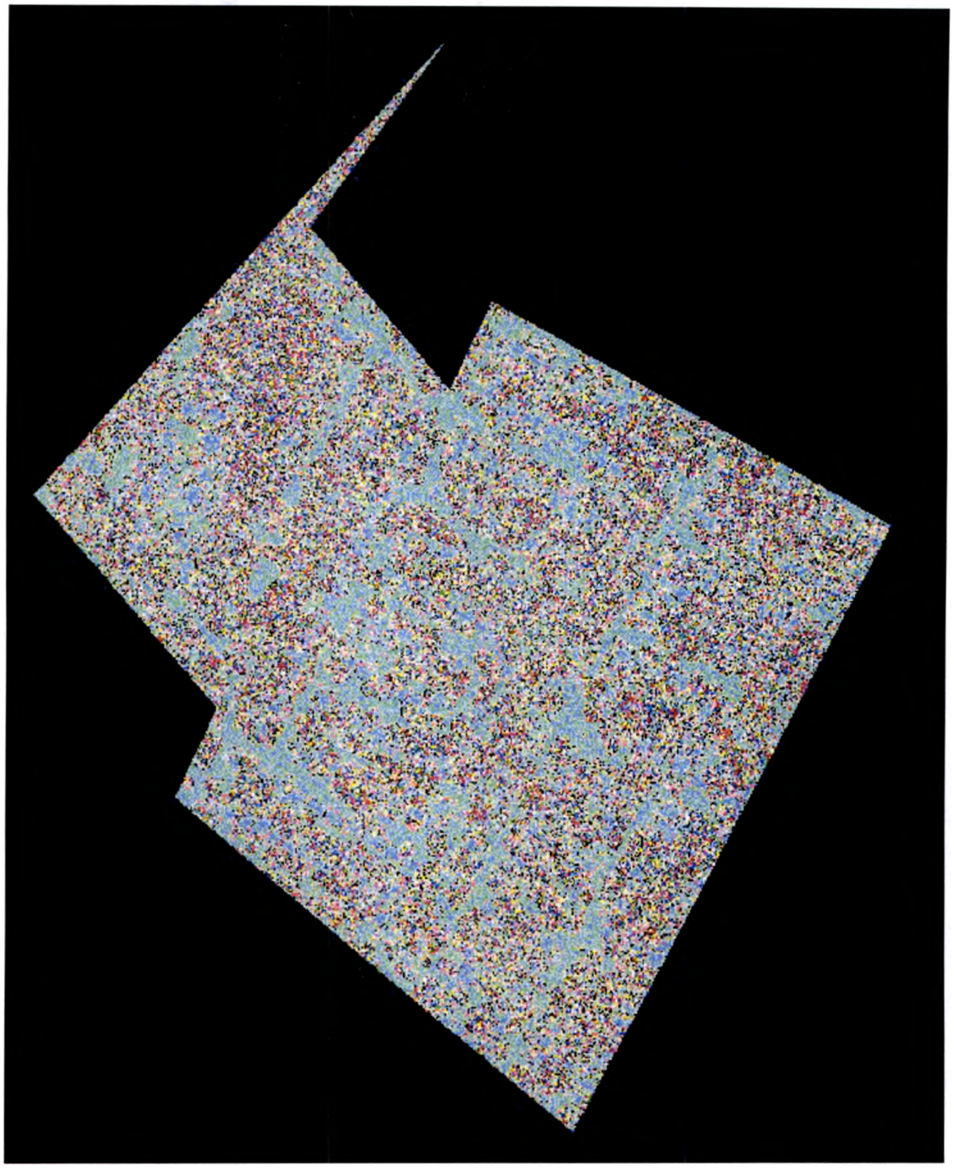

Fig. 4. Census Tract block group number 71 with moderate average home value.

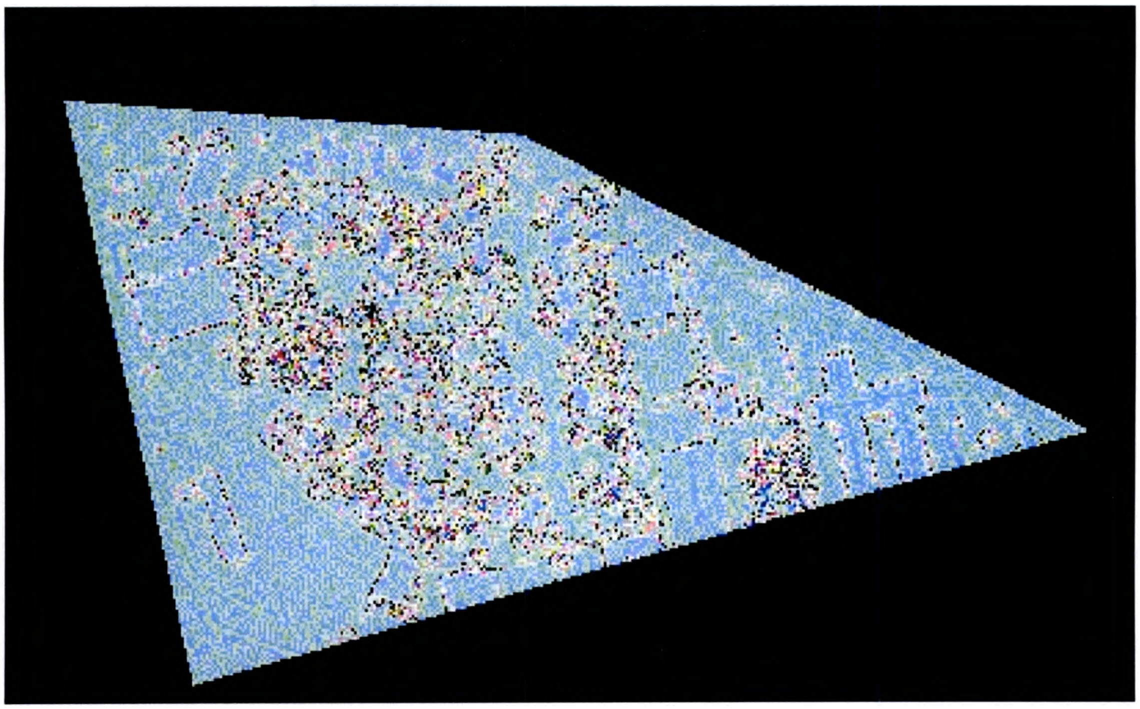

Fig. 5. Census tract block group number 6 with low average home value.

be built on). On the other hand, more moderately priced houses of recent origin are often built close together to make maximum use of the developer's land, and vegetation is completely cleared to allow for easy, systematic construction. The correlation then, between curvature variation and average housing value seems to follow conventional wisdom.

## Average Year Constructed

Calculations of average year constructed showed correlation with elevation, slope and curvature, but a simple measure of elevation achieved the best results. Elevation may show a correspondence with age based on two different factors. First of all, the trees, bushes, and other landscaping which comprise much of the topography of a neighborhood will expand in density and increase in height over time (at least to a point). Secondly, multilevel tract homes have only become popular in Texas over the past two or three decades. Before this, one-story ranch style homes predominated. But these factors would seem to be at odds with one another. One would expect higher elevation values in older neighborhoods stemming from vegetation, but also higher elevations in newer neighborhoods from multi-level structures. But since the regression is looking at the variability amongst 20 elevation classes, older neighborhoods would show a great variety of different elevations of tree canopy. On the other hand, in newer neighborhoods, most elevations would fall into a few distinct classes representative of ground surface, single-level structures, and multilevel structures. Although there may be many two-story houses, they would all tend to have the same height, so their roofs would fall into a single class. Again what seems to emerge is a pattern of more or less variation among the elevation classes.

## Number of Single Detached Dwellings

The number of single detached dwellings per census tract block group also showed a high correlation with all 3 classed data sets--elevation, slope and curvature. But with an $r^2$ value of .872, the curvature frequency count versus number of single detached dwellings coefficient of determination was particularly high. In other words the form of the city, in terms of the 20 Laplacian curvature classes, could explain over 87% of the variation in single family home count. An examination of relevant block group maps again helps to illustrate the process at work.

Census tract block group number 7, just east of Interstate 35 from the University of Texas, is a prime example of an area with a high number of single detached dwellings (see figure 6). These small tract homes, built in the 1940s and 1950s, are closely packed along a trellice pattern of streets. The most notable thing about this area is the lack of open space. The only areas showing any open space at all are the university maintenance facilities and apartments visible in the lower left corner of the map. The rest of the block group is filled with tightly packed, narrow residential streets. The well-developed tree canopy also covers parts of the roads, further complicating the modeled curvature.

Census tract block group 52, on the other hand shows wider streets and some open space (see figure 7). This area represents a medium count of single family homes, for Austin block groups. Like the previous area, block group 52 also lies just east of the Interstate, but incorporates more open space in terms of businesses and parking along the frontage road (left side of block group) and an elementary school in the lower left corner. This helps break up the density of cover within the spatial extent of the block group.

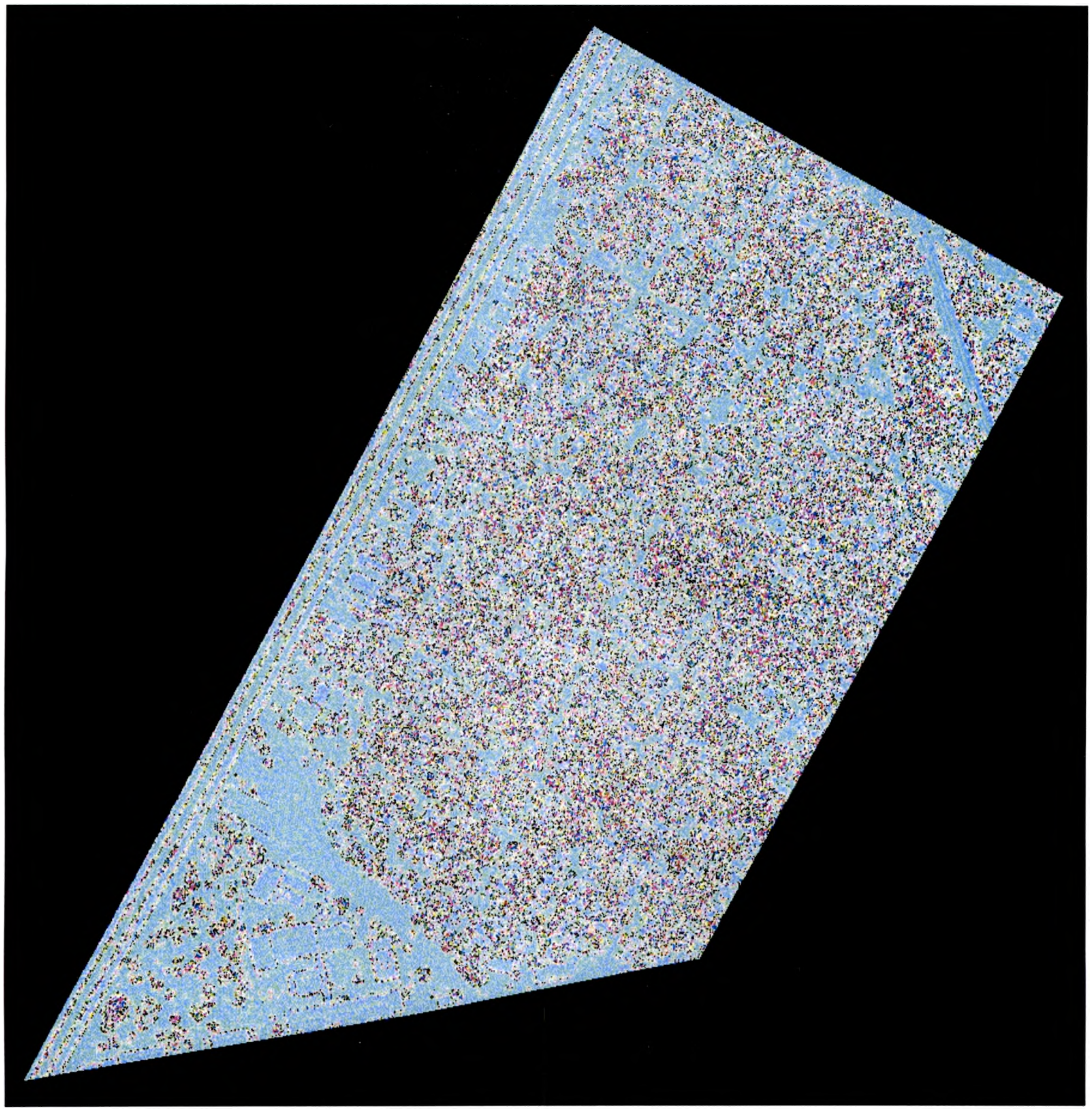

Fig. 6. Census tract block group number 7 with high single detached dwelling count.

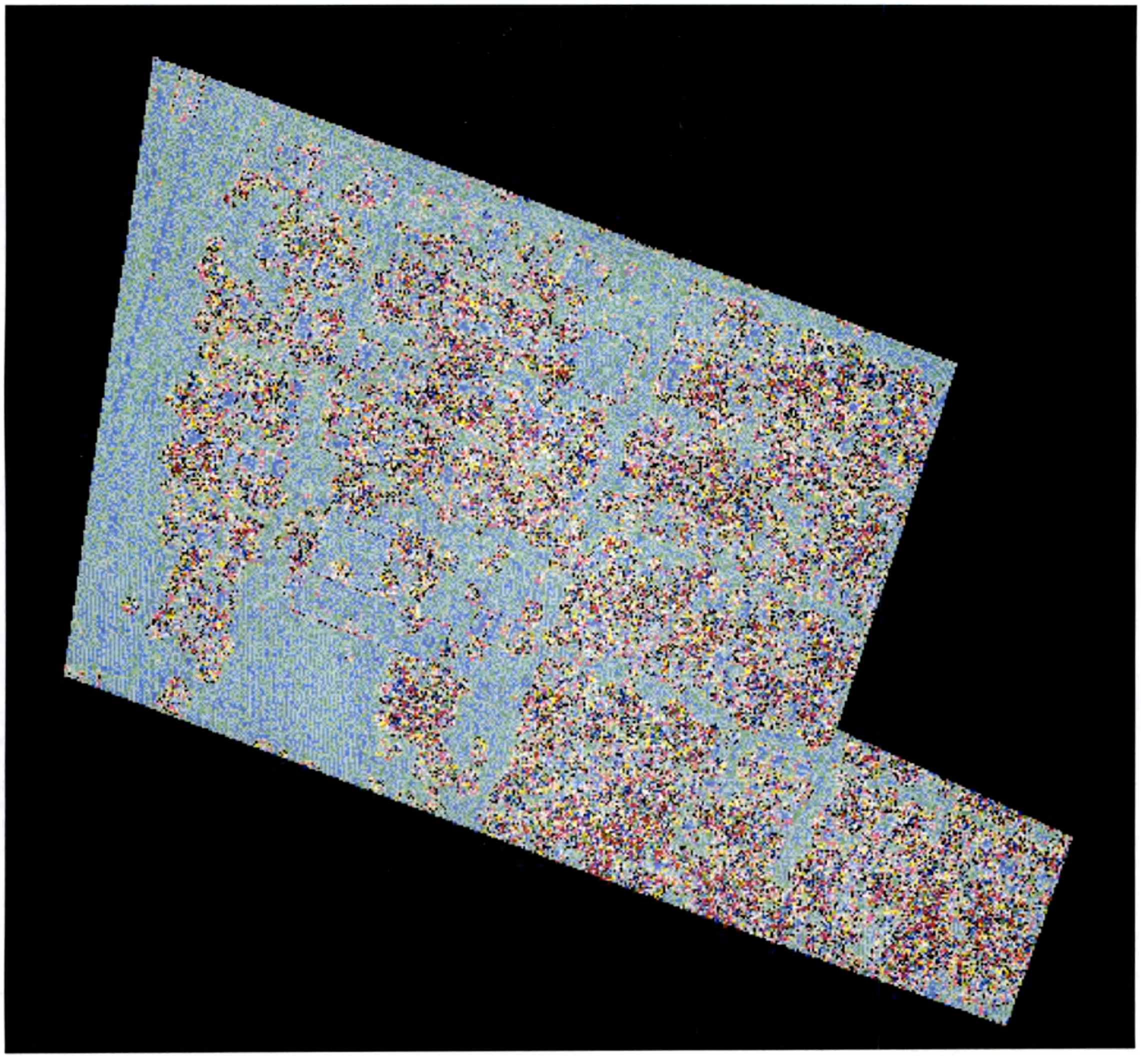

Fig. 7. Census tract block group number 52 with moderate single detached dwelling count.

Census tract block group number 113 represents a low occurence of single family houses. This large tract running along Loop 1 in West Austin incorporates businesses, residential areas, as well as most of Zilker Park, a large urban park along the Colorado River (see figure 8). Certainly the large expanses of this block group covered by such relatively curvature-invariant features as polo grounds and soccer fields (upper right portion of the map), the river itself (upper border of the block group), and sprawling office developments with parking lots (center of tract) help explain the low count of single family homes. But this also gives some indication of why single detached dwellings are so strongly correlated with curvature. The regression appears to be sensitive to some ratio of open space to cover (vegetative or otherwise). This holds true whether the open space is a park, an elementary school, or a shopping mall parking lot. This stands to reason: the more space within a block group that is devoid of convexities and concavities, the lower the occurrence of detached dwellings.

## Average Number of Rooms

The final housing variable, average number of rooms, shows a distinctly different pattern than the other variables. The coefficient of determination is much higher for this variable when regressed against elevation class counts than either slope or curvature. The other three variables seemed to respond to measures of form and shape in general. Number of rooms per home shows a much stronger connection directly with measured height. This may in part be due to the fact that this variable isn't limited to single-family homes but also includes room counts for duplexes, townhomes, and condominiums as well. These larger and often taller structures may be affecting the results. Logic dictates

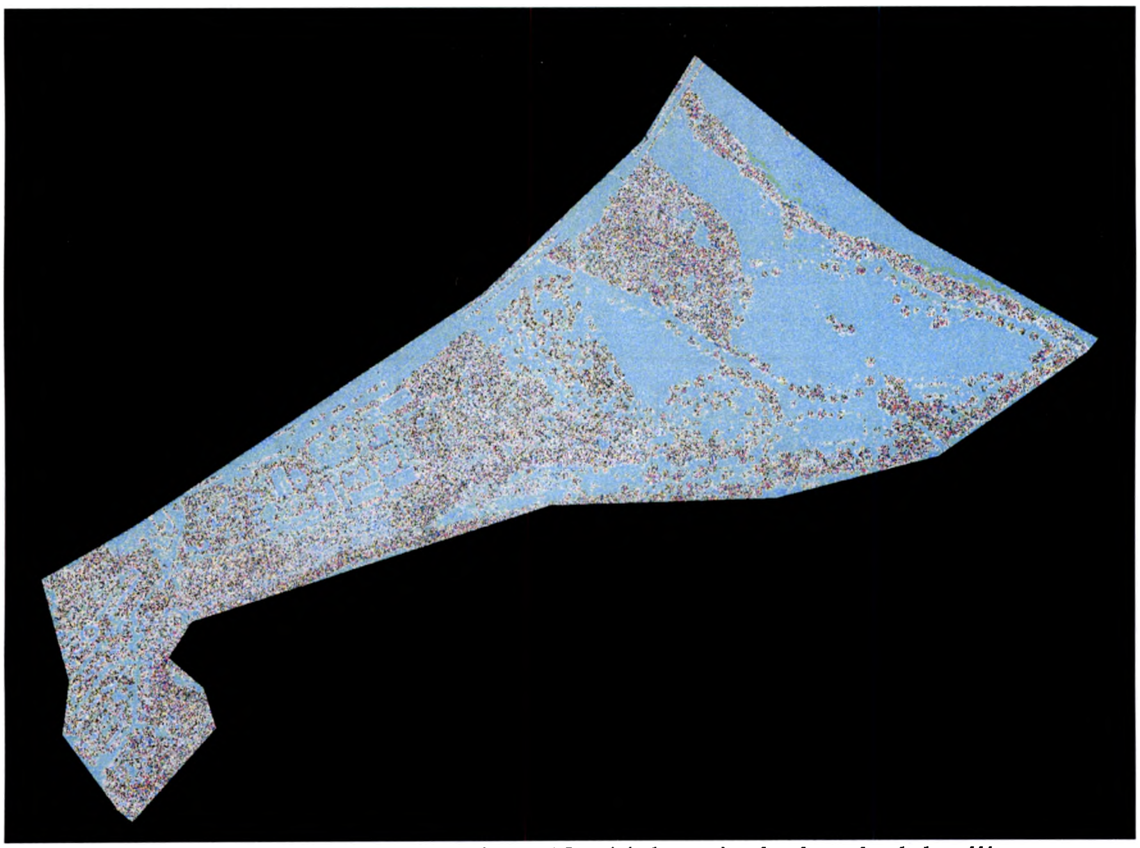

Fig. 8. Census tract block group number 113 with low single detached dwelling count.

that larger or taller structures will likely contain more rooms. The measure of elevation will be sensitive to the amount of space under a roof (or the amount of area enclosed). So not just form but volume makes itself evident in the linear regressions comparing housing variables with classed elevation, slope, and curvature.

# CHAPTER 6

## SUMMARY AND CONCLUSIONS

Like a fingerprint, each city or urban expanse has a unique morphological signature. But these urban traits aren't merely random structural noise. The patterns of streets, houses, and even landscaping on the urban surface appear to serve as a manifestation of a city's residents and their characteristics.

Remote sensing has been used successfully in the past to demonstrate the links between socioeconomic characteristics and the two-dimensional structure evident in reflectance values. Three-dimensional form is then a logical extension of the search for the underlying nature of these relationships. The connections between these remotely-sensed morphometric properties and real world data are two-way. The structures and connections of neighborhoods influence the lives of residents. Yet those same residents reshape the dynamics of the cityscape on a daily basis.

While frequency counts of contextually-classed elevation and slope data show a strong connection between structure and census-derived housing indicators at the block group level, curvature classes seem to provide an even more sensitive measure of urban form. The convexities and concavities of Laplacian curvature are useful for discerning vegetation cover, an especially strong indicator of housing variables such as average value. Curvature class counts can also establish the ratio of open space to land cover within a given spatial unit. Frequency counts of classed data, whether derived from elevation, slope or curvature, provide a measure of the variability of form inside a given area. This can be conceived as a measure of texture for the urban environment.

LIDAR-derived data provides an alternative method of depicting the characteristics of the city, at a different scale and from a different viewpoint than what many planners may be familiar with. The strong correlation between this morphometric representation of the city and housing data such as size or value can assist government officials, planners and policy-makers in recognizing and understanding urban trends. Not only does it help to confirm pre-derived census measures, it also provides a quantitative representation of the built physical (and by extension social) structure of the city. Dynamic processes such as shifting housing values, urban sprawl, and gentrification make themselves evident in frequency-based contextual classification maps of built form. The unique perspective afforded by LIDAR-based city models helps to demonstrate these patterns and elucidate the forces at work within the context of the constructed urban environment.

Given a demonstrable connection between tabular data collected at the census tract or block group level and the three dimensional form as represented in a raster elevation model, several directions for further research are possible. This research was conducted in only one location for one period of time. Further research is warranted to determine if the same relationships discovered in Austin would hold true for other cities or over significant periods of time. Could a shift in demographics within an urban population witnessed over time be seen in the corresponding changes in city form?

Logic dictates that housing variables might have a noticeable effect on measured form, but what about other socioeconomic variables? Since housing value tends to be connected with other measures such as income or education, would these also show a strong relationship to urban form? What about other variables that might have a spatial component influencing them? Could a regression analysis of, for instance, crime versus curvature give the police (and citizens) useful information about the urban morphology of dangerous places?

The morphometry of landscapes has long provided a means of characterizing and understanding the world around us. This usefulness in measuring form appears to extend beyond the modeling of physical processes at work on natural landforms to the social and cultural processes taking place on the three dimensional terrain of modern cityscapes. With slight adjustments to the scale of the form in question and the time required for processes to act on this new terrain, emerging technology allows for a greater understanding of the role of urban form in everyday life.

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## VITA

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