Valuing Urban Greening using Hedonic Pricing: The Middle Rio Grande Valley in the Greater Albuquerque Area

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Picture 1: Aerial view of the city of Albuquerque with the Albuquerque Country Club along the Rio Grande. Source: Google map of Albuquerque City, NM downloaded June 9, 2024.

Picture 2: Aerial view of the Baatan Memorial Park, Albuquerque: Source: Google earth map of Albuquerque City, NM downloaded August 2, 2024.

TABLE OF CONTENTS

List of figures

List of tables

Executive Summary

Using the hedonic pricing method (HPM), the objective of this research is to investigate the impact of heat mitigation and various greenness metrics on property values in the greater Albuquerque area. With a unique dataset of more than 5,500 residential properties listed for sale between October 2022 and February 2024, the econometric analysis examines both the valley floor (properties within the Middle Rio Grande Conservancy District service area) and outside it. Due to confidentiality restrictions of property transaction data in the study area, we sourced publicly available property data from Zillow, including expected price measures and various structural attributes (e.g., number of bedrooms and bathrooms, lot size). We then geolocated each property and integrated neighborhood data (e.g., population density, percentage of white population, etc.). Additionally, we gathered environmental quality variables (e.g., heat mitigation index from the InVEST urban cooling model, enhanced vegetation index, land surface temperature) to create a comprehensive geospatial dataset.

Based on the spatial econometric analysis, the hedonic pricing models yielded several key findings:

1. Results indicate that residents place significant value on proximity to greenspace areas such as parks, open spaces and golf courses. Specifically, distance to the nearest greenspace is a negative and statistically significant determinant of home prices. A mile increase in the distance away from the nearest greenspace corresponds to about a 0.5% decrease in home prices translating to about -$2,337 for the mean list price and -$1,987 for the median list price

2. Distance to the river is associated with a decrease in home prices in the greater Albuquerque area. However, when considering the areas within and outside the Middle Rio Grande Conservancy District (MRGCD) boundaries, the results indicate that residents prefer to live close to the river but not immediately adjacent. In the greater Albuquerque area, a mile increase in the distance from the river is associated with a decrease in home prices by approximately $4,206 and $3,575 for the mean and median list prices, respectively.

3. Across all the models estimated, the heat mitigation index derived from the InVEST urban cooling model was positively correlated with housing prices. Residents within the greater Albuquerque area willing to pay extra to live in cooler areas. Evaluated at the mean house price, a 1-percentage point increase in average cooling capacity within a 0.25mi buffer results in an increase of approximately $5,093, or about a 1.09% in home prices.

4. Land surface temperature (LST) is estimated to be a negative and statistically significant determinant of house prices across all estimated models. Models estimated with LST included outperformed alternative specifications. Results reinforce the preference for cooler areas by residents in the greater Albuquerque area. For every 1-degree Celsius increase in LST, home prices are expected to decrease by 3.2%. The marginal implicit prices (MIPs, hereafter) evaluated at the mean and median prices are -$15,047 and -$12,794, respectively.

5. Variables measuring greenness, such as enhanced vegetation index (EVI) and tree canopy, were positively associated with house prices and statistically significant across all models. Evaluated at the mean home price, the MIP of a 1 percentage point increase in EVI within a 0.25mi buffer is approximately $5,172, or about a 1.1% price increase. For the median price, the MIP for EVI is about $4,398. For tree canopy, a 1% percentage point increase translates to about $2,558 at the mean price and about $2,175 at the median price in home prices.

6. Results indicate that an increase in the density of active domestic wells within 0.25mi of a house is a positive determinant of house price, and this effect is particularly pronounced outside MRGCD boundaries. In the greater Albuquerque area, each additional active domestic well

leads to about a 0.06% increase in home prices. This translates to an increase of about $280 when evaluated at the mean list prices and $230 when evaluated at the median list price.

Housing markets are excellent vehicles for examining preferences – aggregated and in capitalized present value terms. Most simply, green and cool matters in the greater Albuquerque housing market. Results provide substantial evidence that heat mitigation and various green measures are significantly capitalized into the housing market. They illustrate that providing urban green and cooling is one of, if not the largest economic contributions of primary water allocators in the region (e.g., the Conservancy District and municipal providers). Findings emphasize the need for regional planners to consider such values in policy applications ranging from the provision of green infrastructure (e.g., swales and catchments), the use of treated municipal waste water, and the provision and placement of additional parks and greenspaces.

1. Introduction

Recent economics research finds that 97.5% of US metropolitan areas have too little open space, consistent with the expectation of under-provision of public goods (Wu et al., 2023). Consonantly, theoretical models for equilibrium urban development show that when people have preferences for proximity to open space, then "development may not be sprawling enough and that policies to encourage infill development are not welfare improving." (Turner, 2005, p. 19). Relatedly, there is a body of evidence documenting the benefits of greening in urban and peri-urban residential settings (e.g., Scholte et al., 2015; Jim & Chen, 2008; Kim & Brown, 2021). Greenspace provides improved air quality and recreational and aesthetic benefits to society. Trees and associated greenspace help cushion the effect of the *Urban Heat Island* and provide health benefits (e.g., Oliveira et al., 2011; Jones and Fleck, 2018).

Conversely, as a question of urban form and density, given population growth, there is intense pressure for dense infill. Thus, in a time of changing climate, open spaces and greenspaces lie at the heart of tradeoffs between the benefits of urban density (e.g., efficiencies in public transportation, economic network effects, economies of agglomeration, productivity gains, energy efficiencies etc.,) (see: Glaeser, 2012) and the costs (pollution, heat islands, lack of recreational access, rising land prices) (see: Duranton and Puta, 2020). One common avenue for investigating a slice of the total economic benefits provided by greenspace is through isolating any observed effects on housing markets, via the hedonic pricing method (HPM) (Taylor, 2017).

Albuquerque as a modern city has a defining feature that seems important in helping to understand this debate around urban density -- it is one of the relatively least dense large urban areas in the US.[1] Further, as a high desert city, where climate change is expected to continue to significantly raise temperatures and lower streamflows in the middle Rio Grande (Dunbar et al., 2022), Albuquerque represents an important case study for understanding the benefits of *scarce* greenspace. As one of the least dense metropolitan areas in the U.S., the Albuquerque Metropolitan Statistical Area is home to about 900,000 people. Roughly 250,000 people live on the valley floor, with the Rio Grande bisecting the city from north to south.

The focus of this investigation is on the valley floor in the greater Albuquerque area, including areas within and outside the boundaries of the Middle Rio Grande Conservancy District (MRGCD). The MRGCD is a multi-purpose public corporation with an elected board; the MRGCD operates an extensive hydrological system of ditches, canals, acequias, and drains that distribute surface water (and thus green growth). This is also matched by a dense mapping of many thousands of unmetered domestic wells spread across much of the valley floor and tapping into the shallow water tables of the adjacent Rio Grande. Notably, this combined distribution of green occurs beyond the river levees, which contain the *bosque*, and out across much of the valley floor. Juxtaposed against this significant amount of water use is a multi-decadal trend where average annual net farm income has been *negative* in the three counties centered around Albuquerque, and somehow the number of USDA-listed farms is growing at the same time. Clearly, this distribution system is not primarily about providing commercial agricultural production (see Porter et al., 2023). This only underscores the need to better understand the non-market greenspace benefits.

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[1] See:
https://en.wikipedia.org/wiki/List_of_United_States_cities_by_population_density
http://www.usa.com/rank/us--population-density--metro-area-rank.htm
https://filterbuy.com/resources/most-and-least-densely-populated-cities/

Using HPM, the objective of this analysis is to statistically estimate the marginal implicit prices of heat mitigation and proximity to different types of greenspaces for single-family housing in the greater Albuquerque area, also within the boundaries of the MRGCD with areas outside the district as controls. But, to do so required overcoming a significant data limitation. Currently, little, or no empirical work has been done on monetizing the effects of critical amenities on residential real estate anywhere in New Mexico (NM). This is largely attributed to the NM's status as a non-disclosure state, where it is not legal to publicly disclose sales prices of residential housing (Berrens and McKee, 2003). One possibility is to use aggregated Census data (e.g., median block group house values), but this comes with measurement error, lacks detailed matching housing characteristics, and can only crudely accommodate geospatial information. Alternatively, for this study, the residential property price and attribute data collection are extracted (web-scraped) from information posted at Zillow. This is combined with an array of geospatial data (e.g., on the various types of greenspaces) and notably a unique heat mitigation map carefully constructed and verified using the publicly available tools from the suite of modules in InVEST (Zawadzka et al., 2021).

Examining regional housing markets using HPM is compelling in that it reflects preferences over a large group of market participants and presents them in capitalized present values. They capture the expected net benefit stream. This includes the ability to isolate the contribution of ecosystem services, which are otherwise difficult to value directly. Econometrics results, examining both the valley floor and broader study area, indicate that heat mitigation and its correlates - the different measurements of greenness - are significantly capitalized into the housing market in the greater Albuquerque area. In a climate-altered world, where there is significantly less water, we can ask what do people value? and what do they have reason to value if they don't have access (Sen, 1999)? In investigating how water is currently being consumed and economically valued in alternative uses in the Middle Rio Grande region, then the ecosystem service benefits of heat mitigation and providing greenness should be central to any public policy discussions of tradeoffs and water allocations.

2. Background Information

2.1. Chosen Study Area

Our chosen study area, as provided in Figure 1, roughly matches the Albuquerque Metropolitan Statistical Area (MSA),[2] where we expect the housing and labor markets to correspond closely to each other. The Albuquerque MSA had a population of 922,2916 in 2023, with over 89% Census-defined as living in an urban area. In terms of ethnicity, the area is approximately 48% Hispanic or Latino, and in terms of race, the MSA is approximately 52% White. Covering 241 Census Tracts, the MSA is composed of four counties: Bernalillo, Sandoval, Torrance and Valencia. Outside of the cities of Albuquerque (population 562,599) and Rio Rancho (population 105,815), the MSA also contains a number of smaller cities (e.g., Belen), towns (e.g., Belen) and villages (e.g., Bosque Farms, Corrales, and Los Ranchos de Albuquerque). Notably, the study area includes the East Mountain part of Bernalillo County – on the eastern flanks of the Sandia Mountains -- as this is generally considered part of the Albuquerque housing and labor market.

For this analysis, the study area excludes a small number of the MSA's Census Tracts in extremely sparsely populated areas in either the northwestern wing of Sandoval County, or the southeastern wing of Torrance County. Given data sovereignty, we also exclude the various Pueblo Lands (e.g., Sandia Pueblo and Isleta Pueblo). Our study area essentially captures the labor and housing market

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[2] See:
https://www.citypopulation.de/en/usa/metro/10740__albuquerque/

for the greater Albuquerque metropolitan area, as all the sample houses in the area (see Figure 1) would be within roughly 30 minutes driving distance by freeway from the Albuquerque central business district.

In investigating the effects of heat and greenness measures in the housing market, we variously scale or focus; this includes both onto the valley floor itself, with the Rio Grande running north to south and bisecting the study area, as well as outward covering the mesalands both east and west, which were settled later.

The valley floor contains the extensive gravity-fed drainage and conveyance system that disperses river water. Under the umbrella of the Middle Rio Grande Conservancy District (MRGCD) this water allocation system is much larger in total consumptive use than the aggregate municipal water providers in the study area (primarily the Albuquerque Bernalilio County Water Utility Authority (ABCWUA) and Rio Ranch Water Utility. As the largest service provider, ABCWUA had over 214,000 customer accounts in 2024, serving approximately 650,000 people with drinking water.[3] ABCWUA's water soruces include a mix of diverted river water (from the transmountain, San Juan Chama Project outside the Middle Rio Grande Basin), and a system of municipal groundwater wells. Outside of ABCWUA and the city of Rio Rancho, there are several small municipal water providers (e.g., Belen and Bernalillo), and some areas (e.g., Corrales) served primarily by domestic wells.

Given its preeminent role in water allocation, and thus distributing green, across the valley floor, we next turn to some brief background on the MRGCD and its history.

2.2. Development and Impact of the MRGCD

The MRGCD's boundaries are essentially the valley floor. The MRGCD was conceptualized and formed by a small group of civic boosters and urban leaders in the early 1920s. They wanted to develop the city of Albuquerque, and they needed to provide drainage and flood control to a swampy valley floor with an aggraded river. In the von Thunen style development models of the day, providing an irrigated agricultural belt in and around their desired growing city was always part of the boosters' plan.[4]

Reflecting in 1989 on MRGCD's history to an NM Legislative hearing, long-time State Engineer Steve Reynolds simply stated; "It's hard to develop economically in a swamp." (Albuquerque Journal, 8/16/1989, p.29). So, boosters searched, found, pushed, and then got passed a set of multi-purpose rules (or institutional arrangements), which created a new state law: The Conservancy Act of 1923. The law provided tax and finance powers and court-appointed boards. Then, 100 or so folks– composed of mostly Albuquerque businessmen - petitioned and formed the Middle Rio Grande Conservancy District in 1925. The river control, water diversion, distribution, and drainage systems were largely engineered over the next decade. By 1935 the re-organized water system had both changed the hydrology of the valley floor (Crawford et al., 1996), and been brought largely under the governance umbrella of the MRGCD This included straightening and channelizing the river, and to some extend disconnecting it from the bosque (reduction in overbank flooding). It also allowed a kind of massive re-distribution of green across the valley floor around Albuquerque, in the form of many

[3] See
https://www.abcwua.org/your-water-authority-overview/
[4] For a history of the co-evolution of the Ro Grande and modern Albquerque (post 1880), see Fleck and Berrens (2025, forthcoming).

hundreds of miles of ditches, acequias,[5] canals and drains. And Albuquerque quickly grew as a city. Since institutional arrangements "carry history forward" (David, 1994), the provision of irrigated water for agricultural purposes remains a core purpose of the MRGCD, nearly 100 years later and even in urban Bernalillo County, and the surrounding peri-urban towns and villages in our study area. Since, new people also matter, more housing on the valley floor brought an influx of largely unregulated domestic wells – many thousands of them. Outside the river levees, these two sources primarily contribute to the distribution of green on the valley floor, but also include some contributions from outdoor watering for homes serviced by municipal providers (e.g., ABCWUA). Above the valley floor, the distribution of green is sources by either municipally provided water, or domestic wells.

In New Mexico, the richness of agricultural history and land-based culture continue to be instrumental to the quality of life and community – and this includes our greater Albuquerque area. Especially within the urban peri-urban areas of Bernalillo and Sandoval Counties (and to a lesser extent Valencia County) within MRGCD's boundaries, agriculture's contributions are primarily noncommercial (although there are behavioral market trails like greenbelt tax breaks [Porter et al., 2023]). Porter et al. (2023) report that in 2020 the Rio Grande surface flows were used for irrigating 4,388 acres of land in Bernalillo County which represents about 11,000 acre-feet of outdoor water use. Further, there are something on the order of 10,000 un-metered domestic wells scattered across the valley floor in Bernalillo and Sandoval Counties and using the shallow groundwater table. This probably represents a similar order of magnitude of outdoor water use as the MRGCD's distribution of surface waters. For both distributions, much of the use is yards and trees, and a lot of feed fields for horses, even in some cases when there is a low-barrier, agricultural tax break (Porter et al., 2023).

While this is a significant amount of water use, we should not minimize the potential magnitude and importance of the nonmarket values (Champ et al., 2017) derived from the feed fields/yards/trees in the region since they provide, inter alia, recreation, lifestyle opportunities, landscape amenities, subsistence food production, and ecosystem services, such as the cooling effect of ground cover in a desert climate. We must also consider the green provided by nearby or intermixed from municipal water sources, for both homes and public parks. But modern remote-sensing and GIS-based tools and map layers (e.g., bosque, park and ditch boundaries; and Landsat-based Enhanced Vegetation Index [EVI], etc.), can help us sort through different types of greenspaces.

2.3. Overview of the Hedonic Pricing Method

The hedonic pricing model is founded on the notion that the price of a heterogenous good is determined by the combined value of its unobserved qualities (Snyder et al., 2008). This pricing method (HPM) aims to econometrically decompose the observed variation in the price of the heterogeneous good and isolate the impact of its unobserved qualities of interest. The hedonic price theory is centered on two major approaches: utility theory (Lancaster, 1996) and the implicit market theory (Rosen, 1974). These two approaches primarily aim to estimate the marginal implicit amenities prices considering the product's characteristics. As mostly applied in the housing market (Rosen, 1974), researchers have often employed this approach to examine the capitalization effects of environmental amenities or dis-amenities in property values (cites). For instance, the use of the HPM to assess the economic value of air pollution can be traced back to the 1960's. Ridker and Henning

[5] To be clear, the traditional Hispanic acequia irrigation systems, and Pueblo irrigation ditches before them, significantly pre-date the origins of modern Albuquerque, commonly dated to the coming of the railroad in 1880. The Villa de Albuquerque was first established in 1706, with Pueblo origins – and irrigation practices - in the area dating back to time immemorial.

(1967) were probably the first to examine the impact of air pollution levels on single-family property using U.S. cross-sectional census tract data from the St. Louis metropolitan area in 1960. They postulate that aside from the well-established evidence of the impact of air pollution on health, it is reasonable to assume that "many of these detrimental effects are reflected in property values." They specifically quantified the value of sulfation levels in the housing market. Controlling for other variables such as structural, location, and neighborhood characteristics that potentially influence housing prices, their finding underscores the substantial role of environmental quality (air pollution) in explaining the variation in property value. The results of their study revealed that a 0.25mg/100cm3/day decrease in sulfation levels is associated with an increase in property values ranging from $83 to $245. Since then, environmental factors such as urban greenery, water quality and proximity, climate conditions, and others have been studied to examine their effects on property values. Various empirical studies on some of these features are reviewed. However, before delving into these studies, background is provided on the issues associated with selecting housing price variable given its significance in this study.

2.3.1. Literature Review of Studies Utilizing Zillow Price Data

In estimating hedonic price functions, the most used dependent variable is the publicly accessible observed sales prices of housing units. The adoption of this measure is preferred because of its ability to accurately capture real market transactions at the granular level, therefore serving as a dependable predictor of housing prices (Leek et al., 2023). Housing data for HPM studies may typically be available at the County Assessor's office (Frey et al., 2013; Catma, 2021) in areas classified as sales price disclosure states.

However, considering that the specific location being studied is Albuquerque, NM, this approach appears impractical. The reason is that New Mexico is considered a sales price non-disclosure state (Berrens and McKee., 2004). In areas with non-disclosure laws (e.g., NM, TX, UT, WY, etc.), sales prices are undisclosed to the public, hindering the availability of actual transaction data for researchers. This poses a significant challenge for conducting comprehensive HPM studies in such regions. Currently, little, or no empirical work has been done on monetizing the effects of critical environmental amenities on residential real estate anywhere in New Mexico.

An option for navigating the data limitation imposed by NM's non-disclosure status is to use aggregated Census data (e.g., median block group house values). However, this approach comes with several drawbacks: it introduces measurement error, lacks detailed matching housing characteristics, and can only crudely accommodate geospatial information. This approach is not ideal for our investigation since our goal is to relate geo-located-micro-level housing data with an array of geospatial data (e.g., various types of greenery) and unique environmental quality variables (e.g., heat mitigation, land surface temperature, well density, etc.). Additionally, we need to control for individual housing characteristics, which requires more granular data.

Alternatively, for this investigation, we collect residential property prices and attributes data from Zillow, an online real estate database primarily focused on housing property advertisements. Zillow provides a property estimate algorithm known as the "Zestimates" which reveals the housing prices of available or sold single-family units considering public records and market conditions (Huang & tang, 2012). Zillow also provides available list price information. Therefore, we use both "Zestimates" and List Prices as proxies for the observed market prices for housing in the Albuquerque Metropolitan area. One potential concern with this approach is the reliability of these estimates. Still, some studies have attested to their accuracy and reliability (Sohn et al., 2020). In terms of accuracy, the nationwide median error rate for "Zestimate" for on-market homes is 2.4% (Zillow.com: Last updated; April 27, 2023). Additionally, Hagerty (2007) found a median margin error of 7.8% when comparing 1000 actual housing values and Zestimates across seven States. Below are some studies that have used either the listing price or Zestimates in their research of HPM.

Focusing on urban greenery and home prices, Holt and Borsuk (2020) investigated the impact of green infrastructure on median neighborhood property value per square foot. Their study analyzed Zillow-collected data from over 5,000 neighborhoods across 44 States, using the Zillow Home Value Index (ZHVI) as a measure of the median neighborhood estimated home value per square foot. They found that parks and areas with high tree canopy are associated with higher home values, whereas underdeveloped green spaces tend to have negative effects.

Sohn et al. (2020) examined the impact of neighborhood-level detention and retention ponds on single-family housing prices in Houston, Texas, using Zillow data for the period 2007 to 2016. The study adopted Zillow's home value estimates (Zestimate) for the sampled properties. Using a spatial hedonic econometrics model, proximity to green amenities increases property value. To be precise, houses closer to retention ponds have higher market values, while those closer to detention ponds have lower market values.

In their study, Leek et al. (2023) investigated the influence of the adverse side effects associated with oil and oil (O&G) production on property values in the Permian basin. Confronted with comparable data limitations arising from the locations of study (NM & TX), the authors utilized about 6,000 Zillow-collected data on housing properties, including the list price and Zestimates, which served as indicators of observed market values. The study employed a hedonic pricing model to ascertain the impact of environmental factors, notably air pollution (PM 2.5), and the hazards associated with water contamination from injection and disposal wells and residential property values. Their findings indicate that air pollution negatively impacts housing prices, but the pollution caused by O&G production does not significantly impact property values. Additionally, piped water services positively impact home values, offsetting concerns about water contamination.

Mamun et al. (2023) analyzed the economic value of improved lake water quality on property values across the United States. Using a comprehensive dataset that integrates national water quality metrics with property sales information from the just ended (June 2023: as mentioned in Mamun et al., 2023) Zillow's Transactions and Assessment Dataset (ZTRAX), they found that homeowners assign significant value to properties that are near high-quality water bodies. Similarly, using ZTRAX, Miller and Pinter (2021) investigated the effects of large flood events on residential property prices in three U.S. counties (Benton, Oregon; Boulder, Colorado; Cass, North Dakota) and found that floodplain properties in all three counties experience price discounts.

2.3.2. Literature Review on the Impact of Urban Greenery on Housing Prices using HPM

The use of HPM for evaluating the economic benefits of urban green spaces (UGS) may be dated back to the 1970's (Payne, 1973). Subsequently, there has been a growing body of research focused on establishing the marginal implicit values of UGS using the Hedonic Price Model (HPM) method together with advanced statistical tools, electronic transaction data, and sophisticated GIS techniques.

Morales et al (1976) conducted a study to determine whether trees contribute to residential property values in Manchester, Connecticut. The results showed that a house's value increases by 6% when located in areas with plenty of tree cover.

Using a sample of 810 homes, Morancho (2003) estimated a hedonic pricing function for the Spanish city of Castellón. The study found that only the proximity to a greenspace had a statistically significant effect on housing values when three environmental variables ("the existence of views of parks or public garden, distance of a house to the nearest green and the size of the open space in question.") were added to the traditional characteristics used to determine the price of a house. That is property values drop by 300,000 pesetas for every 100 meters spent away from a green space. The study highlighted the importance of being near green areas rather than how big they are.

Conway et al. (2010) used a Spatial lag model to investigate the influence of UGS on the value of residential property in Southern California. Their findings indicate that green space in a community has a noteworthy effect on house prices. In particular, the researchers found that for every 1% increase in greenspace at 200 to 300 meters from a housing unit, there is a corresponding rise of around 0.07% in the sales value of the property. Similar conclusions can be drawn from a study conducted by McCord et al. (2014), which found that urban green space significantly increased the sales price of nearby residential properties, especially in the terrace and apartment sectors, in the Belfast housing market in the UK.

In the same vein, Trojanek et al. (2018) investigated the impact of the distance to urban green spaces (UGS) on the prices of apartments in Warsaw, Poland. The HPM is used with OLS, Median Quantile Regression, and Weighted Least Squares model. The findings confirm that property values align with the anticipated outcomes. That is, proximity to urban green spaces had a much greater impact on the prices of newer apartments (built after 1989) in comparison to older units (built before 1989).

Recently, a study by Ben et al. (2023) using data from 3,338 residential communities and 225 subdistricts in Shanghai districts, China 2020, explored the relationship between housing values and the accessibility of public and community-owned green spaces. Their results follow a similar trend of outcomes in the literature. That is, the overall enhanced accessibility to green spaces, the green ratio within a community, and the distance to the nearest green spaces are all associated with higher home values.

In addition to the often-used indicator of green (proximity to green spaces), green vegetation itself has been shown to impact housing prices (Holt and Borsuk., 2020). Numerous studies examining the impacts of urban greenery on real estate prices have used remotely sensed indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Tree canopy as proxies for urban greenery.

Numerous studies on the impact of urban greenery on property values have utilized remotely sensed indices such as NDVI, EVI, and Tree canopy coverage as measures of urban greenery. Like proximity nearest greenspaces, these remotely sensed indices have been found to have positive effect on home values. For instance, Payton et al., (2008) examined the impact of urban forest, using NDVI from satellite imagery on home prices in Indianapolis/Marion County. Their spatial hedonic price models revealed that house owners within the county place significant value on urban greenery, indicating their willingness to pay extra to live in greener areas. They found that households are willing to pay between $15 and $92 annually for a 1% county-wide increase in urban forest. Mei et al., (2018) examined the capitalization effects of urban green vegetation on home values in Beijing China, using NDVI from time-series Landsat TM 8 remote-sensing imagery. They found that urban green vegetation (NDVI) within 135 m could raise home values by 9.5% -10.59%.

Rossetti (2013) used Hedonic Pricing Models (HPM) and property sales from Australia to indirectly ascertain the marginal implicit prices of green infrastructure in various postcodes. Measuring greenness with the Enhanced Vegetation Index (EVI), Rossetti found that a one-standard-deviation increase in EVI leads to an 8.62% increase in home values with year-fixed effects or a 15.57% increase with state-year fixed effects.

Using a sample of 9,992 single-family housing and the hedonic pricing model, Sander et al. (2010) sought to determine the economic value of urban tree cover in Dakota and Ramsey Counties, MN, USA. Notably, greenness was measured as the percentage of tree cover on parcels and within 100, 250, 500, 750, and 1000 meters. The results of the study revealed that higher percentages of tree cover within 100- and 250-meter radii of a parcel increase home values. Precisely, a 10%-point increase in tree cover within a 100 m radius led to a $1,371 increase in home values. Within 250 meters, a similar increase in tree cover led to an $836 increase in home values.

2.4. Background on the Application of the InVEST Tool Models

Recent studies on urban heat have increasingly utilized remote sensing methods to effectively study large geographic areas over discrete time periods. Remote sensing provides several advantages, including cost-effective measurements, repeatable temporal data collection, and a continuously expanding dataset as ongoing and new satellite missions contribute more information. Moreover, remote sensing encompasses various techniques to evaluate critical aspects of urban heat, such as vegetation density and land use patterns. Although the limitations of remote sensing are well-documented, the field is continually advancing, enhancing its relevance and capabilities.

Building on advancements in remote sensing and GIS-based landscape analysis, a growing array of novel software packages now address specific questions and gaps that remote sensing alone cannot fill. One notable example is the open source InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) software suite developed by the Natural Capital Project at Stanford University (Natural Capital Project, 2024). This software is a recent addition to the toolkit of researchers and land managers focusing on ecosystem services. The software encapsulates a suite of spatially explicit ecosystem services models used in the evaluation of synergies and trade-offs among competing management alternatives of natural resources, resulting in the selection of areas where investment is viable enough to boost both human development and conservation of the environment (Zawadzka et al., 2021; see: https://naturalcapitalproject.stanford.edu/software/invest). The suite includes a specific Urban Cooling model that facilitates new research into the Urban Heat Island (UHI) effect and its implications for human populations. The model computes a heat mitigation index by entering GIS-based information on shade, evapotranspiration albedo, and cooling distance of urban parks and other green spaces.

3. Conceptual Framework

The natural environment in an urban setting plays a crucial role in enhancing the quality of life for residents. In the realm of urban policy planning, the practice of economic valuation enlightens the significance of the economic worth derived from environmental amenities. Over time, economists have developed various valuation techniques to help measure the economic benefits associated with the ecosystem goods provided by these environmental amenities. Environmental valuations have been traditionally categorized as Stated (direct) and Revealed (Indirect). Stated preference approaches entail directly querying consumers about their preferences, and thus determining their willingness to pay. This includes techniques such as the contingent valuation method (CVM) and Choice Experiments (CE). Revealed preference methods on the other hand estimate models of choice for both market and nonmarket goods based on the actual choices consumers make in real-market transactions (Reddy., 2011). Examples include but are not limited to the Hedonic Pricing Model (HPM) and the Travel Cost Model (TCM). For this research, we select the hedonic pricing method. We provide detailed descriptions of its theoretical underpinnings and empirical specifications in subsequent sections

For any heterogeneous good, its observable qualities vary. Heterogeneous goods are commodities whose attributes change in a way that there are different varieties even though sold in one market

(Taylor, 2017). The distinctiveness in attributes of these goods results in price variations. The HPM uses these attributes to establish the econometric relationship between housing prices and characteristics (Price et al., 2010). Precisely, the HPM is used to econometrically isolate the impact of individual attributes of a good or a service on the price of that good or service (Czembrowski & Kronenberg, 2016). Although the model can be used to deconstruct prices of various goods and services, HPM has been widely applied to residential and property markets for decades (Rosen 1974).

Drawing on Rosen's (1974) model and closely following Boslett (2011), in an n-dimensional field, each good denoted as *(h_i)* within a class of goods is distinguished by its various characteristics $z_1, z_2, z_3, \ldots, z_n$. Here, each z_i corresponds to a unique product characteristic. The hedonic price function, P(Z) is ascertained by a vector of attributes as defined mathematically in equation (1).

$$P(h_i) = f(z_1, z_2, z_3, \ldots, z_n) \qquad (1)$$

When applying the Hedonic Pricing Method (HPM) to the housing market, the variables that predominantly influence a consumer's decision to purchase a house are typically grouped into three categories. Namely; the Structural components (S), which mostly consist of the number of bedrooms, bathrooms, lot size, whether or not the property has a garage, and availability of a swimming pool; Neighborhood characteristics (N), mostly including but not limited to distance to nearby highways, quality and distance of the nearest school (elementary, middle or High), unemployment rate, population density, race; and Environmental quality variables (N) as air quality, local parks and water bodies. Given these categories, equation (1) can be modified to reflect the housing market as follows:

$$P(h_i) = f(S_i, N_i, E_i) \qquad (2)$$

The simplifying assumption of the HPM is that a utility-maximizing household chooses a single residence based on a bundle of attributes that maximizes his or her utility subject to their limited income. As such the utility maximization problem over the choice of X, S, N, and E is given as:

$$\text{Max } U = U(X, S, N, E) \text{ subject to: } X + P(h_i) = M \qquad (3)$$

Where X is a composite numeraire good with the price of 1. M is the consumer's entire budget. Thus, the consumer exhausts all his or her budget on the housing unit and the composite good. To value any individual characteristic, such as z_i from either of the three categories (S, N, E), the consumer is assumed to choose levels of the composite good X and the individual characteristic z_i, such that the marginal rate of substitution between the X and z_i equal to the rate at which the two can be exchanged in a market. In other words, the utility tradeoff between z_i and the change in consumption of the composite numeraire good X equals the rate at which the two can be traded at market prices (Pitts et al., 2012). This can be expressed as:

$$\frac{\partial P_h}{\partial P_{z_i}} = \frac{(\partial U/\partial z_i)}{\partial U/\partial X} \qquad (4)$$

Equation (4) captures the consumer's marginal willingness-to-pay or implicit price for the individual characteristic, z_i. At the market equilibrium, where demand for different quantities of attributes meets supply of different quantities of attributes, the equilibrium price established at that point reflects the capitalized value and Willingness to Pay for each characteristic (Boslett, 2011). Empirically, the hedonic pricing function that relates a housing price to its structural features, features of the neighborhood, and environmental quality can be formulated as:

$$P = \alpha + \delta S + \gamma N + \pi E + \varepsilon \qquad (5)$$

Where P is the price of the housing unit; S is a vector of structural characteristics; N is a vector of neighborhood characteristics; E is a vector of environmental quality characteristics; ε is the error term; α is the intercept term; δ, γ and π are vectors of coefficient estimates for the explanatory variables S, N, and E respectively.

The next major step is selecting the functional form. Although well-established in the literature, Cassel and Mendelsohn (1985) assert that Rosen (1974), Freeman (1979), Halvorsen and Pollakowski (1981), and others have emphasized that economic theory does not prescribe an appropriate functional form for the hedonic price function. Given the lack of a solid theoretical basis, the choice of a functional form matters since it determines how the prices are affected by individual housing characteristics and, hence, the marginal implicit prices (Ma, 2017). There are four types of hedonic price functions widely used in the literature: linear, log-linear, double-log, and the more flexible form, Box-Cox Transformations. Amongst these functional forms, previous applied studies seem to recommend the use of the log-linear or double-log models to minimize effects of omitted variable bias.

As a result, our HPM assumes the log-linear functions, which can be expressed as follows:

$$\ln P = \alpha + \delta S + \gamma N + \pi E + \varepsilon \qquad (6)$$

Where ln(P) denotes the natural log of the price of the housing unit; S denotes a vector of the structural characteristics (e.g., bath, area, lot size, availability of garage …); N corresponds to a vector of neighborhood characteristics (e.g., medium income, population density, nearest highway distance, …); E is the environmental quality variables (e.g., Nearest greenspace distance, average cooling capacity, tree canopy…); ε is the error term; α is the intercept term; δ γ and π are vectors of coefficient estimates for the explanatory variables S, N, and E respectively.

For our proposed log-linear model (equation 6), the marginal implicit price for any specific individual characteristic, E_i, is simply the product of the coefficient estimate of the characteristic in question and the mean or median housing price. This can be expressed as follows:

$$\frac{\partial P}{\partial E_i} = \pi \times P \qquad (7)$$

The estimated value for Equation (7) demonstrates the marginal implicit price for E_i and thus π measures the percentage change in P as a result of a unit change in E_i.

4. Data Collection

As indicated earlier, the primary challenge in this research encompassed gathering housing data due to the public non-disclosure of sales property price data in New Mexico. To overcome this, we collected property data for homes listed as "for sale" on Zillow over roughly 16 months (i.e., October 11, 2022, to February 2, 2024). The housing units are first web-scrapped from Zillow using a Google Chrome extension tool called "Export Zillow data to Excel.", which tool pulls publicly available information from Zillow and exports it into a well-arranged Excel format. The data obtained includes street addresses, listed prices, Zestimates, and some default structural characteristics (S).

However, not all our structural characteristics of interest are provided by this tool. Hence, we write Python scripts to extract additional information. One disadvantage of using this tool is that some observations are empty plots of land listed for sale. To address this, we implement a filter to include only single-family homes with at least one bedroom and one bathroom. All the web-scrapped houses are then geolocated using ArcGIS Pro. The final data set consists of 5,543 homes with LIST-PRICE and 3,959 with ZEST. Notably, not every housing unit has each structural, neighborhood, and environmental quality variable, so some variables were dropped from the final dataset for the econometric analysis. Figure 1 presents the map of all geocoded housing points used in this analysis.

4.1. Structural Characteristics

The housing units used in this study are characterized by several structural features, including the number of bathrooms (BATH) and bedrooms (BED), the property's lot size (LOTSIZE), total structure area (AREA), and the age of the house (AGE), GARAGE indicates whether a property has a garage (1= yes, 0 otherwise). POOL indicates whether a housing unit has a pool (1 = yes, 0 other). WAT-SMART is a binary variable indicating whether a property is shown as having water-smart landscaping (1 = yes, 0 otherwise). These housing features are web-scrapped from Zillow. Table 5 presents comprehensive details of all the structural characteristics, including their descriptions, any transformations, and units.

4.2. Neighborhood Characteristics

The neighborhood characteristics considered in this study comprise the distance to the nearest elementary (ELE-SCH), middle (MID-SCH), and high (HIGH-SCH) schools, the ratings of these nearest schools (ELE-RATINGS, MID-RATINGS, HSC-RATINGS), average unemployment rates (AVG_UEMP) at the county level and distance to the nearest highway (HWAY-DIST). Additionally, we included block level median household income (MED-INC), percentage of White people (WHITE-PCT) and population density (POP-DENS).

Distance data to the nearest elementary, middle, and high schools, including their ratings based on the GreatSchools rating criteria (scaled from 1 to 10), are web-scrapped from Zillow using a Python script. The ratings categorize schools as follows: 1-4 as "below average," 5-6 as "average," and 7-10 as "above average."

To account for the local economic conditions, unemployment rates are collected at the county level in which each sampled housing unit is located. This approach is adopted because unemployment data at the block group level is unavailable in the 5-year ACS data (Leek et al., 2023). The Local Area Unemployment Statistics (LAUS) provided by the New Mexico Workforce Connection are collected and averaged over the study period (October 2022 to February 2024) to derive the average unemployment rate (AVG_UEMP) for each housing unit. This variable ensures that the hedonic pricing model incorporates a localized measure of economic stability and reflects how local economic factors might influence housing prices.

The variable "distance to the nearest highway (HWAY-DIST)" denotes, in meters, how far a house is from either the interstate highway I-25 or I-40. To calculate the distance between home addresses and neighborhood or economic variables, data was first collected for variables of interest. An individual shapefile, "New Mexico Road Centerlines – October 2022," is downloaded from the Resource Geographic Information System data repository.[6] The shapefile is queried to show only Interstate 25 and Interstate 40. Near tables were generated in ArcGIS pro between each shapefile and the geocoded addresses, which provided the name of and distance to the nearest interstate from each household. To estimate the census variables (MED-INC, WHITE-PCT and POP-DENS) for all geocoded addresses,

[6] RGIS, 2016; 2022

data tables generated by the American Community Survey in 2021, "Table B19013 – Median Household Income in Past 12 Months" and "P1-Total population" from the 2020 Decennial census were downloaded from the US Census data repository[7]. The most granular census variables available were for census block groups, so a TIGER/Line shapefile of 2021 census block groups was downloaded from the US Census spatial data repository[8]. Block groups were queried to isolate only those contained within the study area. Table 6 presents comprehensive details of all the neighborhood characteristics, including their descriptions, any transformations, and units.

4.3. Environmental Quality Variables

4.3.1. Euclidean Distances to Environmental Amenities

To determine the impact of proximity to environmental amenities on home prices in the study area, Euclidean distances were calculated using the Generate Near Table function in ArcGIS Pro. This analysis included three key variables: the main channel of the Rio Grande (RIVER-DIST), ditches and irrigation conveyances (DITCH-DIST), and greenspaces such as parks, open spaces, and golf courses (GREEN-DIST). Shapefiles depicting each of these features were used as input datasets. By calculating the shortest distance from each geocoded address to these features, we aimed to quantify how proximity to natural and recreational amenities influences housing values. This approach enabled a detailed assessment of the spatial relationship between environmental amenities and real estate prices.

The Rio Grande was isolated from the "USA Rivers and Streams" shapefile hosted on ArcGIS Online (Esri, 2020), while the irrigation conveyances were sourced from the Middle Rio Grande Conservancy District spatial data repository and clipped to the study boundary (MRGCD, 2012). Greenspaces were identified from two separate shapefiles published by the City of Albuquerque GIS department: "Open Spaces" and "Parks" (AGIS, 2024). Parks that lay outside the city of Albuquerque were identified with a Geographic Names Information System (GNIS) point shapefile, and the boundaries of the parks were manually digitized using Esri basemap satellite imagery (Esri, 2024; RGIS, 2019). Any remaining golf courses that were not within the shapefile were manually digitized using the same methodology. The resulting shapefile was a comprehensive dataset of parks, open spaces, and golf courses within the study area.

4.3.2. Enhanced Vegetation Index

A satellite-derived vegetation index was employed to characterize the vegetation density, or "greenness," of the study area. Vegetation density impacts local temperatures, as areas with higher vegetation density generally exhibit cooler temperatures due to increased shading and evapotranspiration. In addition, greenness itself may be an attribute that is capitalized in home prices and was thus studied independently of temperature metrics. The Enhanced Vegetation Index (EVI) was used due to its superior performance in providing atmospheric and background noise corrections and its enhanced ability to capture dense vegetation compared to other indices like the Normalized Difference Vegetation Index (NDVI) (USGS, n.d.). Using a Google Earth Engine script, average EVI rasters were generated for the study area, with Sentinel-2 imagery serving as the input dataset. The cloud-based computing capabilities of Google Earth Engine eliminated the need to download and manually process individual images prior to compositing. The script queried images acquired between May 1 and September 1 of 2022 and 2023, calculated EVI, and composited these into two rasters representing the average EVI for both summers. Zonal averaging was applied to calculate the

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[7] ACS, 2020
[8] USCB, 2021

average EVI value—representing average vegetation density—within a 0.25-mile buffer around each housing point.

4.3.3. Tree Canopy

A very high-resolution raster dataset depicting tree canopy was sourced from the Mid-Region Council of Governments in Albuquerque, NM (MRCOG, 2020); the dataset shows tree canopy across the entire MRCOG jurisdictional area, which includes the focal area for this study. The dataset was generated using National Agricultural Imagery Program (NAIP) imagery acquired in 2020 by the USGS. The imagery was classified using Google Earth Engine to identify all trees, using a binary classification scheme where 0 indicates no tree canopy in the pixel and 1 indicates tree canopy present in the pixel. In addition to being high-resolution and accurate, the dataset also functions well with zonal statistics, allowing for easy calculations of the ratio of average tree canopy, which was performed for each census block group in the study area. This dataset was used as an input to the InVEST Urban Cooling model, as well as for independent analysis to determine if tree canopy itself is capitalized in the housing market.

4.3.4. Fine Particulate Air Pollution

Fine particulate air pollution ($PM_{2.5}$ – airborne particulates finer than 2.5μm) data was sourced from the Washington St. Lous University Atmospheric Composition Analysis Group (ACAG, 2022). The Global/Regional estimates (V5.GL.04) dataset was used for this study; the dataset provides both annual and monthly ground-level $PM_{2.5}$ estimates (van Donkelaar et al., 2021). An averaged composite of yearly $PM_{2.5}$ data from 2018 to 2022 was generated in ArcGIS Pro, providing a comprehensive overview of air quality over a five-year period. The original dataset, with a resolution of 0.01 arc degrees, was bilinearly resampled to a 30-meter resolution to ensure compatibility with other datasets used in the study. This resampling process allowed for more precise spatial analysis and facilitated the integration of $PM_{2.5}$ data with other environmental and socioeconomic variables. By leveraging this dataset, we aimed to assess the spatial distribution of air pollution and its potential impacts on public health and property values within the study area.

4.3.5. Land Surface Temperature

Land Surface Temperature (LST) was derived from two U.S. Geological Survey (USGS) satellite missions, Landsat-8 and Landsat-9. Both satellites use identical sensors, making the images collected from both satellites comparable to one another. Level 2 Collection 2 imagery was used from both satellites, as the collection has been accurately georeferenced and pre-processed to correct for atmospheric effects (USGS, 2023). Images were compiled from May 1 – September 1 in 2022 and 2023, with only the images without cloud cover over the study area being selected. Each image was then scaled to represent temperature in degrees Celsius prior to compositing; all images were composited using the Mosaic tool in ArcGIS Pro to generate a single output image representing the mean LST across the entire study area for the summers of 2022 and 2023. Using the Zonal Statistics tool in ArcGIS Pro, the mean LST was calculated for a 0.25mi buffer around each housing point.

Remotely sensed LST is advantageous as it provides discrete temperature measurements across the entire study area, capturing the inherent variability in landscape temperatures. A limitation of LST lies in the inclusion of NDVI (Normalized Difference Vegetation Index) in the imagery preprocessing by the USGS, which makes LST measurements influenced by vegetation, regardless of its structure; grasslands and croplands affect LST measurements similar to forests, even though forests offer more shade and reduce air temperatures more effectively (USGS, 2023). As a result, the specific impact of shade is not apparent in LST measurements.

4.3.6. Active Domestic Wells

Domestic well density was calculated by first generating a 0.25mi buffer around each geocoded address. This buffer shapefile was then spatially joined with the domestic well shapefile (which had first been queried to only show active domestic wells). One of the outputs of the spatial join was the "Join Count" attribute, which specifies the exact number of point features – domestic wells in this case – that lie within the 0.25mi buffer around each house. This join count number is the value used for well density in this study, thus well density represents the number of domestic wells within 0.25mi of each geocoded address.

4.4. InVEST Urban Cooling Model

4.4.1. Model Inputs

The InVEST Urban Cooling model requires input data in three different forms; some variables are spatial data, some are entered as variables in the model graphical user interface (GUI), while additional variables are entered into a CSV-format "biophysical table" which is then uploaded for each model run. The biophysical table maps the input values to each land use type present in an input Land Use/Land Cover (LULC) dataset. LULC data is generated by classifying satellite imagery into different LULC types, such as forest, shrubland, developed area, and more, allowing for granular studies to be performed (Anderson et al., 1976). By tying values in the biophysical table to each LULC type, the model is then able to translate tabular data into a spatial format on which the model functions. All inputs required for the InVEST Urban cooling model are presented in Table 1.

The LULC raster used in this study was the most recent iteration of the National Land Cover Dataset (NLCD) published by Multi-Resolution Land Characteristics Consortium (MRLC), a partnership between several government agencies. The LULC dataset represents land cover in 2021, has a spatial resolution of 30m, and uses the Anderson Level II classification scheme. The Anderson classification scheme offers a standardized methodology to classify land cover using remotely sensed data; the system has a series of nested classifications that become progressively more detailed (Anderson et al., 1976). Level II data is intended for regional studies and, while more granular data would be beneficial for the InVEST model, it is difficult to source from public repositories and even more complex to generate from scratch.

Reference air temperature was derived from the NOAA Monthly U.S. Climate Gridded Dataset (NClimGrid), published by NOAA (NOAA, 2024). NClimGrid is a nationwide gridded dataset derived from daily temperature data from in situ weather stations, which is averaged into a monthly mean temperature dataset; it is updated every month, with records extending back several decades. The "maximum temperature" dataset from NClimGrid was used, and monthly values for May through August of 2022 and 2023 were averaged across the study area to represent the average maximum temperature across both summers. The mean value of the resulting raster (in other words, the average value of all individual cells in the raster) was used as the input value for Reference Air Temperature in the Urban Cooling model.

The UHI Effect was calculated from the max temperature raster generated for both summers combined, using the NOAA NClimGrid dataset. The UHI Effect variable is expressed as the difference in temperature between undeveloped land as compared to the city center. A value equal to 2 standard deviations below the mean was used as the input variable for UHI Effect in the model, as this was found to be a reasonable and repeatable figure.

The remaining required input variables in the GUI—air Blending Distance, Maximum Cooling Distance, and the relative weights of shade, albedo, and evapotranspiration in calculating cooling capacity—were taken from the suggested values in the InVEST User Guide (Natural Capital, 2024).

4.4.2. Area of Interest Shapefile

Two areas of interest shapefiles were generated to facilitate varying levels of spatial analysis. The first shapefile consisted of the 2021 Census Block Groups contained within the study area, providing a comprehensive delineation of demographic and socioeconomic units for the region. This shapefile allowed for the integration of population and housing data with environmental metrics, which were sourced from the 2021 American Community Survey 5-Year Estimates. Block groups were chosen, as they are the most granular level of detail for certain demographic factors. The second shapefile was created by generating a 0.25-mile circular buffer around each geocoded address within the study area, with no dissolving in areas where one buffer overlapped another. This approach enabled a localized analysis of environmental variables and their immediate impact on residential properties. By using these two distinct shapefiles, we ensured that our analysis could capture both broader census block group trends and fine-scale variations around individual addresses. The InVEST model calculated the average cooling capacity index for each individual polygon in both shapefiles.

4.4.3. Biophysical Table

The biophysical table functions by assigning one value for each variable to each LULC class; a consequence of this is that the InVEST model does not account for variation within each land use type to be examined, but instead calculates variation between classes. As a result, the outputs are not as granular as satellite-derived LST, but the InVEST model offers the advantage of modeling the impacts of shade and air mixing on temperatures. For this study, values for the biophysical table were determined using remotely sensed data. Table 2 presents all the inputs required by the biophysical table.

To determine representative values for the biophysical table, zonal statistics were used to calculate means for crop coefficient, shade, and albedo across each LULC class. The same tree canopy dataset used for independent analysis was leveraged for this purpose, with the zonal average representing the average shade value for each LULC type; the zonal means were calculated as a 0-1 ratio that the InVEST model requires, with 0 representing no tree canopy and 1 representing full canopy coverage (MRCOG, 2020).

An albedo raster across the study area was calculated using Level 2 Collection 1 Landsat-8/9 imagery, as this dataset has not been calibrated to reflect surface reflectance; images with no cloud cover over the study area were selected for the time period between May 1 and September 1 of 2022 and 2023 – a total of six images were selected for each year. Bands 2, 4, 5, 6 and 7 were selected from each image and corrected to represent Top of Atmosphere (TOA) reflectance. Following this, albedo was calculated for all six images using the ArcGIS Pro raster calculator (Naegeli et al., 2017). The resulting albedo raster had values between 0 and 1 to represent the ratio of broadband solar radiation reflected by the landscape. The albedo images calculated for each image date were then averaged and mosaicked to produce an average albedo raster for across the summers of 2022 and 2023.

In order to calculate crop coefficient (K_c) for each LULC class, two separate input rasters were utilized. The first raster used was the potential evapotranspiration (ET_0) dataset published by the CGIAR Consortium for Spatial Information (CGIAR, 2019). The second was a raster depicting average summer ET in the study area, sourced from OpenET through Google Earth Engine. With both an ET and an ET_0 dataset with full coverage over the study area, the raster calculator in ArcGIS Pro was used to calculate the single crop coefficient (Allen et al. 1998). The resulting K_c raster was then sampled using zonal statistics to find the average K_c value for each LULC class.
The final variable required by the biophysical table in the "Green Area" variable, with a binary input value to indicate either a yes (1) or no (0). With a value of 1, the model will treat all cells of a LULC type as being a "green area," meaning that contiguous cells totaling over 2ha (4.9ac) in size provide

an additional cooling benefit that extends outward into neighboring cells with different LULC values. The decision about which LULC classes merit being classified as a "green area" is up to the end-user of the model. For this study, the percentage of shade was the primary indicator used to determine which LULC class would be assigned a value of 1. Vegetation indices, such as the Enhanced Vegetation Index (EVI), or data regarding the percentage of permeable surface in a given LULC class may also be used, if such datasets are available. The LULC types included in the model, with the green area determination for each, are presented in Table 3.

The resulting outputs from the InVEST Urban Cooling model are a raster layer depicting cooling capacity, as well as a vector shapefile of the input AOI shapefile with calculated attributes for average cooling capacity value in each individual polygon – in this case, for each census block group and for each 0.25mi buffered housing point. Table 7 presents comprehensive details of all the environmental quality characteristics, including their descriptions, any transformations, and units.

4.5. Summary Statistics

Table 8 presents the summary statistics for the estimated list price (LIST-PRICE) and Zestimates (ZEST) in our study region. The average estimated list price is about $467,308, which is marginally higher than the average Zestimate of $458,834. Similarly, the median estimated list price (LIST-PRICE) is $397,325, compared to the median Zestimate (ZEST) of $391,900.

Table 9 summarizes the housing characteristics. On average, homes in the study area have 3.4 bedrooms (BED) and 2.5 bathrooms (BATH). The average age of each housing unit (AGE) is 29 years old. A large majority of properties, about 83 percent, have an attached garage (GARAGE). Swimming pools are uncommon; only 4.4% of homes listed during the study period have an inground pool (POOL). The average living area (AREA) of housing units is 2,197 square feet, and the average lot size (LOTSIZE) is 0.5 acres. Water-smart landscaping is not common, with only about 28 percent of housing featuring this type of landscaping.

Summary statistics for the neighborhood characteristics are provided in table 10. The average household median income (MED-INC) is $76,694. The average distance from a housing unit to the nearest highway (HWAY-DIST) is 3.39mi. The average unemployment rate in the county in which a home is located is estimated to be about 3.5%. The average distance from each property to the nearest elementary (ELE-SCH), middle (MID-SCH), and high schools (HIGH-SCH) is about 1.50mi, 2.52mi and 3.57mi, respectively. The average schools' ratings for all school levels considered (MSCH-RATINGS, MSCH-RATINGS, and HSCH-RATINGS) is approximately 4, indicating below-average quality based on the GreatSchools ratings criteria. The average population density (POP-DENS) within the block group where the housing unit is located is about 37 people per square mile, and about 61.4% of the population in a typical block group identify as White (WHITE-PCT).

Table 11 presents the summary statistics for the environmental variables considered in this study. Several of these variables were averaged for 0.25mi buffers around each geocoded address, as well as across every census block group with those results spatially joined to each geocoded address. The difference in values between 0.25mi buffers and census block groups was very low for most variables, reflecting that both methods are comparable in this study, and the best-fit method was selected for each variable.

Particulate matter pollution under 2.5 microns ($PM_{2.5}$) was bet fit when averaged at the census block group level, with an average of 5.8μg/m^3, a median of 5.8μg/m^3, and a standard deviation of 0.5μg/m^3. This represents a somewhat low overall variability across the entire study region. However, it is important to consider that $PM_{2.5}$ is only one of many airborne pollutants one can consider in similar studies. Tree canopy was also best fit at the block group level, with a mean of 0.09 (or 9% canopy cover), a median of 0.07 (7% canopy cover), and a standard deviation of 0.09 (9% canopy cover). The high standard deviation indicates a great deal of variability across the study region, and this is reflected in maps of the study area. The mountainous areas of the study region, as well as the riverside forest alongside the Rio Grande, hold considerably higher tree canopy coverage than the rest of the study region. This pattern is typical of arid high deserts, where tree cover is often restricted to high elevations or areas near water sources.

Domestic well density was calculated by counting the number of active domestic wells within a 0.25mi buffer of each geocoded address. The average number of wells was 7.2, with a very high standard deviation of 24.0. This indicates that there is a huge degree of variation in the number and density of domestic wells across the study area. Domestic well density is influenced by many factors, such as whether a domestic water agency supplies a given area, or whether the groundwater basin is open to development, among other factors. With over 10,000 domestic wells in the study area, many geocoded addresses are in areas where the number of wells within 0.25mi is massive. Conversely, many houses also occur within the densified city of Albuquerque, which is supplied by a metropolitan water agency, rendering domestic wells largely superfluous; many of these homes indeed have no wells within 0.25mi. The Euclidean distance between geocoded addresses and the nearest individual well was also calculated, with an average of 0.58mi, median of 0.39mi, and standard deviation of 0.58mi. The high standard deviation again indicates a great deal of variation across the study area. But the low average distance of just over half a mile, despite the fact that many addresses occur quite far from a domestic well, indicates just how incredibly dense domestic wells are in some areas of the study region.

The Euclidean distance between each geocoded address and a few environmental amenities was also calculated – distance to the Rio Grande, distance to the nearest irrigation ditch, and distance to the nearest greenspace were all considered. The average distance to the Rio Grande was 4.3mi, with a median of 3.7mi and standard deviation of 3.5mi. The high standard deviation indicates that many addresses lie quite far away from the Rio Grande, however the modest overall average of just over 4mi points to the majority of houses being somewhat close to the river. Similarly, the average distance to the nearest ditch was 3.3mi, with a median of 2.5mi and standard deviation of 3.5mi illustrating the same pattern as distance to the Rio Grande. This is to be expected, given that the ditches are fed by the Rio Grande and are, by nature, within a close distance of the river. Distance to the nearest greenspace was an average of 1.7mi, with a median of 0.4mi, and standard deviation of 2.6mi which shows an interesting trend. The high standard deviation indicates an uneven distribution of greenspaces across the study region – indeed, a disproportionate number of them occur within or near Albuquerque. The low average distance then points to the fact that a disproportionate number of houses for sale occur within the city of Albuquerque.

5. Econometric Modeling Approach

The specification of our models begins with a traditional semi-log regression hedonic price function as defined generally in equation (6). Given the pooled cross-section nature of our data, we address the problem of heteroskedasticity by using robust standard errors clustered at the census block group level. Additionally, we include month-year fixed effects, μ_t, to capture any significant temporal changes, such as variations in mortgage rates over the data collection period. Our baseline model specifications incorporate a set of structural (S) characteristics, neighborhood characteristics (N), and a broad set of physical environmental attributes (E). The selection of these variables is based on concerns about multicollinearity. Thus, the Variance Inflation factor (VIF) was used to test the models for the presence of multicollinearity (Greene, 2012). Variables with a VIF value greater than 10 are omitted from the model. We focus primarily on LIST-PRICE as our dependent variable for most models due to the ample sample size available in our data. The baseline models[9] are structured such that the list price (LIST-PRICE_{ijkt}) of individual property (i), in a block group (j), in a county (k), at time (t) is specified in the following model:

$$\begin{aligned}\ln\text{LIST-PRICE}_{ijkt} = {} & \alpha + \delta_1\text{BATH}_i + \delta_2\text{AREA}_i + \delta_3\text{LOTSIZE}_i + \delta_4\text{POOL}_i + \delta_5\text{WAT-SMART}_i + \\ & \delta_6\text{GARAGE}_i + \delta_7\text{AGE}_i + \gamma_1\text{POP-DENS}_j + \gamma_2\text{WHITE-PCT}_j + \gamma_3\text{MED-INC}_j + \\ & \gamma_4\text{AVG-UEMP}_k + \gamma_5\text{HWAY-DIST}_i + \pi_1\text{GREEN-DIST}_i + \pi_2\text{RIVER-DIST}_i + \\ & \pi_3\text{PM2.5-BG}_j + \mu_t + \varepsilon_{ijkt}\end{aligned} \tag{8}$$

Next is the extension of the baseline model (equation 8) to include our main environmental variables of interest. To evaluate the impacts of heat and its correlates (AVG-ACC, LST, EVI, T-CANOPY-BG), and well density (WELL-DENS), we extend the baseline model to include each of these variables respectively. Given the nature of these environmental quality variables, there is a significant likelihood of a perfect linear relationship among them. Therefore, we conduct a correlation test to detect multicollinearity amongst our environmental quality variables. Multicollinearity can cause problems such as difficulty in making precise estimates and very high goodness of fits (R^2) but statistically insignificant coefficient estimates (Dormann et al., 2013). Table 4 presents the correlation tests for the environmental quality variables.

An examination of the pairwise correlations among the environmental quality variables presented in Table 5 reveals strong associations between AVG-CCI, LST, EVI, and T-CANOPY-BG. Consequently, these variables cannot be combined into a single model. Instead, we include each variable separately in individual models. For instance, to assess the impact of AVG-CCI, we extend our model by incorporating AVG-CCI into equation (8). The extended model is shown as follows:

$$\begin{aligned}\ln\text{LIST-PRICE}_{ijkt} = {} & \alpha + \delta S + \gamma N + \pi_1\text{GREEN-DIST}_i + \pi_2\text{RIVER-DIST}_i + \pi_3\text{PM2.5-BG}_j + \\ & \pi_4\text{AVG-CCI}_i + \mu_t + \varepsilon_{ijkt}\end{aligned} \tag{9}$$

Equation (9) specifies an extended model specification for AVG-CCI, where π_4 measures the impact of cooling capacity on property prices in our study region. All Subsequent model specifications follow this structure, incorporating the same set of Structural (S) and Neighborhood (N) characteristics defined in equation (8) above. By including each environmental quality variable separately, we aim to isolate and understand their individual impacts on property values without the confounding effects of multicollinearity. This approach ensures a more robust and interpretable results, contributing to a clear understanding of how different environmental factors impact property values.

Given our log-linear hedonic price function, to ascertain the marginal implicit prices (MIPs) for any continuous environmental quality variable (e.g. GREEN-DIST), the computation is expressed as:

$$\frac{\partial\text{LIST-PRICE}_{ijkt}}{\partial\text{GREEN-DIST}_i} = \pi_1 \times \text{LIST-PRICE}_{ijkt} \tag{10}$$

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[9] The second baseline model is almost identical equation 8. The only difference is that RIVER-DIST is replaced with DITCH-DIST as a result of multicollinearity issues. The correlation results in table 4 revealed that RIVER-DIST and DITCH-DIST are strongly correlated ($|r|= 0.9747$) and hence cannot be included in a single model.

Equation (10) can be interpreted as the percentage change in the housing value resulting from a one-unit change in the variable of interest which in this case is GREEN-DIST. In the case of a dummy variable, the percentage impact is computed as $100 \times (e^{\hat{\beta}} - 1)$. For our focal variables, the computation and interpretation of the MIPs differs slightly. For instance, since the values of AVG-CCI, LST and T-CANOPY-BG range from 0-1, and EVI ranges from -1 to 1, it is more appropriate to consider the percentage change in the housing value resulting from a one-percentage point change in any of these variables. In that regard, the marginal implicit price for example AVG-CCI is given as:

$$\frac{\partial \text{LIST-PRICE}_{\text{ijkt}}}{\partial \text{AVG-CCI}_{\text{i}}} = 0.01(\pi_4) \times \text{LIST-PRICE}_{\text{ijkt}} \qquad (11)$$

Based on the background presented in section 2 and the theoretical environmental economics perspective, the following hypothesis can be formulated regarding the relationship between urban greenery, cooling capacity, land surface temperature, and property values:

1. Our first hypothesis is based on the notion that there is a negative relationship between property values and the proximity to nearby greenspace (GREEN-DIST). As previously mentioned, these areas substantially impact air quality and provide opportunities for leisure, aesthetic enjoyment, and enhance overall well-being, all of which may be directly associated with increased house prices. As such, the general expectation is that individuals are willing to pay a premium for properties located close to green spaces (e.g. parks, golf courses, etc.)

2. Our second hypothesis asserts that individuals are willing to pay a premium for properties situated in regions with a higher density of vegetation (EVI). As mentioned, regions with a higher density of vegetation experience milder temperatures due to evapotranspiration and shading.

3. The third hypothesis posits that individuals are willing to pay additional fees for properties in areas with increased tree coverage (T-CANOPY-BG). In urban areas, trees contribute to the reduction of UHI effects, air quality improvements, reductions in UHI effects, and carbon sequestration, all of which can have a positive impact on housing prices.

4. For our fourth hypothesis, we anticipate a positive relationship between average cooling capacity index (AVG-CCI) and property values. Cooling capacity reflects the ability of an area to mitigate heat, which is particularly valuable in arid regions. As a result, the expectation is that individuals will pay extra for houses in more chilly areas.

5. Finally, we propose that there is a negative relationship between property values and land surface temperature (LST). The general expectation is properties in hotter areas may face a reduction in value as a result of the inconvenience, increased water and energy consumption, and other factors associated with the harsh summer weather.

5.1. Spatial Considerations

Tobler's (1970) first law of geography states that "everything is related to everything else, but near are related than distant things". Residential properties exhibit a greater probability of spatial interdependence, particularly among surrounding homes and nearby suburban areas (Thomy, 2017). Chan (2014) explains that the hedonic pricing method, which utilizes Ordinary Least Square (OLS) incorporates spatial effects by considering location attributes such as the property's location, and its proximity to parks, airports, business centers, etc., as well as neighborhood characteristics like income, population density, etc. Nevertheless, it fails to include the spatial interaction or spill-over effect that occurs between properties. Spatial dependence occurs when the price of a neighborhood is affected by the prices of adjacent neighborhoods (Holt and Borshuk., 2014). In this study, spatial dependence occurs when the value of a house in a census block group (i) is influenced by both its own housing and environmental characteristics, as well as the values and environmental characteristics of homes in neighboring census block groups (Iźon et al., 2010). Therefore, estimating hedonic price functions using OLS without accounting for spatial dependence results in biased, inefficient, and inconsistent parameter estimates (Anselin, 1998). To ensure the models are free from spatial dependency issues, we incorporated spatial diagnostics into our modeling strategy.

First, we tested for the presence of spatial autocorrelation in the OLS regression residuals using the Moran's I test. The Moran's I test formally quantifies the linear association between a vector of observed values and a weighted average of neighboring values, or spatial lag (Anselin 1996, as cited in Thomy, 2016). The test results in all cases indicated a positive and statistically significant spatial dependence of housing price values. To account for spatial dependence, we adopted the spatial two most commonly used spatial models: the spatial autoregressive model (SAR) and the spatial error model (SEM). The choice of the appropriate spatial model specification between the two is dependent on the Lagrange Multiplier test (LM test) results. The LM test is used to determine whether the value of a given house is still influenced by the values of its surrounding houses after correcting for spatial correlation, using the spatial lag and spatial error models (Holm, 2021). The LM test for spatial error assumes no spatial dependency in the error terms in the SEM[10], whereas the LM test for spatial lag assumes no dependency on the dependent variable in the SAR[11] (Ma, 2017). As noted by (Ma, 2017), simple LM tests, while having power against the incorrect alternative, tend to overlook other spatial autoregressive processes, potentially leading to the rejection of the null hypothesis regardless of the true spatial autoregressive process. Therefore, a more reliable approach involves using the robust LM tests developed by Anselin et al. (1996), which are more robust against the presence of other spatial autoregressive processes. The robust LM error test statistic examines spatial dependency in the errors while considering the presence of spatially lagged dependent variables. Conversely, the robust LM lag explores the relationship between the dependent variables amidst spatially correlated error terms (Ma, 2017).

According to Kim et al. (2003), the spatial autoregressive model (SAR) assumes that the price of each house in a neighborhood is influenced by both its structural and neighborhood characteristics (direct effects) and the spatially weighted average housing prices of the surrounding area (indirect effect). Conversely, the spatial error model (SEM) assumes that there is or are more omitted variables in the hedonic price function that vary spatially. In short, the SEM assumes that the spatial dependence is present in the error term (Kim et al., 2003). The spatial lag model hedonic price function can be expressed as:

$$P = \rho WP + \alpha + \delta S + \gamma N + \pi E + \varepsilon \tag{12}$$

where ρ is the spatial autocorrelation parameter, W is an $(n \times n)$ row-standardized spatial weight matrix, S, N, and E are matrices of structural, neighborhood, and environmental quality characteristics respectively as defined before, with ε assumed to be a vector of independent and identically distributed (i.i.d) error terms. This approach is appropriate when capturing neighborhood spillover effects. That is the model specification assumes that the weighted sum of neighboring

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[10] Rejection of H_0 ($\lambda = 0$) of the LM test for spatial error indicates the presence of spatial dependency in the error term
[11] Rejection of H_0 ($\rho = 0$) of the LM test for spatial lag indicates the presence of spatial dependency in the lag term.

housing prices enters as an explanatory variable in the specification of housing price formation (Kim et al., 2003).
The spatial error hedonic housing price function on the other hand can also be expressed as:

$$P = \delta S + \gamma N + \pi E + \varepsilon$$
$$\varepsilon = \lambda W \varepsilon + \mu \qquad (13)$$

where λ is the spatial autoregressive coefficient, W is the standardized weight matrix, and μ is assumed to be a vector of i.d.d errors, with S, N, and E matrices of structural, neighborhood, and environmental quality characteristics, respectively. Here, the price at any location is not only a function of the local characteristics but also of the omitted variables at neighboring locations (Kim et al., 2003).

Next is the construction of the spatial weight matrix to capture the spatial dependence in our models. There are many approaches to determining spatial weight matrices, such as contiguity-based matrices, distance-based matrices, k-nearest neighbors, and inverse distance (Anselin and Rey, 1991). For our analysis, we employed the Queen's contiguity method to create the row-standardized weight matrix, **W**. We assumed that each of the nearby houses would contribute to determining the price of a given house. Thus, the weights of nearby houses were given 1 if they shared an edge or a corner and 0 otherwise. A sensitivity analysis was conducted using 4-nearest neighbors, 8-nearest neighbors, and 0.5mi inverse-distance band matrices. However, the models produced results similar to the Queen's contiguity approach. As such, the Queen's contiguity method is applied in all spatial analyses conducted in this study

Finally, as part of the empirical approach, we conducted the following robustness assessments. Initially, we partitioned the data into two distinct categories: residences located inside the confines of the MRGCD, and residences situated outside of these bounds (designated as control regions). This enabled us to analyze the effects of our environmental factors individually for each group. Subsequently, we replaced lnLISTED with lnZEST in our model estimations, using the smaller sample sizes available for Zestimate. Finally, we replaced the use of robust standard errors with clustering at the census tract level with spatial HAC errors, also known as Conley standard errors (Conley, 1999).

6. Econometric Results

6.1. Spatial Diagnostic Results

All the log-linear hedonic price functions, including baseline and extended models[12] were first estimated using the OLS regression approach in STATA 17. Given our concern about the presence of heteroskedasticity in the data, we re-estimated models with month-year fixed effects and clustered standard errors at the block group level. Despite the good-of-fit for the re-estimated models (fixed effects), our primary interest was the presence of spatial autocorrelation in the data. To address this, we performed Moran's I test and LM tests to examine the spatial correlation in all models using GeoDa,[13] a state-of-the-art software developed for spatial analysis. Regarding our full sample (N =

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[12] The extended models consist of 5 different specifications, each model building on the baseline model by incorporating one additional environmental quality variable at a time. That is; Model 1 incorporates the baseline model plus AVG-ACCI, model 2 builds on the baseline by including LST, model 3 adds EVI to the baseline model, Model 4 includes T-CANOPY-BG to the baseline model, and Model 5 also extends the baseline model by adding WELL-DENS.
[13] GeoDa is spatial econometrics open-source software developed by the Center for Spatial Data Science (CSDS) at the University of Chicago.

5,113), tables 12 and 13 present the Moran's I test statistics using the Queen's contiguity weights for the baseline and extended models, respectively. The calculated Moran's statistic for both sets of models was positive and statistically significant at 1% level indicating the presence of spatial autocorrelation in the data.

Subsequently, both simple and robust LM tests were performed to determine the type of spatial autocorrelation present. For both sets of models (baseline and extended), the results indicated that both simple and robust LM tests are significant for the spatial error and spatial lag process. However, the simple and robust LM test statistics for spatial error were higher than the simple and robust LM test for spatial lag, thus suggesting that spatial error dependency is more prominent in the full sample dataset[14] (Anselin and Rey, 2014). As such, we corrected for spatial error dependency by estimating SEM models using MLE in GeoDa.

6.2. Full Sample Estimation Results

The results of the OLS regressions and the OLS with month-year fixed effects clustered at the block group level for both the baseline and extended model specifications are presented in Tables A1, A2, A3 and A4, respectively. The model results fit well in both cases with R^2 around 0.7 in all models. In general, all structural, neighborhood and environmental quality variables are statistically significant and exhibit signs consistent with theoretical expectations. However, given the presence of spatial autocorrelation in our OLS residual as indicated earlier, we selectively present the results of our preferred spatial hedonic price model which in this case is the SEM. We subsequently present the MIPs for our focal environmental variables (heat and its correlates) using the estimates from the SEM.

Tables 14 and 15 present the SEM results for the baseline and extended models, respectively. The SEM model fit shows an overall improvement over the OLS fit models, with R^2 averaging 0.81 and lesser AICs. The structural characteristics had both positive and negative effects on listed house prices. Across all models, the number of bathrooms (BATH) is positively associated with house prices, with each additional BATH increasing the list house price by approximately 2.3%. The MIPs for an additional BATH evaluated for the mean and median listed house prices are about \$10,748 and \$9,138, respectively. Similarly, an increase in the living area (AREA) is positively associated with housing prices. That is the listed price of a home increases by 0.02% to 0.03% (0.025% on average) for each additional square foot, equating to about \$117 for the mean home value and about \$99 for the median home value. Lot size (LOTSIZE) is positively correlated with house price: increasing lot size by 1 acre raises home prices by approximately 2.4% or about \$11,215 and \$9,535 for the mean and median listed prices, respectively. The presence of POOL, WAT-SMART, and GARAGE are associated with higher home prices across all model specifications. Specifically, the presence of a swimming pool increases home prices by approximately 3.4% or about \$15,888 for the mean house and about \$13,509 for the median house price. Similarly, a home shown to having Water-Smart landscaping is associated with a 2.8% to 3.8% (3.3% on average) increase in prices, translating to about \$15,421 for the mean price and about \$13,111 for the median price. The presence of a garage increases home values by approximately 4.5% or about \$21,028 for the mean home value and \$117,880 for the median home value. Lastly, the age of a house (AGE) is negatively associated with housing values. Each additional year in the age of a home corresponds to a decrease in house prices by approximately 0.3% or about \$1,402 and \$1,192 for the mean and median prices, respectively. In general, all the structural attributes are statistically significant across all models at the 1% level.

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[14] The ad hoc rule for selecting the appropriate spatial model as noted by Holm et al (2021) is to select the model with the highest test statistics. Given that the LM test statistics for spatial error were higher than spatial lag, we follow this rule and estimate SEM as the preferred model for the full sample.

Further analysis of the neighborhood variables shows that across all models in Tables 14 and 15, the population density within the Census block where a house is situated (POP-DENS) is negatively related to house prices, consistent with findings in Dahal et al. (2019). Median household income (MED-INC) and the percentage of white residents (WHITE-PCT) within the Census block group are positively related to housing prices. The average unemployment rate in the county where a house is situated (AVG-UEMP) is found to be negatively associated with housing prices. Additionally, proximity to the nearest highway (HWAY-DIST) is estimated to be a negative determinant of housing prices.

For the environmental variables, the coefficient estimates of the distance from a house to the nearest greenspace, including golf courses (GREEEN-DIST), is consistently negative and statistically significant at a 10% level across all models in Tables 14 and 15 (except for Models 1 and 4 in table 15). A one-mile increase in distance away from a greenspace decreases housing prices by approximately 0.5%, translating to about -\$2,337 for the mean price and about -\$1,987 for the median price. Distance to the Middle Rio Grande (RIVER-DIST) is found to be negative and statistically significant at a 1% level for only Model 2 in Table 15. Housing prices fell by approximately 0.9% for a one-mile increase in distance to the river. This is about -\$4,206 for the mean price and about -\$3,575 for the median price. The air pollution variable $PM_{2.5}$ for the Census block group corresponding to a home (PM2.5-BG) is associated with a house price increase of 1.8% to 2.4% (2.1% on average) across all models in Tables 14 and 15. This translates to an approximate increase of \$9,813 at the mean price and \$8,344 at the median price. Notably, while one would expect air pollution to be an environmental dis-amenity. However, the results proved otherwise, indicating $PM_{2.5}$ is an environmental amenity. The reason could be that air pollution levels in the study are extremely low[15] (average of 6 $\mu g/m^3$), reflecting economic activities in the area rather than being perceived as health hazard by residents.

Table 15 presents coefficient estimates for heat and its correlates as well as wells density. All the variables have the theoretically expected signs and are statistically significant. In Model 1, the average cooling capacity within a 0.25mi buffer of a home (AVG-ACC) shows a positive and statistically significant relationship at a 1% level. Evaluated at the mean house price, the marginal implicit price of a 1 percentage point increase in average cooling capacity within a 0.25mi buffer is approximately \$5,093, or about a 1.09% increase in home prices. For the median home price, the MIP is approximately \$4,330. In model 2, the coefficient estimate of land surface temperature within a 0.25mi buffer of a home (LST) is negative and statistically significant at a 1% level. For each 1-degree Celsius increase in LST, home prices decrease by 3.2%. The MIPs evaluated at the mean and median prices are -\$15,047 and -\$12,794, respectively. In Model 3, the enhanced vegetation index within a 0.25mi buffer (EVI) shows a positive and statistically significant association with home prices at a 1% level. Evaluated at the mean home price, the MIP of a 1 percentage point increase in EVI within 0.25mi is approximately \$5,172 or about a 1.1% price increase. For the median price, the MIP for EVI is about \$4,398. In model 4, tree canopy at the Census block group (T-CANOPY-BG) is associated with higher home values. The coefficient estimate is positive and statistically significant at 1%. A 1 percentage point increase in T-CANOPY-BG corresponds to about a 0.5% increase in home price, translating to about \$2,558 at the mean price and about \$2,175 at the median price. Lastly, Model 5 contains Well-Density. The coefficient estimates for the number of active domestic wells within a 0.25mi (WELL-DENS) shows that WELL-DENS is a positive and statistically significant determinant of home prices. That is, home prices increase by approximately 0.06% for each

[15] The average levels of $PM_{2.5}$ of the study is not within the non-attainment status (12 $\mu g/m^3$) as defined by the EPA.

additional increase in the number of active domestic wells in 0.25mi buffer. At the mean price, the MIP is approximately $280, and approximately $238 at the median price.

6.3. Zestimate Results

Our first robustness check involves replacing lnLIST-PRICE with lnZEST as the dependent variable of the log-linear hedonic price functions. The same analysis is performed for the full sample and the results of the preferred model[16] (SEM) is presented in Table 16. Consistent with the results presented in Table 15, all the structural and neighborhood characteristics still exhibit the theoretically expected signs and are generally statistically significant across all models, except for HWAY-DIST.

Regarding the environmental variables, GREEN-DIST is only a negative significant determinant in model 5 (when WELL-DENS is added to the baseline model). RIVER-DIST is only negative and statistically significant at 5% levels in models 2 and 3 only. $PM_{2.5}$ is consistently positive and statistically significant at 1% across all models in Table 16. The coefficient estimate of AVG-ACC is found to be positively related to home prices. That is, a 1 percentage point increase in AVG-ACC is associated with a 0.9% increase in home prices. Conversely, LST is associated with a reduction in home prices by approximately 2.8% for every 1-degree Celsius increase. A 1 percentage point increase in EVI leads to about 1.1% increase in home prices. T-CANOPY-BG increases home prices by approximately 0.6% for every 1 percentage point increase. Lastly, each additional active domestic well increases home prices by 0.06%. Importantly, the coefficients estimate for heat and its correlates exhibit the expected sign and are all statistically significant at 1% levels.

6.4. Conley Standard Errors Results

As part of our robustness checks, we replaced the clustered standard errors with the Conley standard errors while maintaining lnLIST-PRICE as the dependent variable. The idea here is that this approach allows for the correction of any spatial autocorrelation present in the dataset. Table A7 and A8 present the results for this approach. In general, we see a similar pattern of results as obtained in tables 14 and 15 above. Most importantly, heat and correlates show the expected sign and all statistically significant at 1%.

6.5. Boundaries Within and Outside the MRGCD

The full sample dataset is partitioned into two different subsamples: houses within MRGCD boundaries and control houses (outside the MRGCD boundaries).[17] Log-linear hedonic price functions are estimated for both samples, with lnLIST-PRICE as the dependent variable. Summary statistics for the structural, neighborhood, and environmental quality variables for these subsamples are presented in Tables A18 to A25. To determine the preferred model estimates for each sample, spatial diagnostics test results are performed for each sample as shown in Tables A13, A15 and A17. The spatial diagnostic results presented in Tables A13 and A15 indicate that the SAR is more appropriate for the MRGCD houses, while the SEM is more suitable for the control houses or houses outside the boundaries of the MRGCD. As such we present the SAR[18] results for MRGCD houses and SEM for the control houses.

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[16] We still maintain SEM as the preferred given the spatial diagnostics test results. It is evident that simple and robust LM test for spatial error is higher than the spatial lag suggesting that the SEM is more appropriate. See table A11 for spatial diagnostics tests.
[17] See Figure 13 for the map of geocoded address within and outside the boundaries of the MRGCD.
[18] For houses within the MRGCD boundaries, the spatial diagnostics tests indicate that spatial lag dependency is more prominent in the dataset, as indicated by the results of the simple and robust LM tests.

As shown in Tables 17 and 18, BATH is a positive and statistically significant determinant of housing prices at the 1% level, but only within the MRGCD boundaries as indicated in Table 17. AREA is positively correlated to house prices in both samples at a 1% level. LOTSIZE is also shown to positively impact housing prices in both samples, though the extent of the impact varies significantly. For houses within the MRGCD, house prices increase by approximately 9%[19], compared to a 1% increase for houses outside the MRGCD boundaries. POOL and WAT-SMART positively influence house prices outside the MRGCD only. The coefficient estimates for GARAGE and AGE are generally positive and statistically significant at a 1% level in both samples. However, residents within the MRGCD boundaries place significant value on houses with garages attached to them as compared to residents in the control areas. To be precise, the results indicate about 11% increase in house prices within the MRGCD boundaries, compared to about 3% in the control areas. POP-DENS and WHITE-PCT exhibit the expected signs and have statistically significant coefficient estimates at the 1% level in both samples. AVG-UEMP is found to be negatively associated with housing prices in both samples. HWAY-DIST is found to be negatively associated with housing prices in the control areas. This denotes that houses in the control areas that are closer to the highway command higher prices than houses that are farther away. The coefficient estimates for GREEN-DIST are generally negative and statistically significant at the 5% level in only the areas within the MGRCD boundaries. For the control areas, GREEN-DIST is found to be a negative and statistically significant (at 5% level) determinant of housing prices in only Model 5. Interestingly, RIVER-DIST is estimated to be positively associated with house prices within the MRGCD boundaries (coefficient estimates are statistically significant at 10% across all models except Model 5 in Table 17). Conversely, RIVER-DIST is found to be negatively related to housing prices in the controlled counties (see Table 18, Model 2). Overall, the results for RIVER-DIST indicate that residents prefer houses closer to the river but not adjacent to the river. An increase in $PM_{2.5}$ levels corresponds to a housing price increase within the MRGCD boundaries only. For heat and its correlates, the coefficients estimate exhibit the expected signs are generally statistically significant at a 1% level except for AVG-ACC in Model 1 of Table 18. WELL-DENS is a positive and statistically significant (at 1% level) determinant of housing prices in the control areas. However, the coefficient estimate of WELL-DENS is found to be positive but statistically insignificant within the MRGCD boundaries due to the lack of variation in WELL-DENS within those boundaries.

Lastly, the Models in Table 17 are re-estimated with DITCH-DIST replacing RIVER-DIST. The results are presented in Table 19. Overall, the coefficient estimates, signs, and statistical significance for the structural, neighborhood, and environmental characteristics are consistent with the results in Table 17. The coefficient estimate of the DITCH-DIST is positive and statistically significant at the 1% level across all models in Table 19. For every 1-mile increase in distance from a house to the nearest ditch, house prices within the MRGCD increase by approximately 6% to 8%. This indicates that residents within the MRCGD prefer houses that are farther away from ditches.

7. Discussion and Conclusions

This study examines the impact of heat mitigation and different measures of greenness in the Albuquerque Metropolitan area using on-sale housing price information web scraped from Zillow for the period 2022-2024. The information gathered from Zillow consisted of Zillow list price, Zillow

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[19] The calculation of MIPs varies depending on the type of model. For the SAR, MIP is calculated as: $\left(\frac{1}{1-\rho}\right) \times \widehat{\beta} \times$LIST-PRICE. For the SEM, the calculation for MIPs are calculated in the same way as the OLS model.

"Zestimate" and all other structural characteristics of homes considered in this study. The data gathered was then geocoded and matched with a variety of geospatial data, at different scales. Census block group characteristics (such as percentage of white residents, and population density) including unemployment at the county level were collected from various sources and matched with the housing data. Environmental quality variables such as heat mitigation index obtained from the state-of-the-art InVEST tool models, land surface temperature, enhanced vegetable index, tree cover, and active domestic well information was also collected and spatially joined to the housing data for the econometric analysis.

Our modeling strategy focused on the use of the list price information (lnLIST-PRICE) as the dependent variable in most cases as it had the larger sample available. The Log-linear OLS and Log-linear OLS with month-year fixed effects clustered at the block group levels hedonic prices functions were estimated and results were presented in the study. However, in the face of spatial autocorrelation, spatial models were favored and reported based on the results of the spatial diagnostics tests.

For our full sample, the econometric results indicated that the SEM models fit showed an overall improvement over the OLS and OLS with month-year fixed effects clustered at block group level models, with R^2 averaging 0.81. The structural variables had the expected signs and were generally significant at 1%. For the neighborhood variables, the coefficient estimates exhibited the expected signs and were generally significant except for the ratings of the nearest middle school which were found to be positive but statistically insignificant across all the models. Median household income is shown to be positively significant across all the models.

For the environmental variables, distance to the nearest greenspace, including golf courses were found to be negatively associated with housing prices indicating the residents within the Albuquerque metropolitan area value houses near greenspaces. Distance to the Middle Rio Grande was also seen as an environmental amenity as houses closer to the river commanded higher prices. Across most of the econometric results presented in this study, $PM_{2.5}$ is a positive and statistically significant determinant of housing prices – but $PM_{2.5}$ average values are all well within federal air quality attainment standards. Focusing on the main environmental quality variables, heat, and correlates, the coefficient estimates of these variables showed the theoretical expected signs and were generally statistically significant. For example, the heat mitigation index (AVG-ACC) was found to be positively associated with housing prices. That is, residents in the Albuquerque Metropolitan area place significant value on houses located in cooler areas. Land surface temperature is found to be negatively correlated with house prices indicating that hotter areas within our study region experience lower house prices. The enhanced vegetable index measuring the density of greenness in our study was estimated to be a positive determinant of housing prices. Tree canopy was also found to be positively associated with house prices in the Albuquerque metropolitan area. Switching to the number of active domestic wells, we found that they are positively correlated with house prices.

Partitioning the dataset into two distinct categories: areas within the boundaries of the MRGCD and areas outside the boundaries of the MRGCD still mostly showed the general trend of results as obtained in the case of the full sample. The new and interesting findings were that residents within the MRGCD generally prefer houses that are farther away from the river while residents in the control areas preferred houses closer to the river. Suggests residents would like to live closer to the river but not adjacent to it. Also, residents within MRGCD boundaries preferred houses that are farther away from the ditches. The number of wells within the 0.25mi buffer was estimated to be positively associated with house prices in the control areas. Well density was also found to be positive but statistically insignificant for houses within the MRGCD boundaries due to the enormous number of wells scattered across those areas.

As a general conclusion, results provide substantial evidence that in the Albuquerque Metropolitan area, both within and outside the MRGCD boundaries, heat and its correlates are significantly capitalized into house prices, as indicated across our econometric modeling. Examining regional housing markets using HPM is compelling in that it reflects preferences over a large group of market participants and presents them in capitalized present values. They capture the expected net benefit stream. This includes the ability to isolate the contribution of ecosystem services, which are otherwise difficult to value directly. In terms of limitations, it is hoped that in future research we will be better able to isolate lawns from trees, in providing heat mitigation and cooling capacity.

Our findings underscore the need for urban and economic development planners, and others to consider the value of heat mitigation, and green amenities, as evidenced in the housing market. The range of examples include: (i) consideration of alternative uses for treated municipal water (e.g., Olofinsao et al., 2024); and (ii) improvements in green infrastructure (e.g., swales and catchments) and additional public places (e.g., parks of all shapes and sizes, etc.) as they are associated with the reduction in the UHI effects. It also points to the need for environmental justice considerations and how different census tracts (see Davis, 2024), neighborhoods, schools, etc. do or don't provide equitable access to heat mitigation and cooling capacity. We have not investigated such questions here and have restricted our initial focus to the single-family, residential housing market. Equity considerations may be particularly important for the rental housing market. We also leave these as important avenues for future research.

Finally, in a climate-altered world, where there is significantly less water in the arid Southwestern U.S., we can ask what do people value? and what would they have reason to value if they didn't (or don't) have access (Sen, 1999)? In investigating how water is currently being consumed and economically valued in alternative uses in the Middle Rio Grande region, we conclude that the ecosystem service benefits of heat mitigation (cooling capacity) and providing greenness should be important admissible information in any public policy deliberations over tradeoffs and alternative water allocations.

8. References

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9. Figures

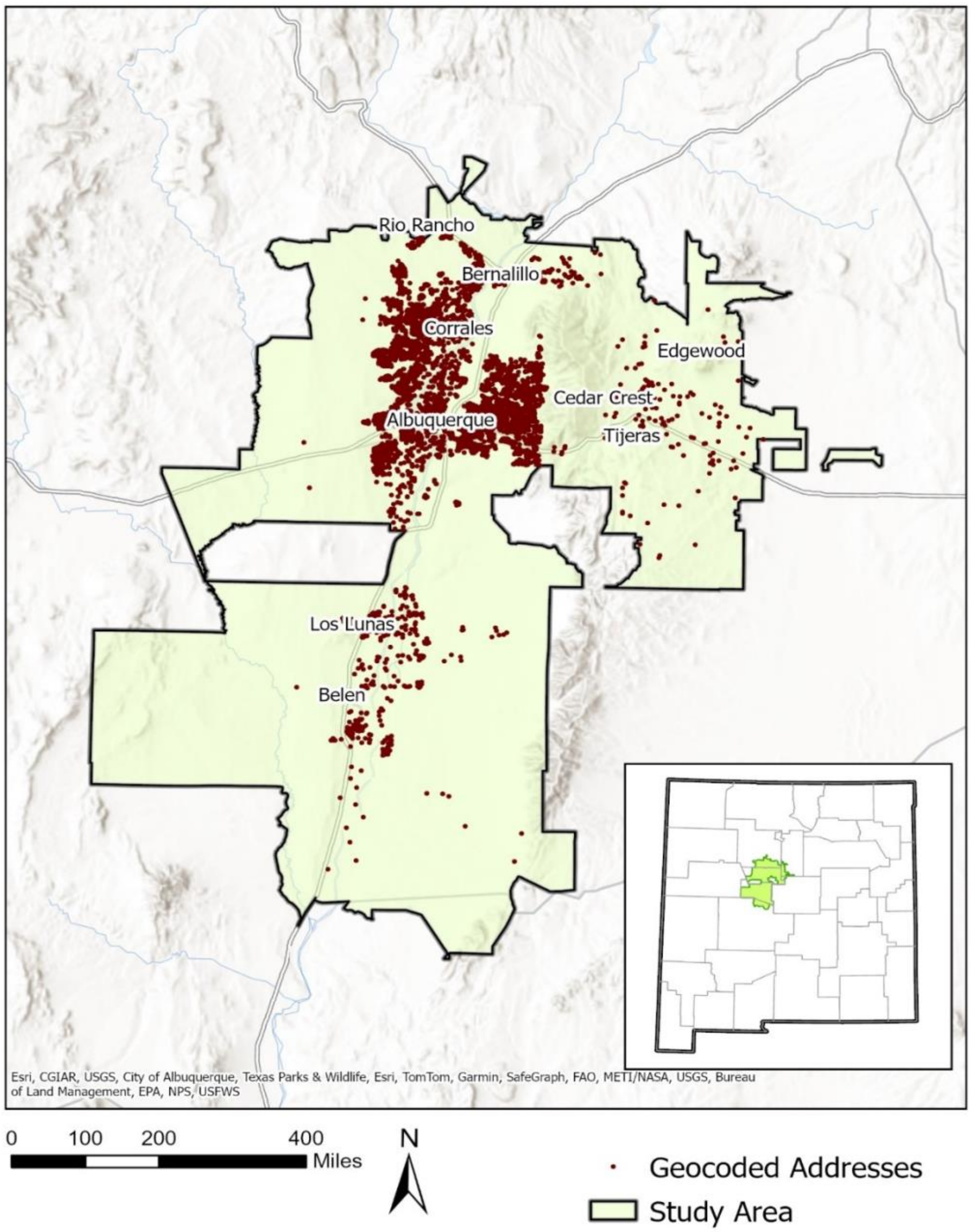

Figure 1: Distribution of sample geocoded addresses in the study area. Notes: The geolocation for the 5,543 houses is done using ArcGIS Pro. Sources: Zillow and ArcGIS Pro.

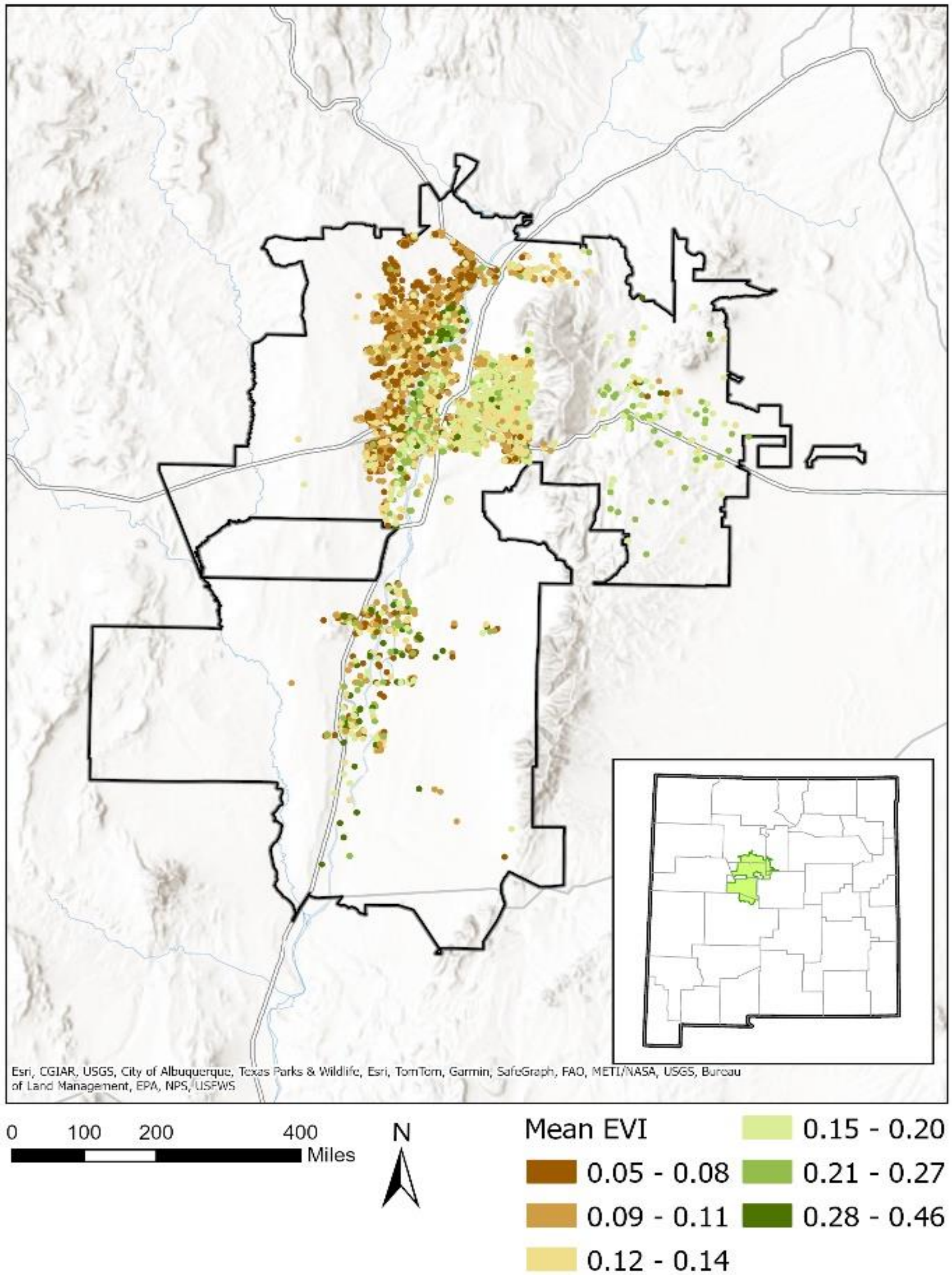

Figure 2: Average enhanced vegetation index within 0.25mi buffer around each housing point.
Sources: Data generated using Sentinel-2 imagery in Google Earth Engine and ArcGIS Pro.

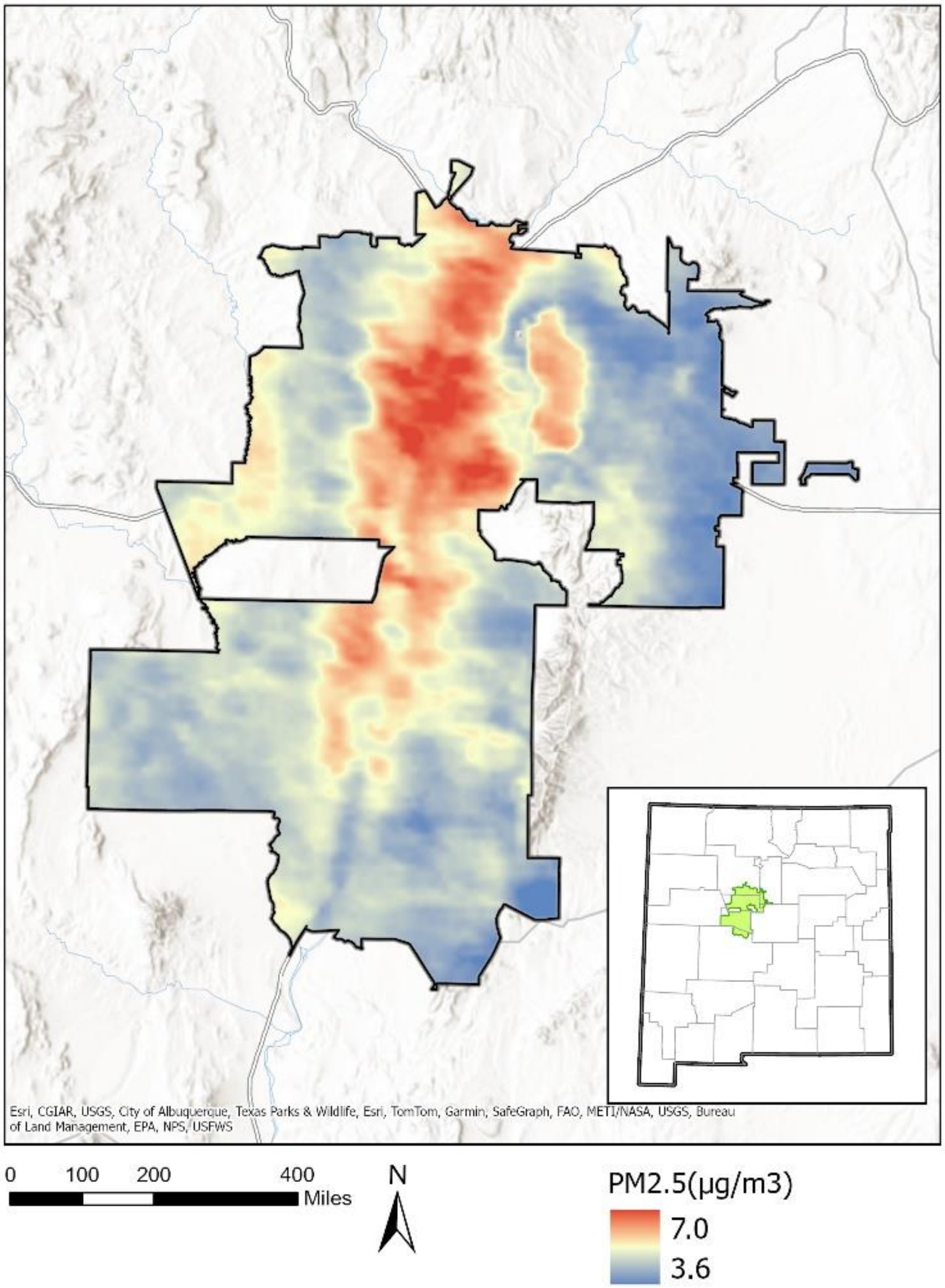

Figure 3: Fine particulate air pollution ($PM_{2.5}$) in the study area. Notes: Averaged composite of yearly $PM_{2.5}$ data from 2028-2022. Sources: Washington St. Louis University Atmospheric Composition Analysis Group (ACAG, 2022), ArcGIS Pro.

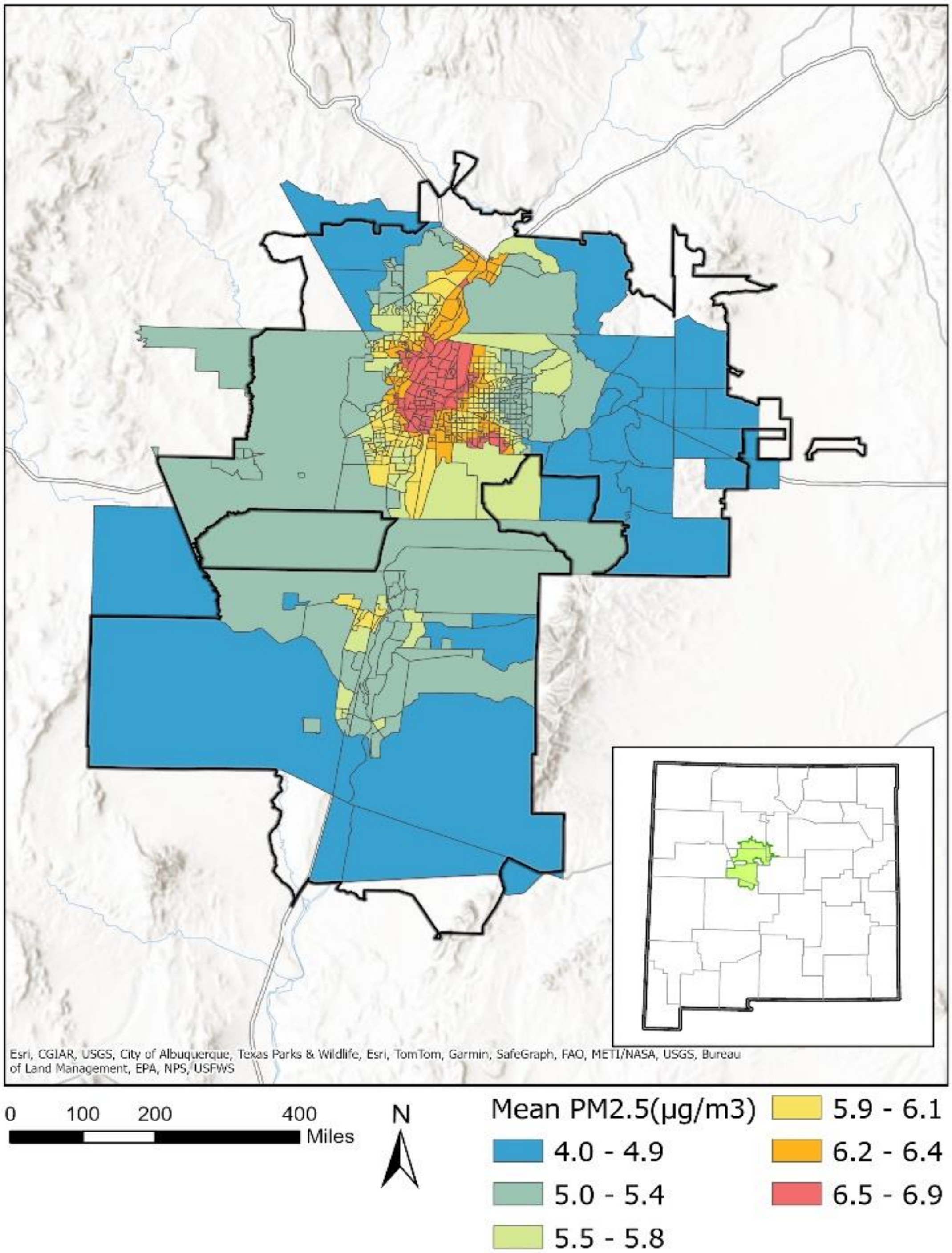

Figure 4: Fine particulate air pollution ($PM_{2.5}$) averaged at the census block group level. Sources: Washington St. Louis University Atmospheric Composition Analysis Group (ACAG, 2022) and ArcGIS Pro.

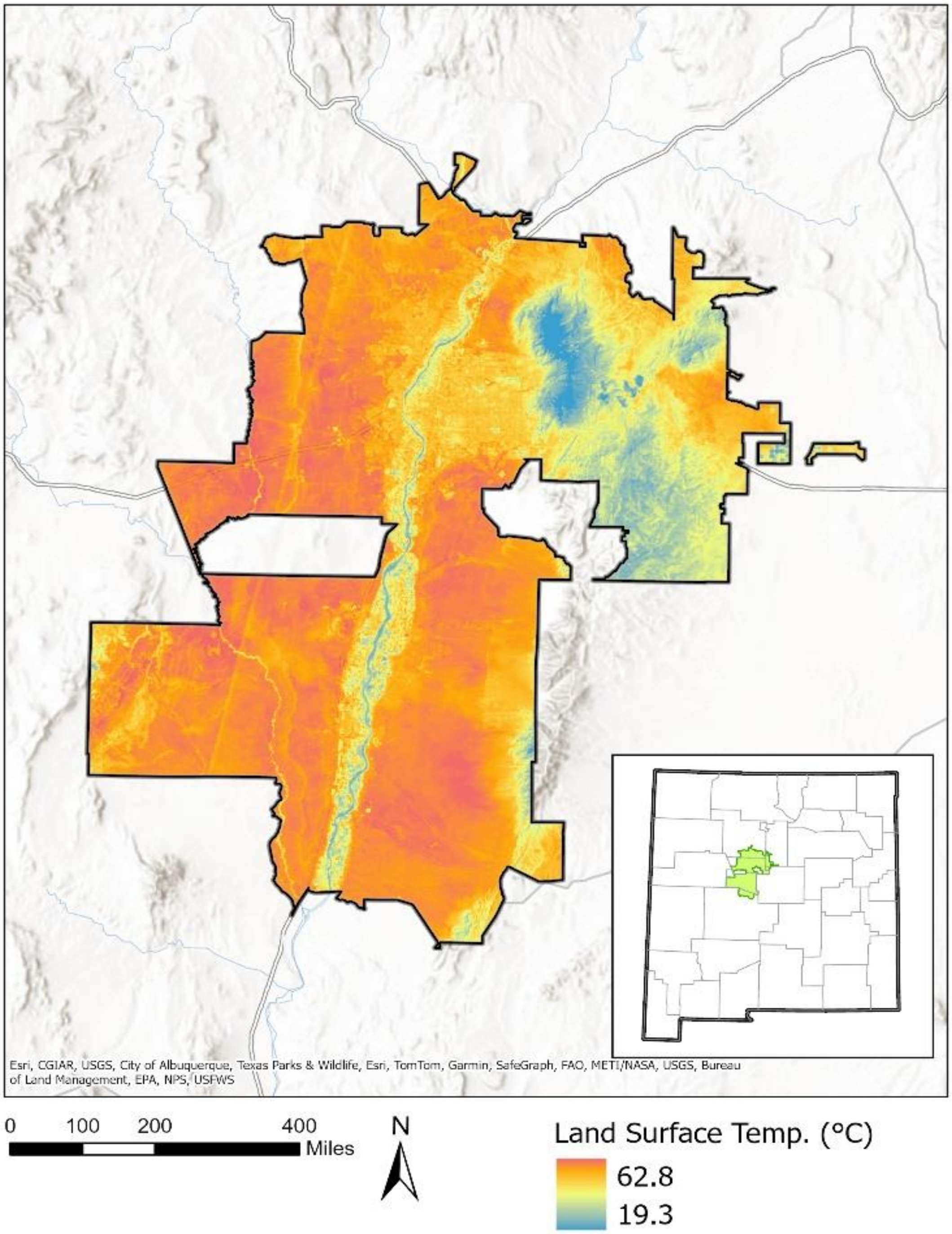

Figure 5: Remote sensed average land surface temperature of the study area. Sources: U.S Geological Survey and ArcGIS Pro.

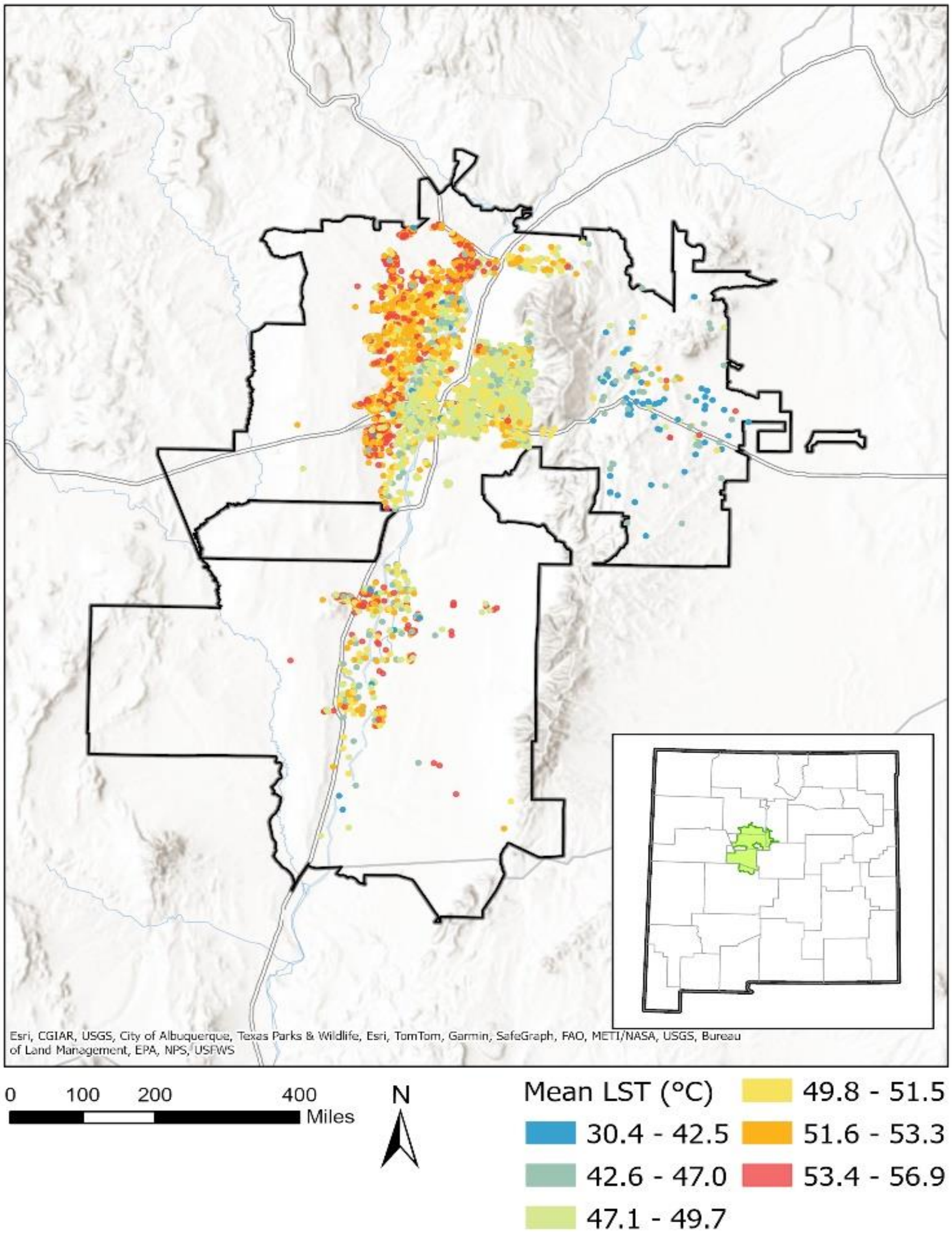

Figure 6: Remote sensed average land surface temperature within 0.25mi buffers around each housing point. Sources: U.S. Geological Survey and ArcGIS Pro.

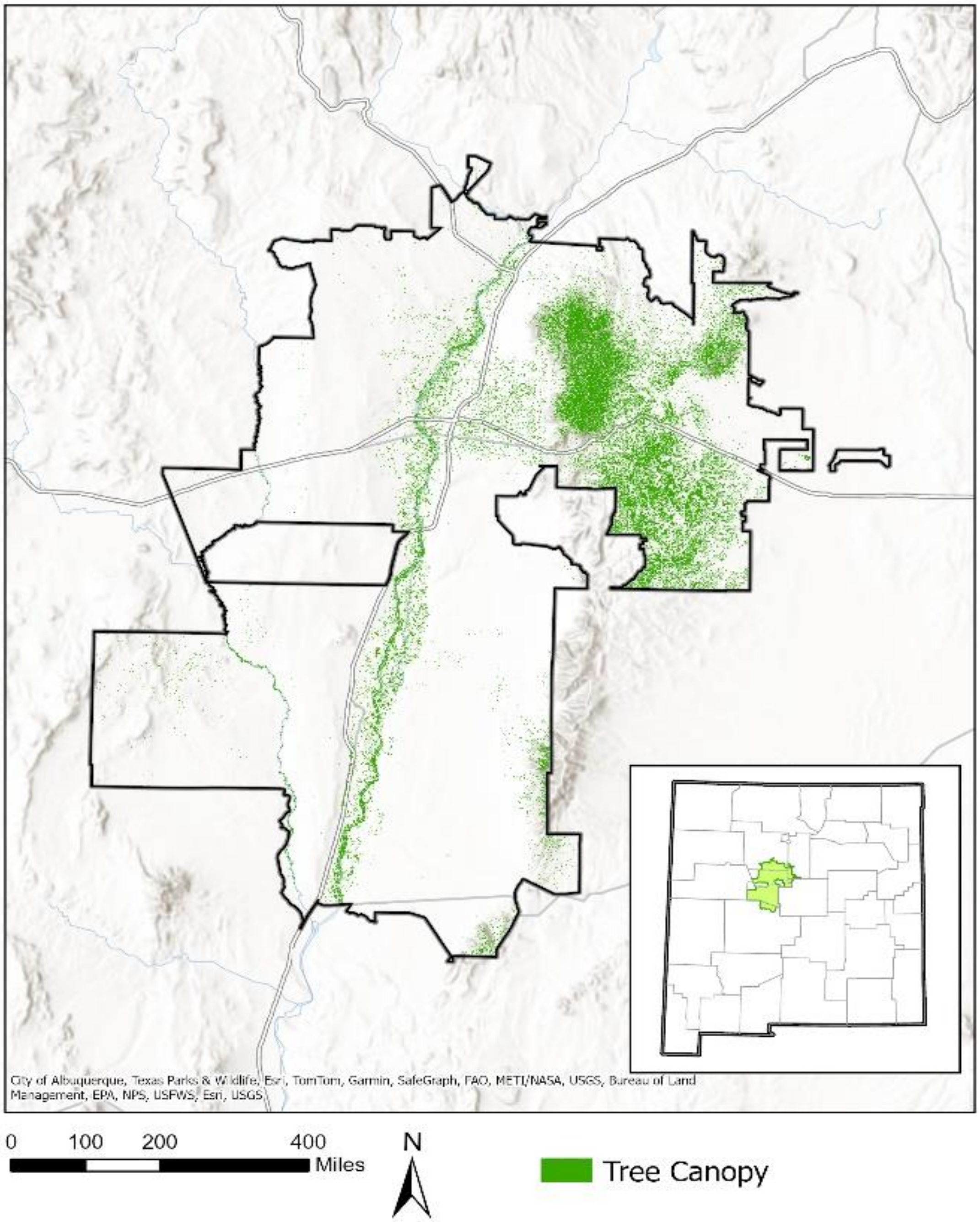

Figure 7: High resolution tree canopy cover of the study area. Sources: Data generated using National Agricultural Imagery Program (NAIP) acquired in 2020 by the USGS, Google Earth engine and ArcGIS Pro.

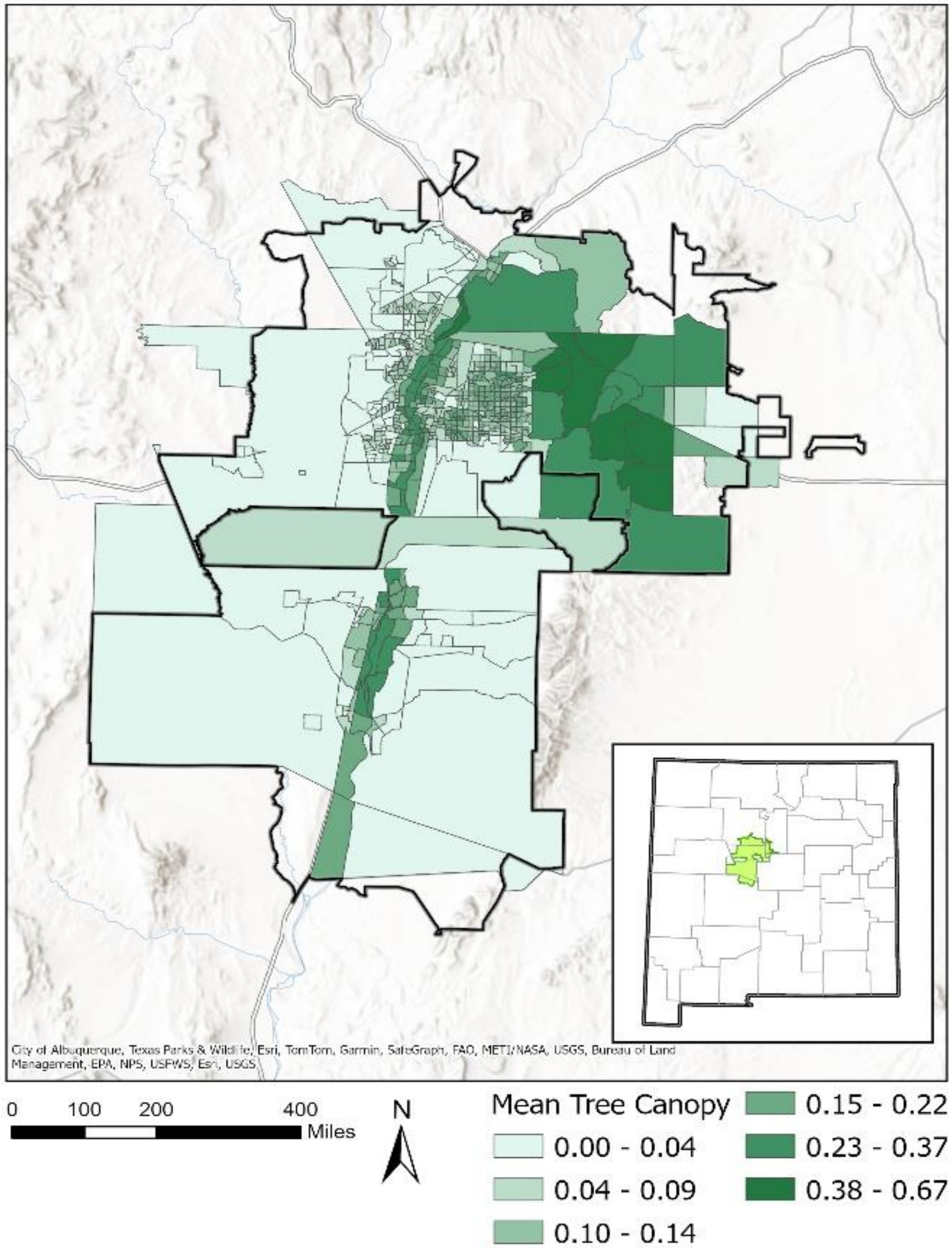

Figure 8: High resolution tree canopy cover averaged at the census block group level. Sources: Data generated using National Agricultural Imagery Program (NAIP) acquired in 2020 by the USGS, Google Earth engine and ArcGIS Pro.

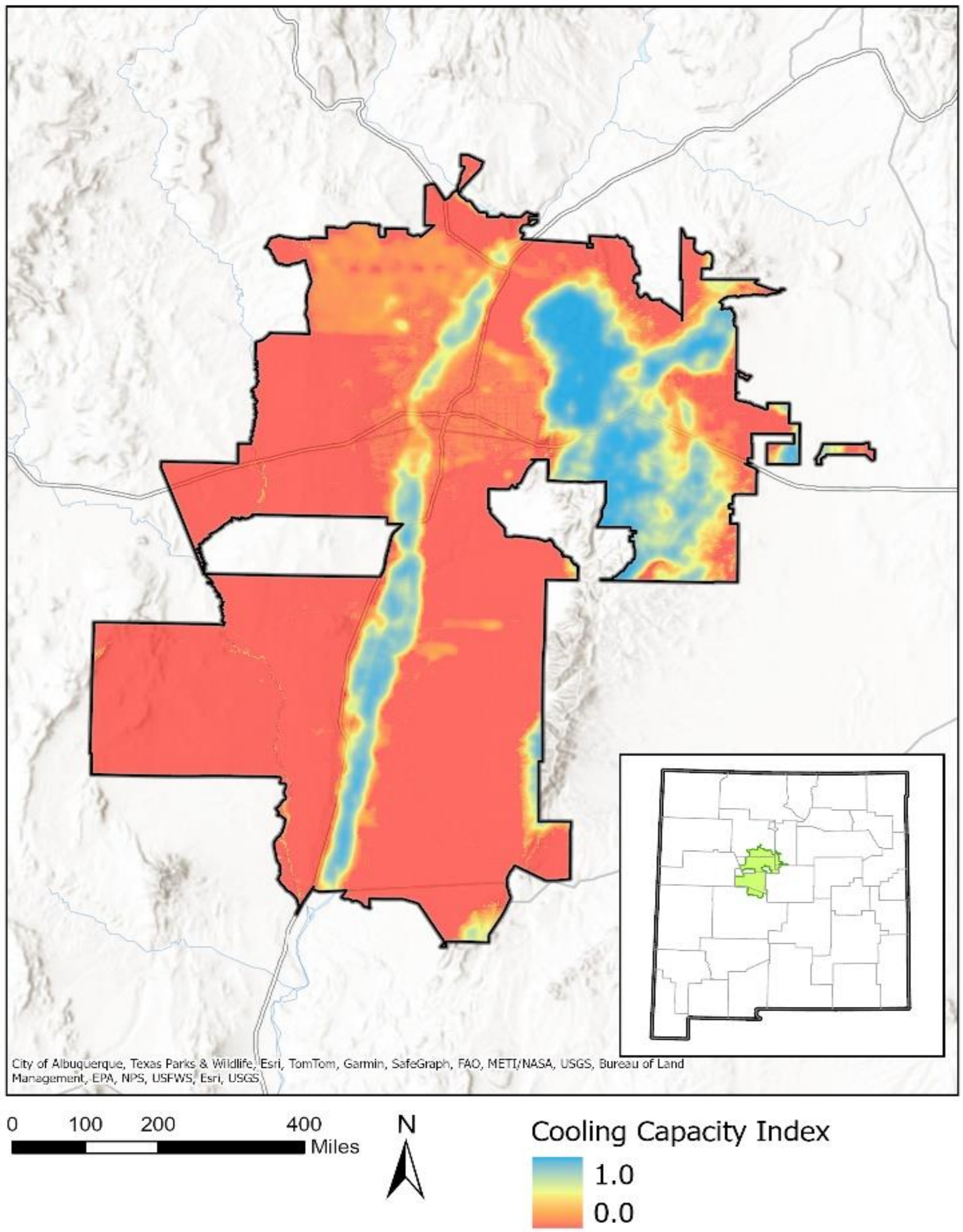

Figure 9: Average cooling capacity index of the study area. Sources: Data generated from the InVEST Urban Cooling model and ArcGIS Pro.

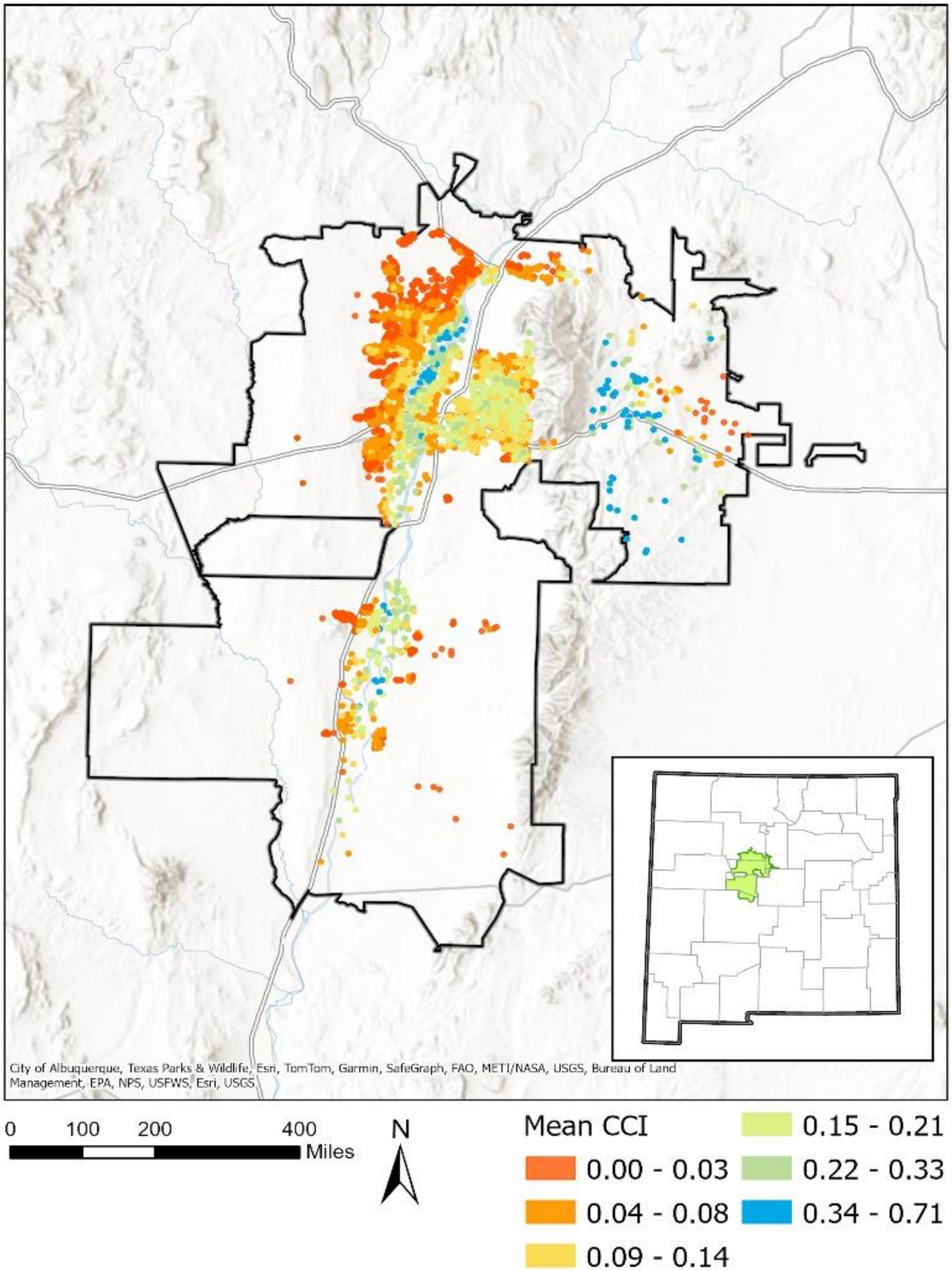

Figure 10: Average cooling capacity index within 0.25mi buffer around each housing point.
Sources: Data generated from the InVEST Urban Cooling model and ArcGIS Pro.

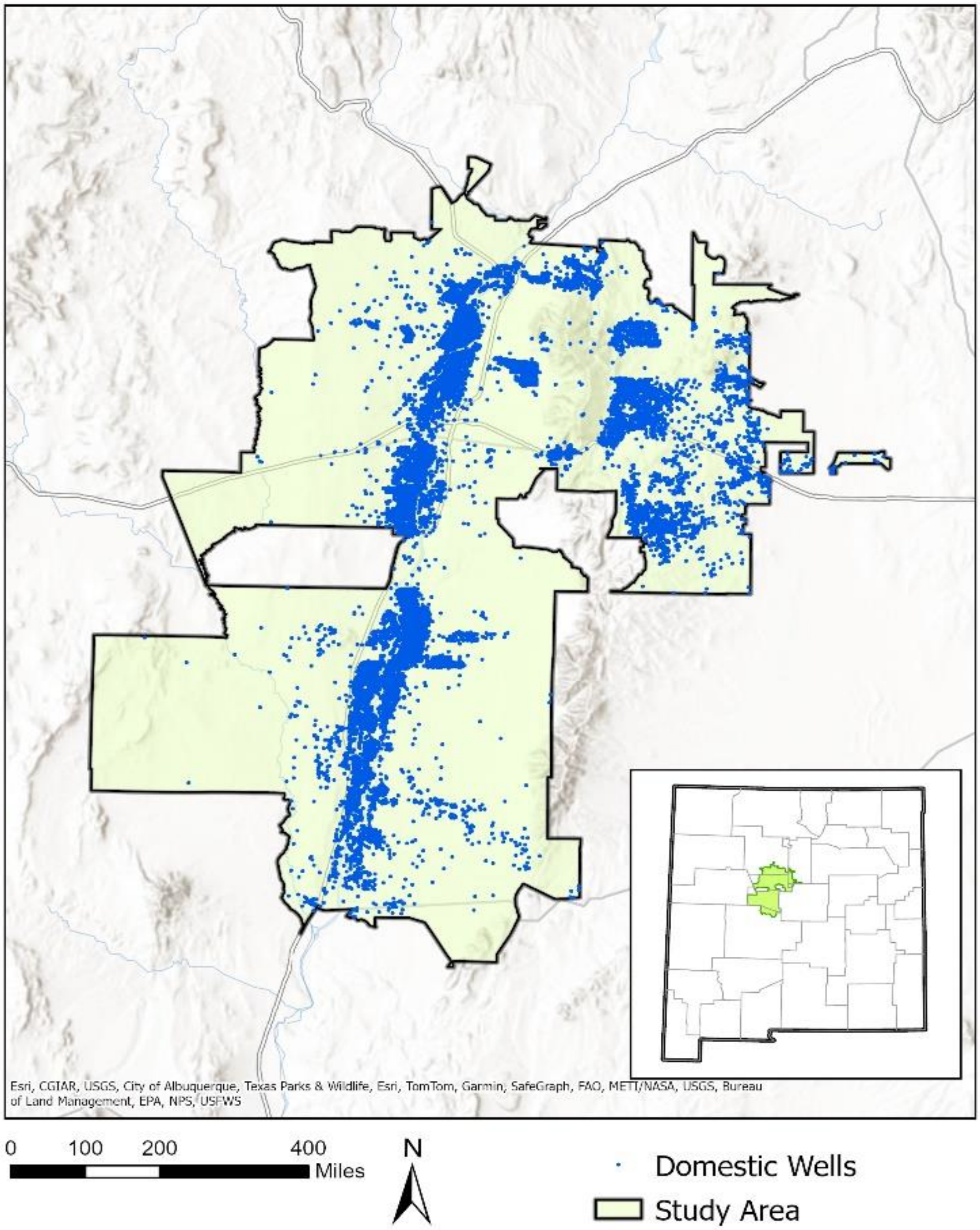

Figure 11: Active domestic wells distribution in the study area. Sources: NM Office of the State Engineer spatial data repository and ArcGIS Pro.

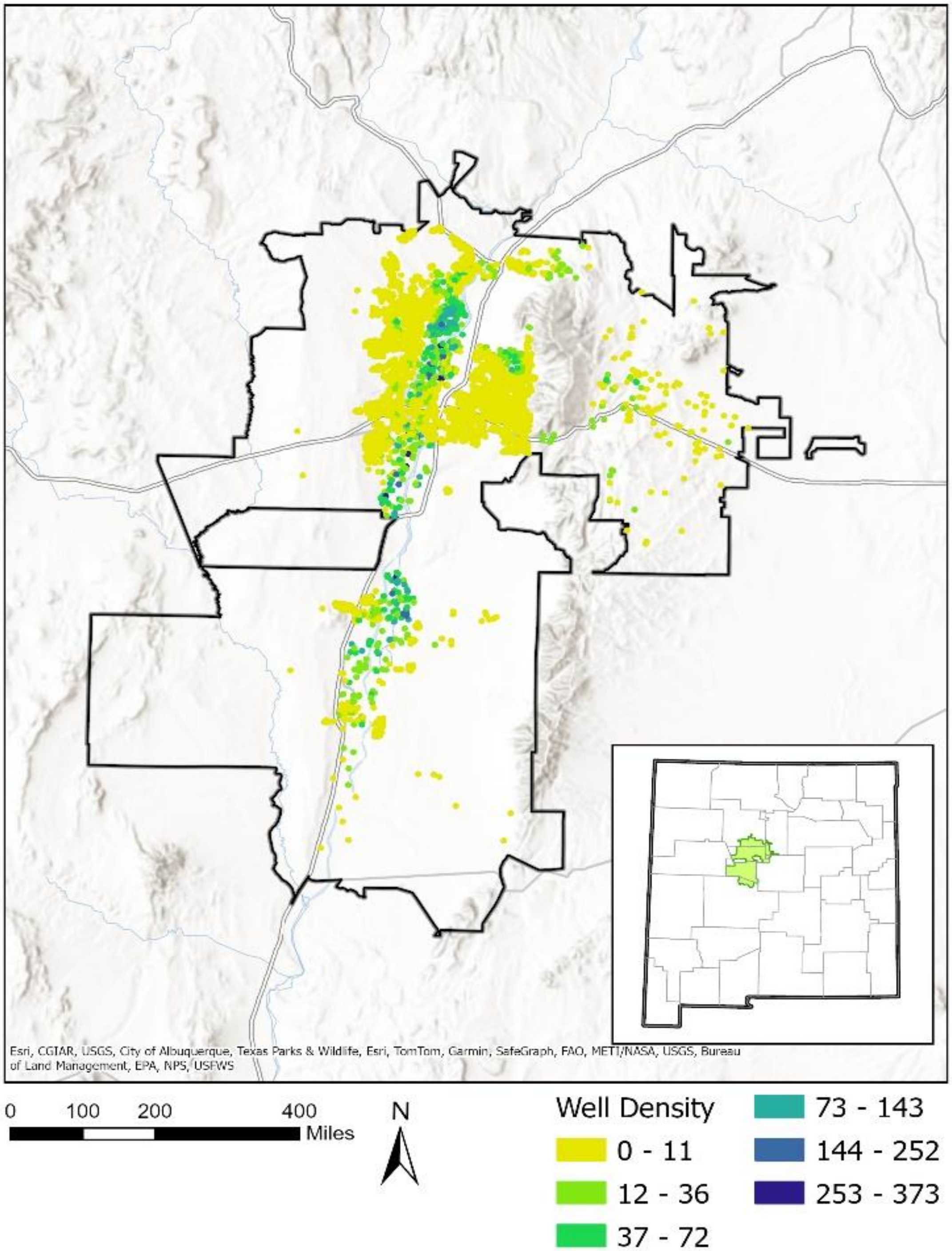

Figure 12: Number of active domestic wells within 0.25mi buffer around each housing point.
Sources: NM Office of the State Engineer spatial data repository and ArcGIS Pro.

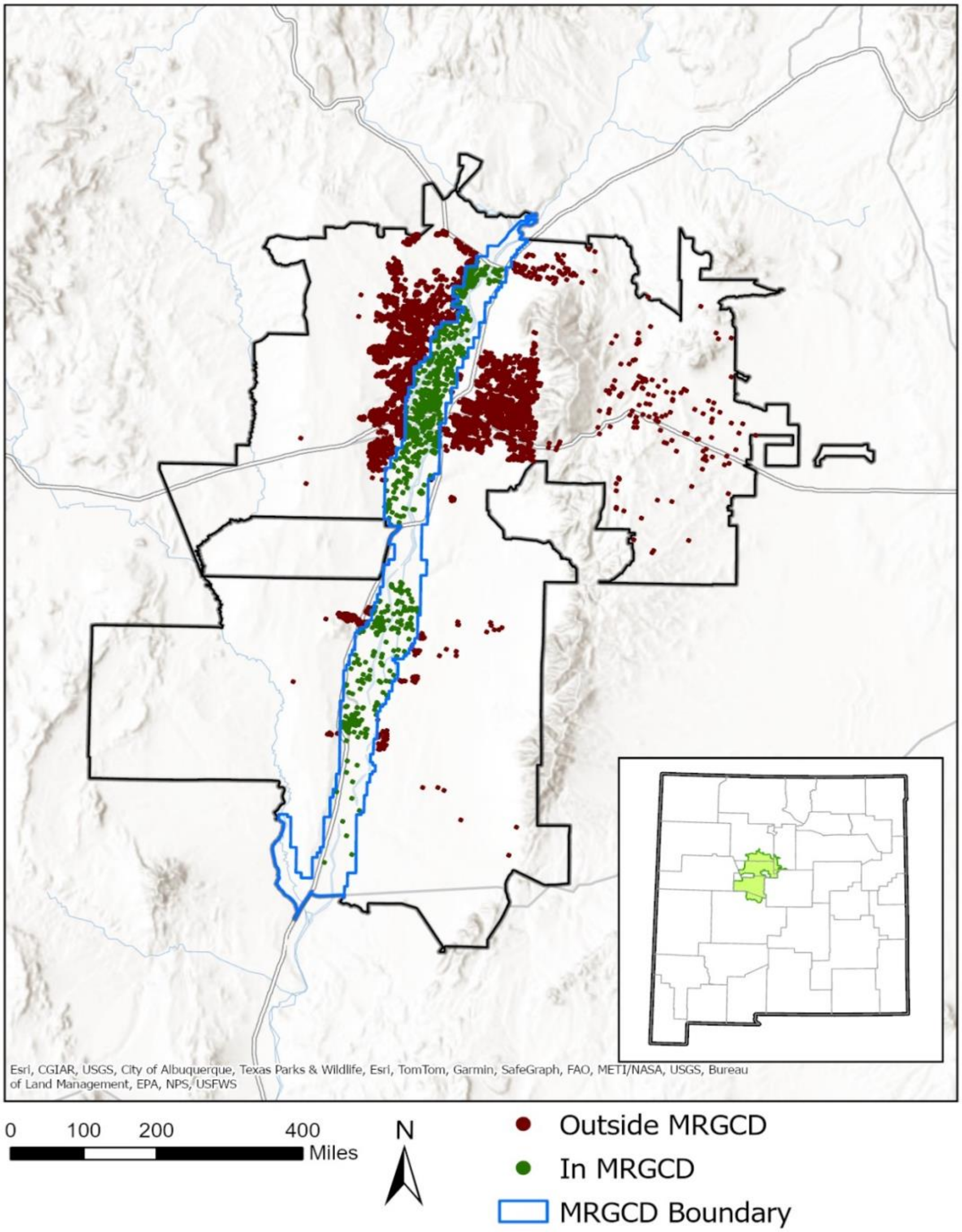

Figure 13: Distribution of Sample geocoded addresses within and outside the boundaries of the MRGCD. Sources: Zillow and ArcGIS Pro.

10. Tables

Table 1. All Inputs Required for the InVEST Urban Cooling Model to Function

Input Variables	Format	Value	Sources
Land Use/Land Cover (LULC)	Spatial Data	N/A	MRLC, 2021
Reference Evapotranspiration	Spatial Data	N/A	CGIAR, 2019
Area of Interest	Spatial Data	N/A	User generated
Biophysical Table	CSV Table	N/A	User generated
Reference Air Temperature	Input Value	31°C	NOAA, 2024
UHI Effect	Input Value	3°C	NOAA, 2024
Air Blending Distance	Input Value	500m	InVEST User Guide
Maximum Cooling Distance	Input Value	450m	InVEST User Guide
Shade/Albedo/ET Weight	Input Values	0.6 / 0.2 / 0.2	User Guide

Notes: The inputs include a combination of tabular data, user-inputs into a GUI, and spatial data.

Table 2: All Inputs Required by the Biophysical Table for the InVEST Urban Cooling Model

Biophysical Table Variable	Value	Source
Land Use Code	LULC code	MRLC, 2021
Crop Coefficient (kc)	Unitless integer	CGIAR, 2019; OpenET, 2024
Green Area	Binary 0 or 1	User decision
Shade	Range from 0 to 1	MRCOG, 2020
Albedo	Range from 0 to 1	USGS, 2022; USGS, 2023

Table 3: The LULC Types Included in the Model, with the "Green Area" Determination for Each

LULC Type	Green Area
Open Water	Yes
Developed, Open Space	Yes
Developed, Low Intensity	No
Developed, Medium Intensity	No
Developed, High Intensity	No
Barren Land	No
Deciduous Forest	Yes
Evergreen Forest	Yes
Mixed Forest	Yes
Shrub/Scrub	No
Grassland/Herbaceous	No
Pasture/Hay	Yes
Cultivated Crops	Yes
Woody Wetlands	Yes
Emergent Herbaceous Wetlands	Yes

Table 4: Correlation Matrix for Environmental Quality Variables

	GREEN-DIST	DITCH-DIST	RIVER-DIST	PM-2.5	AVG-CCI	LST	EVI	T-CANOPY-BG	WELL-DENS
GREEN-DIST	1.0000								
DITCH-DIST	0.1219	1.0000							
RIVER-DIST	0.0510	0.9747	1.0000						
PM-2.5	-0.3009	-0.4572	-0.4602	1.0000					
AVG-CCI	-0.0743	0.1749	0.1715	-0.0294	1.0000				
LST	0.1686	-0.3101	-0.3183	0.0335	-0.7671	1.0000			
EVI	-0.0803	0.0239	0.0482	0.0511	0.7118	-0.8076	1.0000		
T-CANOPY-BG	-0.2230	0.1587	0.1833	0.0824	0.7077	-0.7833	0.7568	1.0000	
WELL-DENS	0.0007	-0.1890	-0.1955	0.0924	0.2690	-0.2153	0.3699	0.2475	1.0000

Table 5: Description of Structural Characteristics

Variable	Description
LIST-PRICE	Listed sales price of each residential housing unit provided by Zillow (US$)
ZEST	An estimated housing price for each sampled single-family housing unit provided by using both public records and local market conditions (US$) as obtained from Zillow
BED	Number of bedrooms in each housing unit as obtained from Zillow (count)
BATH	Number of bathrooms in each housing unit as obtained from Zillow (count)
AGE	Age of each housing unit as obtained from Zillow. Calculated as 2024 minus the year of built (years).
GARAGE	A binary variable indicating if a housing unit has a garage attached to it as obtained from Zillow. 1= Yes, 0 = No
POOL	A binary variable indicating if a housing unit has a private swimming pool as obtained from Zillow. 1= Yes, 0 =No
AREA	Total living area of each housing unit measured in square feet as obtained from Zillow.
LOTSIZE	Lot size of each housing unit in acres as obtained from Zillow. Descriptions measured in square feet but converted to acres using 43,560 square feet = 1 acre
WAT-SMART	A binary variable indicating whether a housing unit is shown as having “Water-Smart Landscaping” as obtained from Zillow (interpretated generally as including anything from simple piped irrigation to more efficient, metered systems). 1=Yes, 0 = No.

Table 6: Description of Neighborhood Variables

Variable	Description
MED-INC	Median annual household income (in US$) for the block group where housing unit is situated as obtained from the 2021 American Community Survey (ACS) 5-Year Estimates. Values are scaled by thousands.
HWAY-DIST	Euclidean distance (in miles) from a housing unit to the nearest highway (either Interstate 20 or 40). Shape file obtained from Resource GIS at the University of New Mexico (UNM). https://rgis.unm.edu/rgis6/dataset.html?uuid=50d2b2fc-7563-490c-947b-894a471f0e6d
AVG-UEMP	Average unemployment rate, measured from Oct 2022 to February 2024 in the county of the property unit. Data is obtained from Local Area Unemployment Statistics (LAUS) website (New Mexico Workforce Connection, 2024). https://www.jobs.state.nm.us/vosnet/analyzer/resultsNew.aspx?session=labforce&qlink=1&plang=E
ELM-SCH	Euclidean distance from a housing unit to the nearest elementary school as obtained from Zillow.
MID-SCH	Euclidean distance from a housing unit to the nearest middle school as obtained from Zillow
HIGH-SCH	Euclidean distance from a housing unit to the nearest high school as obtained from Zillow
ESCH-RATINGS	GreatSchools ratings for the nearest elementary school to the property unit as obtained from Zillow. Ratings are based on a scale of 1-10 (with 1-4 as “below average”, 5-6 as “average” and 7-10 as “above average”). https://www.greatschools.org/gk/ratings/
MSCH-RATINGS	GreatSchools ratings for the nearest high school to the property unit as obtained from Zillow. Ratings are based on a scale of 1-10 (with 1-4 as “below average”, 5-6 as “average” and 7-10 as “above average”). https://www.greatschools.org/gk/ratings/
HSCH-RATINGS	GreatSchools ratings for the nearest high school to the nearest property as obtained from Zillow. Ratings are based on a scale of 1-10 (with 1-4 as “below average”, 5-6 as “average” and 7-10 as “above average”). https://www.greatschools.org/gk/ratings/
POP-DENS	Population density within the block group, where the housing unit is situated. Calculated as 2021 ACS population figure divided by land area of block group, measured in squared miles.
WHITE-PCT	Percentage of the population within the block group who are white, as obtained from the 2021 ACS 5-Year Estimates.

Table 7: Description of Environmental Quality Variables

Variable	Description
LST	Average Land Surface Temperature measured in degrees Celsius of a 0.25-mile buffer around each house, for the summer months (between May and August) of 2022 and 2023 as obtained from the USGS data portal. https://www.usgs.gov/landsat-missions/landsat-collection-2-surface-temperature
LST-BG	Average Land Surface Temperature measured in degrees Celsius for the block group where the house is located for the summer months (between May and August) of 2022 and 2023, as obtained from the USGS data portal. https://www.usgs.gov/landsat-missions/landsat-collection-2-surface-temperature
AVE-CCI	Cooling Capacity Index (ranging from 0 to 1, with 0 being the lowest and 1 being the greatest relative cooling capacity within the modeled extent) for a 0.25-mile buffer around each house, as derived from the InVEST Urban Cooling Model.
AVE-CCI-BG	Cooling Capacity Index (ranging from 0 to 1, with 0 being the lowest and 1 being the greatest relative cooling capacity within the modeled extent) for the block group where the house is located as derived from the InVEST Urban Cooling Model.
T-CANOPY	Tree Canopy cover (ranging from 0 to 1, representing a ratio from zero to 100% canopy cover) for a 0.25-mile buffer around each house, as obtained from high-resolution tree canopy classification data published by the Mid-Region Council of Governments (MRCOG). Tree canopy classified from 2020 National Agriculture Imagery Program imagery. https://www.arcgis.com/home/item.html?id=721be54c4f8647bab3c8f13a1fc337a0
T-CANOPY-BG	Tree Canopy Classification (ranging from 0 to 1, representing a ratio from zero to 100% canopy cover) for the block group where the house is located as obtained from high-resolution tree canopy classification data published by the Mid-Region Council of Governments (MRCOG) https://www.arcgis.com/home/item.html?id=721be54c4f8647bab3c8f13a1fc337a0
EVI	Enhanced Vegetation Index (ranging from -1 to 1, with values of 0.2 to 0.8 representing healthy vegetation), which quantifies vegetation density and greenness, for a 0.25-mile buffer around each house. Generated using Sentinel-2 imagery in Google Earth Engine. https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_SR_HARMONIZED
EVI-BG	Enhanced Vegetation Index (ranging from -1 to 1, with values of 0.2 to 0.8 representing healthy vegetation), which quantifies vegetation density and greenness, for the block group where the house is located. Generated using Sentinel-2 imagery in Google Earth Engine. https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_SR_HARMONIZED
RIVER-DIST	Euclidean distance (in miles) from a house to the Middle Rio Grande measured in meters. Shape file obtained from the Esri USA Rivers

	and Streams shapefile hosted on ArcGIS Online. https://hub.arcgis.com/datasets/esri::usa-rivers-and-streams/about
DITCH-DIST	Euclidean distance (in miles) from a house to the nearest ditch. Ditches identified from the MRGCD Conveyances/Facilities shapefile hosted on the MRCGD spatial data repository. https://www.mrgcd.com/mapping-gis/
GREEN-DIST	Euclidean distance (in miles) from a house to the nearest greenspace including golf courses. Shapefile derived from the City of Albuquerque spatial data repository. Golf courses that were not included in the AGIS shapefile were manually digitized in ArcMap using Esri basemap imagery for reference. https://www.cabq.gov/gis/geographic-information-systems-data
WELL-DIST	Euclidean distance from a house to the nearest domestic well. Shape file obtained from NM Office of the State Engineer spatial data repository. https://geospatialdata-ose.opendata.arcgis.com/search?groupIds=fabf18d6e0634ae38c86475c9ada6498
WELL-DENS	Number of active domestic wells within 0.25 miles of a house. Calculated in ArcMap from shape file obtained from NM Office of the State Engineer spatial data repository. https://geospatialdata-ose.opendata.arcgis.com/search?groupIds=fabf18d6e0634ae38c86475c9ada6498
PM-2.5	5-year Average (2018 –2022) $PM_{2.5}$ for a 0.25-mile buffer where the housing unit is situated. Data set accessed from the University of Washington St. Louis Atmospheric Composition Analysis Group. Values measured in micrograms per cubic meter. https://sites.wustl.edu/acag/datasets/surface-pm2-5/
PM2.5-BG	5-year Average (2018 –2022) $PM_{2.5}$ for the block group where the housing unit is situated. Data set accessed from the University of Washington St. Louis Atmospheric Composition Analysis Group. Values measured in micrograms per cubic meter. https://sites.wustl.edu/acag/datasets/surface-pm2-5/

Table 8: Summary Statistics for Price Variables

Variable	N	Mean	Median	Std. Dev.
LIST-PRICE	5,543	467,308	397,325	292,809
ZEST	3,959	458,834	391,900	281,697

Table 9: Summary Statistics for Structural Characteristics

Variable	N	Mean	Median	Std. Dev.
BED	5,380	3.416914	3	0.7822939
BATH	5,381	2.531175	2	0.8431975
AGE	5,543	29.16489	23	25.88273
GARAGE	5,543	0.8316796	1	0.3741843
POOL	5,543	0.0436587	0	0.2043529
AREA	5,395	2,196.811	2,018	930.7519
LOTSIZE	5,238	0.5026519	0.18	1.749159
WAT-SMART	5,543	0.2798124	0	0.4489474

Table 10: Summary Statistics for Neighborhood Characteristics

Variable	N	Mean	Median	Std. Dev.
MED-INC	5,486	76.69399	74.519	30.17789
HWAY-DIST	5,543	3.385539	2.656566	2.600476
AVG-UEMP	5,543	3.50074	3.4	0.1925943
ELM-SCH	5,543	1.497583	0.8	2.762998
MID-SCH	5,543	2.518275	1.5	2.971408
HIGH-SCH	5,543	3.565957	2.5	3.279033
ESCH-RATINGS	5,543	4.329785	4	1.319096
MSCH-RATINGS	5,543	4.051416	4	0.2208651
HSCH-RATINGS	5,543	4	4	0
POP-DENS	5,498	36.71421	28.63834	36.69418
WHITE-PCT	5,510	0.614881	0.5970696	0.2342742

Table 11: Summary Statistics for Environmental Quality Characteristics

Variable	N	Mean	Median	Std. Dev.
LST	5,543	49.55807	50.14924	2.653741
LST-BG	5,529	49.59902	50.09949	2.985142
AVE-CCI	5,543	0.1541544	0.1509787	0.0313111
AVE-CCI-BG	5,529	0.1546311	0.1493127	0.0359192
T-CANOPY	5,543	0.0943152	0.0730278	0.0857866
T-CANOPY-BG	5,543	0.0938757	0.0743853	0.0867356
EVI	5,543	0.1323124	0.1196823	0.0579743
EVI-BG	5,529	0.1351292	0.1184752	0.0572202
RIVER-DIST	5,543	4.26244	3.65538	3.477391
DITCH-DIST	5,543	3.265622	2.457331	3.467209
GSPACE-DIST	5,543	1.698923	0.3975538	2.638755
WELL-DIST	5,543	0.5811208	0.3865771	0.5773076
WELL-DENS	5,543	7.226231	0	24.02882
PM-2.5	5,543	5.803308	5.807342	0.5241856
PM2.5-BG	5,529	5.770552	5.781796	0.5235383

Table 12: Spatial Dependence Diagnostics for Baseline Classical OLS Results

Dependent Variable: lnLP			
Models	Test	MI/DF	Value
Model 1	Moran's I (error)	0.3202	39.5316***
	LM (lag)	1	830.5378***
	Robust LM (lag)	1	214.8161***
	LM (error)	1	1536.2193***
	Robust LM (error)	1	920.4976***
Model 2	Moran's I (error)	0.3206	39.5715***
	LM (lag)	1	833.0702***
	Robust LM (lag)	1	215.4985***
	LM (error)	1	1539.3017***
	Robust LM (error)	1	921.7300***

Notes: MI indicates the Moran's I score; DF indicates the degrees of freedom in the LM test; Significance is expressed as; *** p<0.01, ** p<0.05, * p<0.1

Table 13: Spatial Dependence Diagnostics for Extended Classical OLS Results

Dependent Variable: lnLP			
Models	Test	MI/DF	Value
Model 1	Moran's I (error)	0.3229	39.8847***
	LM (lag)	1	801.3222***
	Robust LM (lag)	1	194.5966***
	LM (error)	1	1561.8083***
	Robust LM (error)	1	955.0826***
Model 2	Moran's I (error)	0.3161	39.0499***
	LM (lag)	1	655.7981***
	Robust LM (lag)	1	132.3446***
	LM (error)	1	1496.7838***
	Robust LM (error)	1	973.3304***
Model 3	Moran's I (error)	0.3141	38.7997***
	LM (lag)	1	695.5914***
	Robust LM (lag)	1	155.4008***
	LM (error)	1	1477.6435***
	Robust LM (error)	1	937.4528***
Model 4	Moran's I (error)	0.3091	38.1937***
	LM (lag)	1	718.5398***
	Robust LM (lag)	1	174.1534***
	LM (error)	1	1431.5192***
	Robust LM (error)	1	887.1330***
Model 5	Moran's I (error)	0.3108	38.3841***
	LM (lag)	1	764.4280***
	Robust LM (lag)	1	194.1023***
	LM (error)	1	1446.5383***
	Robust LM (error)	1	876.2126***

Notes: MI indicates the Moran's I score; DF indicates the degrees of freedom in the LM test.
Significance is expressed as; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 14: Baseline Models, and Physical Features; SEM Results (N=5,113)

Dependent Variable: lnLP		
Variables	Model 1	Model 2
BATH	0.0233***	0.0233***
	(0.0052)	(0.0052)
AREA	0.0002***	0.0002***
	(0.0000)	(0.0000)
LOTSIZE	0.0238***	0.0238***
	(0.0019)	(0.0019)
POOL	0.0325**	0.0326**
	(0.0129)	(0.0129)
WAT-SMART	0.0279***	0.0279***
	(0.0061)	(0.0061)
GARAGE	0.0416***	0.0416***
	(0.0083)	(0.0083)
AGE	-0.003***	-0.003***
	(0.0002)	(0.0002)
POP-DENS	-0.0005***	-0.0005***
	(0.0001)	(0.0001)
WHITE-PCT	0.0516***	0.0518***
	(0.0136)	(0.0136)
MED-INC	0.0002*	0.0002*
	(0.0001)	(0.0001)
AVG-UEMP	-0.2786***	-0.2731***
	(0.0471)	(0.0478)
HWAY-DIST	-0.0055**	-0.0058**
	(0.0023)	(0.0023)
MSCH-RATINGS	0.0056	0.0054
	(0.0133)	(0.0133)
GREEN-DIST	-0.0055*	-0.0058**
	(0.0029)	(0.0029)
RIVER-DIST	0.0006	
	(0.002)	
PM2.5-BG	0.0183**	0.0187**
	(0.0074)	(0.0074)
DITCH-DIST		0.0013
		(0.0021)
SPATIAL ERROR (λ)	0.6869***	0.6868***
	(0.0132)	(0.0132)
Constant	13.2157***	13.1934***
	(0.1885)	(0.1905)
R-squared	0.8109	0.8109
AIC	-1865.72	-1866.04

Notes: AIC denotes the Akaike information criterion. Significance expressed as *** p<0.01, ** p<0.05, * p<0.1

Table 15: Extended SEM Results (N=5,113)

Dependent variable: lnLP					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0244***	0.023***	0.0242***	0.0232***	0.0235***
	(0.0052)	(0.0056)	(0.0052)	(0.0052)	(0.0052)
AREA	0.0002***	0.0003***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0238***	0.0239***	0.0227***	0.0241***	0.0224***
	(0.0019)	(0.002)	(0.0019)	(0.0019)	(0.0019)
POOL	0.0331***	0.0382**	0.0319**	0.0334**	0.0331**
	(0.0129)	(0.0138)	(0.0129)	(0.0129)	(0.0129)
WAT-SMART	0.0293***	0.0378***	0.0319***	0.0299***	0.0283***
	(0.0061)	(0.0065)	(0.0061)	(0.0061)	(0.0061)
GARAGE	0.0418***	0.0472***	0.0414***	0.0412***	0.0437***
	(0.0083)	(0.0088)	(0.0083)	(0.0083)	(0.0083)
AGE	-0.0031***	-0.0034***	-0.0034***	-0.0033***	-0.003***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
POP-DENS	-0.0005***	-0.001***	-0.0006***	-0.0006***	-0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
WHITE-PCT	0.0529***	0.0767***	0.0522***	0.0494***	0.0536***
	(0.0135)	(0.0142)	(0.0135)	(0.0136)	(0.0136)
MED-INC	0.0002*	0.0005***	0.0002**	0.0002**	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AVG-UEMP	-0.2874***	-0.2907***	-0.3217***	-0.2752***	-0.2857***
	(0.0463)	(0.029)	(0.0436)	(0.0444)	(0.0462)
HWAY-DIST	-0.0047**	-0.0003	-0.0035	-0.0031	-0.0057**
	(0.0023)	(0.0018)	(0.0022)	(0.0022)	(0.0023)
MSCH-RATINGS	0.0039	0.0053	0.0073	0.007	0.0063
	(0.0132)	(0.0136)	(0.0132)	(0.0132)	(0.0133)
GREEN-DIST	-0.0045	-0.0051***	-0.0045*	-0.004	-0.0057**
	(0.0028)	(0.002)	(0.0027)	(0.0027)	(0.0028)
RIVER-DIST	-0.0012	-0.0087***	-0.0007	-0.0019	-0.0012
	(0.002)	(0.0015)	(0.0019)	(0.002)	(0.002)
PM2.5-BG	0.0188**	0.024***	0.0163**	0.0177**	0.0182**
	(0.0074)	(0.0077)	(0.0074)	(0.0074)	(0.0074)
AVG-CCI	1.0898***				
	(0.1596)				
LST		-0.0322***			
		(0.0018)			
EVI			1.1068***		
			(0.0974)		
T-CANOPY-BG				0.5474***	
				(0.0645)	
WELL-DENS					0.0006***
					(0.0001)
SPATIAL ERROR (λ)	0.6811***	0.3883***	0.6547***	0.6617***	0.6779***
	(0.0133)	(0.0193)	(0.014)	(0.0138)	(0.134)
Constant	13.0852***	14.7875***	13.2374***	13.159***	13.2286***
	(0.1869)	(0.168)	(0.1771)	(0.1801)	(0.1855)
R-squared	0.8122	0.7917	0.8132	0.8116	0.8109
AIC	-1909.91	-2025.53	-1984.93	-1931.35	-1880.09

Notes: AIC denotes the Akaike information criterion. Significance expressed as *** p<0.01, ** p<0.05, * p<0.1

Table 16: Extended SEM Results with lnZEST (N=3,674)

Dependent variable: lnZEST					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0105***	0.0116**	0.012**	0.01**	0.01**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
AREA	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0215***	0.0214***	0.0205***	0.0222***	0.0219***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
POOL	0.0278**	0.0272*	0.0269*	0.0293**	0.0284**
	(0.0147)	(0.0147)	(0.0147)	(0.0148)	(0.0148)
WAT-SMART	0.0233***	0.0257***	0.0272***	0.0239***	0.022***
	(0.0071)	(0.0071)	(0.0071)	(0.0071)	(0.0071)
GARAGE	0.0368***	0.037***	0.0357***	0.0371***	0.0396***
	(0.0096)	(0.0096)	(0.0096)	(0.0096)	(0.0097)
AGE	-0.0029***	-0.0032***	-0.0033***	-0.0031***	-0.0028***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
POP-DENS	-0.0007***	-0.0007***	-0.0007***	-0.0008***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
WHITE-PCT	0.0727***	0.0697***	0.0734***	0.0688***	0.0747***
	(0.016)	(0.0159)	(0.0159)	(0.016)	(0.016)
MED-INC	0.0002**	0.0002**	0.0003**	0.0003**	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AVG-UEMP	-0.295***	-0.281***	-0.3372***	-0.2818***	-0.2911***
	(0.0454)	(0.042)	(0.0429)	(0.0433)	(0.0451)
HWAY-DIST	-0.0031	0.0017	-0.001	-0.0008	-0.0038
	(0.0024)	(0.0023)	(0.0023)	(0.0023)	(0.0024)
MSCH-RATINGS	0.023	0.0209	0.0258*	0.0248	0.0239
	(0.0152)	(0.015)	(0.015)	(0.0151)	(0.0152)
GREEN-DIST	-0.0043	-0.0026	-0.0039	-0.0034	-0.0054
	(0.0029)	(0.0027)	(0.0028)	(0.0028)	(0.0029)
RIVER-DIST	-0.0001	-0.0047**	-0.0003	-0.0015	-0.002
	(0.002)	(0.002)	(0.0019)	(0.002)	(0.002)
PM2.5-BG	0.0282***	0.0274***	0.0263***	0.0271***	0.0285***
	(0.0084)	(0.0083)	(0.0083)	(0.0084)	(0.0084)
AVG-CCI	0.9041***				
	(0.1706)				
LST		-0.0283***			
		(0.0024)			
EVI			1.1481***		
			(0.1022)		
T-CANOPY-BG				0.5674***	
				(0.0683)	
WELL-DENS					0.0006***
					(0.0001)
SPATIAL ERROR (λ)	0.5991***	0.5595***	0.5683***	0.5730***	0.5942***
	(0.0149)	(0.0158)	(0.0156)	(0.0155)	(0.015)
Constant	12.9745***	14.4972***	13.1265***	13.0227***	13.0829***
	(0.1898)	(0.2166)	(0.1809)	(0.183)	(0.1883)
R-squared	0.8083	0.8106	0.811	0.8082	0.8073
AIC	-1513.37	-1503.03	-1604.24	-1549.81	-1502.78

Notes: AIC denotes the Akaike information criterion. Significance expressed as *** p<0.01, ** p<0.05, * p<0.1

Table 17: Extended SAR Results; Within MRGCD Boundaries (N=962)

Dependent variable: lnLP					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0854***	0.0847***	0.0847***	0.0859***	0.0852***
	(0.0146)	(0.0145)	(0.0145)	(0.0146)	(0.0147)
AREA	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0617***	0.0593***	0.0601***	0.063***	0.0642***
	(0.0061)	(0.006)	(0.0061)	(0.006)	(0.006)
POOL	0.0642	0.0559	0.0645	0.0638	0.0738*
	(0.0434)	(0.0432)	(0.0433)	(0.0433)	(0.0434)
WAT-SMART	0.0209	0.0266	0.0252	0.0205	0.0168
	(0.0227)	(0.0226)	(0.0228)	(0.0226)	(0.0226)
GARAGE	0.0791***	0.0804***	0.0785***	0.0802***	0.0816***
	(0.022)	(0.0219)	(0.022)	(0.022)	(0.0222)
AGE	-0.0022***	-0.0024***	-0.0024***	-0.0023***	-0.0022***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
POP-DENS	-0.0014***	-0.0013***	-0.0013***	-0.0014***	-0.0014***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
WHITE-PCT	0.1025**	0.0975**	0.1033**	0.0988**	0.1048**
	(0.0467)	(0.0464)	(0.0466)	(0.0466)	(0.0468)
MED-INC	0.0003	0.0004	0.0004	0.0003	0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
AVG-UEMP	-0.149***	-0.1777***	-0.1698***	-0.1427***	-0.1282***
	(0.0492)	(0.0489)	(0.05)	(0.048)	(0.0478)
HWAY-DIST	0.0017	0.0012	0.0023	0.0028	0.004
	(0.0078)	(0.0078)	(0.0076)	(0.0076)	(0.0077)
MSCH-RATINGS	-0.0143	-0.0163	-0.0129	-0.0142	-0.0193
	(0.0392)	(0.0389)	(0.0391)	(0.0391)	(0.0392)
GREEN-DIST	-0.01***	-0.0077**	-0.0093***	-0.0089***	-0.0105***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0035)
RIVER-DIST	0.0178*	0.0263**	0.018**	0.0192**	0.0116
	(0.0104)	(0.0104)	(0.0101)	(0.0102)	(0.0099)
PM2.5-BG	0.0883***	0.0785***	0.0864***	0.0808***	0.091***
	(0.0219)	(0.022)	(0.022)	(0.0222)	(0.022)
AVG-CCI	0.6399**				
	(0.3216)				
LST		-0.0184***			
		(0.0042)			
EVI			0.4302***		
			(0.1441)		
T-CANOPY-BG				0.3062***	
				(0.1024)	
WELL-DENS					0.0002
					(0.0002)
SPATIAL LAG (ρ)	0.3414***	0.3226***	0.3302***	0.3326***	0.3417***
	(0.026)	(0.0265)	(0.0267)	(0.0263)	(0.261)
Constant	7.7456***	9.1558***	8.0097***	7.9483***	7.7777***
	(0.4564)	(0.5741)	(0.4703)	(0.4628)	(0.4593)
R-squared	0.7921	0.7949	0.7929	0.793	0.7916
AIC	272.154	256.868	267.047	267.142	274.805

Notes: AIC denotes the Akaike Information Criterion. Significance expressed as *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 18: Extended SEM Results; Outside MRGCD Boundaries (N=4,151)

Dependent variable: lnLP					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0049	0.0051	0.005	0.0042	0.0046
	(0.0051)	(0.0051)	(0.0051)	(0.0051)	(0.0051)
AREA	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LOTSIZE	0.0135***	0.0143***	0.0134***	0.0136***	0.0133***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
POOL	0.0213*	0.0218*	0.0209*	0.0219*	0.0187
	(0.0118)	(0.0118)	(0.0118)	(0.0118)	(0.0118)
WAT-SMART	0.0294***	0.0302***	0.0304***	0.0299***	0.0305***
	(0.0054)	(0.0054)	(0.0054)	(0.0054)	(0.0054)
GARAGE	0.0284***	0.0287***	0.0276***	0.0283***	0.0285***
	(0.0081)	(0.0082)	(0.0081)	(0.0081)	(0.0081)
AGE	-0.0036***	-0.0038***	-0.0039***	-0.0038***	-0.0037***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
POP-DENS	-0.0003***	-0.0004***	-0.0004***	-0.0004***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
WHITE-PCT	0.0464***	0.0451***	0.0452***	0.0446***	0.0469***
	(0.0123)	(0.0124)	(0.0123)	(0.0123)	(0.0123)
MED-INC	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AVG-UEMP	-0.4576***	-0.3734***	-0.4345***	-0.4272***	-0.4618***
	(0.0614)	(0.0577)	(0.0592)	(0.0599)	(0.0591)
HWAY-DIST	-0.0076***	-0.005**	-0.007***	-0.0066***	-0.0073***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
MSCH-RATINGS	0.0111	0.0096	0.0121	0.0125	0.0098
	(0.0122)	(0.0122)	(0.0122)	(0.0122)	(0.0122)
GREEN-DIST	-0.0047	-0.0029	-0.0037	-0.0038	-0.0056**
	(0.0029)	(0.0028)	(0.0029)	(0.0029)	(0.0028)
RIVER-DIST	0.0007	-0.0039*	-0.0008	-0.001	0.002
	(0.0021)	(0.0021)	(0.002)	(0.002)	(0.002)
PM2.5-BG	0.0076	0.0079	0.0066	0.0081	0.0061
	(0.0069)	(0.0069)	(0.0069)	(0.0069)	(0.0069)
AVG-CCI	0.1585				
	(0.1812)				
LST		-0.0203***			
		(0.0029)			
EVI			0.6964***		
			(0.1457)		
T-CANOPY-BG				0.3473***	
				(0.0817)	
WELL-DENS					0.0031***
					(0.0005)
SPATIAL ERROR (λ)	0.7408**	0.7142**	0.7288**	0.7312**	0.7299**
	(0.013)	(0.0138)	(0.0134)	(0.0133)	(0.0133)
Constant	13.9159***	14.6789***	13.7929***	13.8089***	13.9549***
	(0.2333)	(0.2411)	(0.224)	(0.2254)	(0.2222)
R-squared	0.8399	0.8397	0.8399	0.8399	0.8404
AIC	-3091.32	-3133.49	-3112.32	-3107.92	-3124.39

Notes: AIC denotes the Akaike Information Criterion. Significance expressed as *** p<0.01, ** p<0.05, * p<0.1.

Table 19: Extended SAR Results with Ditches; Within MRGCD Boundaries (N=962)

Dependent variable: lnLP					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0833***	0.0823***	0.0824***	0.0838***	0.0836***
	(0.0146)	(0.0145)	(0.0145)	(0.0146)	(0.0146)
AREA	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LOTSIZE	0.0637***	0.0618***	0.0619***	0.0652***	0.0662***
	(0.0061)	(0.006)	(0.0061)	(0.006)	(0.006)
POOL	0.0634	0.0558	0.0633	0.0631	0.0747*
	(0.0433)	(0.043)	(0.0431)	(0.0431)	(0.0433)
WAT-SMART	0.0238	0.0289	0.0293	0.0232	0.0192
	(0.0227)	(0.0225)	(0.0227)	(0.0225)	(0.0226)
GARAGE	0.0809***	0.0826***	0.0804***	0.0822***	0.0839***
	(0.0219)	(0.0218)	(0.0219)	(0.0219)	(0.0221)
AGE	-0.0022***	-0.0023***	-0.0023***	-0.0022***	-0.0021***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
POP-DENS	-0.0015***	-0.0014***	-0.0013***	-0.0015***	-0.0014***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
WHITE-PCT	0.1008**	0.0976***	0.1012**	0.0971**	0.1025**
	(0.0464)	(0.0462)	(0.0463)	(0.0463)	(0.0466)
MED-INC	0.0003	0.0003	0.0003	0.0002	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
AVG-UEMP	-0.1146**	-0.1339***	-0.1367***	-0.1057**	-0.0974**
	(0.0491)	(0.0489)	(0.0497)	(0.0483)	(0.0484)
HWAY-DIST	-0.0085	-0.0082	-0.0092	-0.0072	-0.0063
	(0.0085)	(0.0083)	(0.0084)	(0.0084)	(0.0085)
MSCH-RATINGS	-0.0243	-0.0285	-0.0233	-0.0249	-0.0282
	(0.0391)	(0.0388)	(0.039)	(0.039)	(0.0391)
GREEN-DIST	-0.0128***	-0.0111***	-0.0123***	-0.0119***	-0.013***
	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
DITCH-DIST	0.0465***	0.051***	0.0511***	0.0474***	0.0416***
	(0.0142)	(0.014)	(0.0142)	(0.014)	(0.0139)
PM2.5-BG	0.092***	0.0836***	0.0899***	0.0843***	0.0943***
	(0.0219)	(0.0219)	(0.0218)	(0.022)	(0.0219)
AVG-CCI	0.7054**				
	(0.3118)				
LST		-0.0178***			
		(0.004)			
EVI			0.498***		
			(0.1437)		
T-CANOPY-BG				0.32***	
				(0.1001)	
WELL-DENS					0.0003
					(0.0002)
SPATIAL LAG (ρ)	0.3384***	0.3192***	0.3252***	0.3293***	0.3395***
	(0.0259)	(0.0265)	(0.0266)	(0.0262)	(0.026)
Constant	7.7019***	9.0735***	8.0014***	7.9142***	7.738***
	(0.4564)	(0.567)	(0.4689)	(0.4624)	(0.4588)
R-squared	0.7937	0.7962	0.7949	0.7946	0.7931
AIC	264.376	249.958	257.331	259.268	267.298

Notes: AIC denotes the Akaike Information Criterion. Significance expressed as *** p<0.01, ** p<0.05, * p<0.1.

Table 20: MIPs for Heat and Its Correlates Based on SEM Results (N = 5,113)

Variables	MIP at the mean price	MIP at the median price
AVG-ACC	$5,093	$4,330
LST	-$15,047	-$12,794
EVI	$5,172	$4,398
T-CANOPY-BG	$2,558	$2,175

11. Appendices

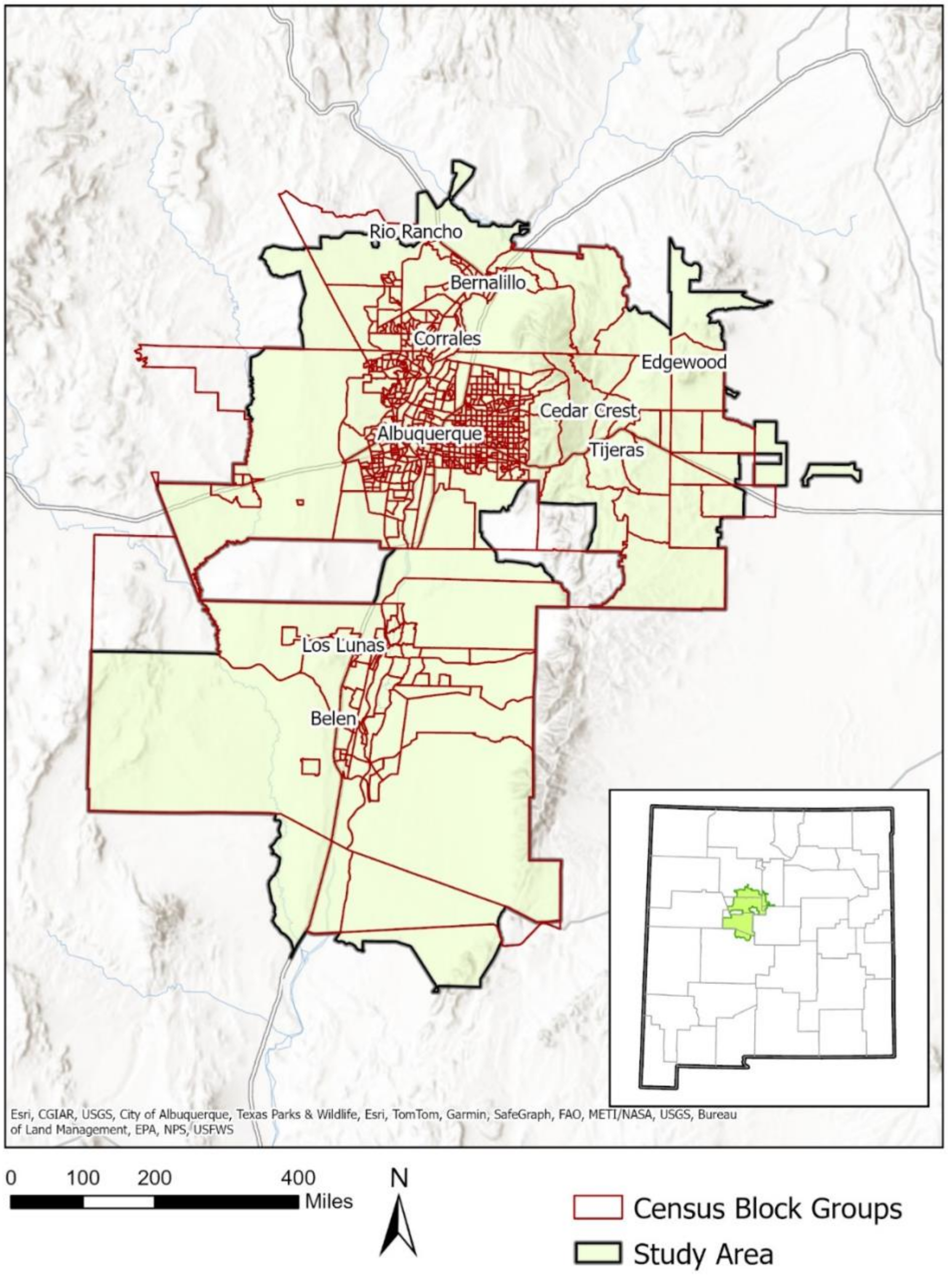

Figure A1: **A map of the study area showing the census block groups of the major cities within the study area.** Source: ArcGIS Pro

Table A1: Baseline Models, and Physical Features; Classical OLS Results (N=5,113)

Dependent Variable: lnLP		
Variables	Model 1	Model 2
BATH	0.0163**	0.0164**
	(0.0065)	(0.0065)
AREA	0.0003***	0.0003***
	(0.0000)	(0.0000)
LOTSIZE	0.0269***	0.0266***
	(0.0021)	(0.0021)
POOL	0.0571***	0.0571***
	(0.0160)	(0.0160)
WAT-SMART	0.0447***	0.0447***
	(0.0074)	(0.0074)
GARAGE	0.0479***	0.0474***
	(0.0102)	(0.0102)
AGE	-0.0022***	-0.0022***
	(0.0002)	(0.0002)
POP-DENS	-0.0016***	-0.0016***
	(0.0001)	(0.0001)
WHITE-PCT	0.1498***	0.1500***
	(0.0158)	(0.0158)
MED-INC	0.0011***	0.0011***
	(0.0001)	(0.0001)
AVG-UEMP	-0.2916***	-0.2901***
	(0.0225)	(0.0233)
HWAY-DIST	-0.0075***	-0.0075***
	(0.0014)	(0.0014)
MSCH-RATINGS	0.0339**	0.0338**
	(0.0146)	(0.0146)
GREEN-DIST	-0.0095***	-0.0092***
	(0.0015)	(0.0016)
RIVER-DIST	-0.0026**	
	(0.0012)	
PM2.5-BG	0.0390***	0.0417***
	(0.0084)	(0.0083)
DITCH-DIST		-0.0020
		(0.0012)
Constant	12.8052***	12.7800***
	(0.1266)	(0.1285)
R-squared	0.7183	0.7182
AIC	-431.114	-428.824
VIF > 10	No	No

Notes: Significance expressed as *** p<0.01, ** p<0.05, * p<0.

Table A2: Extended Models; Classical OLS Results (N=5,113)

Dependent variable: lnLP					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0181***	0.0199***	0.0200***	0.0184***	0.0185***
	(0.0064)	(0.0062)	(0.0063)	(0.0063)	(0.0064)
AREA	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0249***	0.0237***	0.0224***	0.0238***	0.0250***
	(0.0021)	(0.0020)	(0.0020)	(0.0020)	(0.0021)
POOL	0.0577***	0.0523***	0.0511***	0.0549***	0.0579***
	(0.0159)	(0.0155)	(0.0156)	(0.0156)	(0.0158)
WAT-SMART	0.0489***	0.0508***	0.0532***	0.0497***	0.0472***
	(0.0074)	(0.0072)	(0.0072)	(0.0072)	(0.0073)
GARAGE	0.0499***	0.0542***	0.0476***	0.0520***	0.0572***
	(0.0101)	(0.0098)	(0.0099)	(0.0100)	(0.0101)
AGE	-0.0024***	-0.0032***	-0.0034***	-0.0030***	-0.0023***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
POP-DENS	-0.0016***	-0.0014***	-0.0015***	-0.0016***	-0.0015***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
WHITE-PCT	0.1545***	0.1351***	0.1492***	0.1374***	0.1552***
	(0.0158)	(0.0153)	(0.0154)	(0.0155)	(0.0157)
MED-INC	0.0011***	0.0010***	0.0011***	0.0011***	0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AVG-UEMP	-0.3022***	-0.2923***	-0.3518***	-0.2943***	-0.3052***
	(0.0224)	(0.0217)	(0.0221)	(0.0220)	(0.0223)
HWAY-DIST	-0.0065***	-0.0012	-0.0049***	-0.0035**	-0.0075***
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
MSCH-RATINGS	0.0295**	0.0133	0.0336**	0.0305**	0.0327**
	(0.0145)	(0.0141)	(0.0142)	(0.0143)	(0.0145)
GREEN-DIST	-0.0088***	-0.0068***	-0.0083***	-0.0071***	-0.0088***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
RIVER-DIST	-0.0039***	-0.0100***	-0.0037***	-0.0063***	-0.0005
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
PM2.5-BG	0.0404***	0.0347***	0.0362***	0.0326***	0.0378***
	(0.0083)	(0.0081)	(0.0081)	(0.0082)	(0.0083)
AVG-CCI	0.8931***				
	(0.1158)				
LST		-0.0300***			
		(0.0015)			
EVI			1.1557***		
			(0.0669)		
T-CANOPY-BG				0.6991***	
				(0.0448)	
WELL-DENS					0.0015***
					(0.0001)
Constant	12.7216***	14.4834***	12.9466***	12.8488***	12.8411***
	(0.1264)	(0.1492)	(0.1234)	(0.1237)	(0.1253)
R-squared	0.7216	0.7380	0.7339	0.7312	0.7245
AIC	-488.515	-799.867	-720.554	-667.634	-542.119
VIF > 10	No	No	No	No	No

Notes: Significance expressed as *** p<0.01, ** p<0.05, * p<0.1

Table A3: Baseline Models, and Physical Features (N=5,113)

Dependent Variable: lnLP		
Variables	Model 1	Model 2
BATH	0.0166	0.0167
	(0.0118)	(0.0119)
AREA	0.0003***	0.0003***
	(0.0000)	(0.0000)
LOTSIZE	0.0263***	0.0261***
	(0.0061)	(0.0060)
POOL	0.0608***	0.0607***
	(0.0201)	(0.0201)
WAT-SMART	0.0460***	0.0459***
	(0.0084)	(0.0084)
GARAGE	0.0461***	0.0456***
	(0.0149)	(0.0149)
AGE	-0.0022***	-0.0022***
	(0.0003)	(0.0003)
POP-DENS	-0.0016***	-0.0016***
	(0.0002)	(0.0002)
WHITE-PCT	0.1535***	0.1536***
	(0.0286)	(0.0285)
MED-INC	0.0012***	0.0012***
	(0.0002)	(0.0002)
AVG-UEMP	-0.2868***	-0.2879***
	(0.0439)	(0.0455)
HWAY-DIST	-0.0075**	-0.0075**
	(0.0034)	(0.0034)
MSCH-RATINGS	0.0322*	0.0324*
	(0.0166)	(0.0167)
GREEN-DIST	-0.0093***	-0.0089***
	(0.0032)	(0.0032)
RIVER-DIST	-0.0037*	
	(0.0020)	
PM2.5-BG	0.0386***	0.0412***
	(0.0124)	(0.0125)
DITCH-DIST		-0.0032
		(0.0020)
Constant	12.7481***	12.7304***
	(0.2113)	(0.2144)
R-squared	0.7248	0.7246
VIF > 10	No	No

Notes: All models include month-year fixed effects and robust standard errors. Significance expressed as: ***p<0.01, **p<0.05, *p<0.1

Table A4: Extended Models (N=5,113)

Dependent Variable: lnLP					
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0182	0.0200*	0.0201*	0.0186	0.0188
	(0.0117)	(0.0112)	(0.0113)	(0.0115)	(0.0117)
AREA	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0246***	0.0233***	0.0219***	0.0235***	0.0245***
	(0.0053)	(0.0046)	(0.0050)	(0.0052)	(0.0056)
POOL	0.0612***	0.0558***	0.0547***	0.0585***	0.0614***
	(0.0201)	(0.0188)	(0.0193)	(0.0197)	(0.0201)
WAT-SMART	0.0496***	0.0517***	0.0544***	0.0505***	0.0484***
	(0.0084)	(0.0084)	(0.0085)	(0.0083)	(0.0083)
GARAGE	0.0480***	0.0525***	0.0460***	0.0503***	0.0552***
	(0.0151)	(0.0151)	(0.0150)	(0.0152)	(0.0149)
AGE	-0.0024***	-0.0031***	-0.0034***	-0.0030***	-0.0023***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
POP-DENS	-0.0016***	-0.0014***	-0.0015***	-0.0016***	-0.0014***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
WHITE-PCT	0.1579***	0.1396***	0.1534***	0.1415***	0.1588***
	(0.0289)	(0.0273)	(0.0281)	(0.0282)	(0.0286)
MED-INC	0.0012***	0.0010***	0.0011***	0.0012***	0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
AVG-UEMP	-0.2971***	-0.2895***	-0.3485***	-0.2904***	-0.3004***
	(0.0410)	(0.0483)	(0.0444)	(0.0423)	(0.0416)
HWAY-DIST	-0.0066**	-0.0013	-0.0049	-0.0036	-0.0075**
	(0.0033)	(0.0034)	(0.0034)	(0.0034)	(0.0033)
MSCH-RATINGS	0.0287	0.0129	0.0325*	0.0295*	0.0312*
	(0.0174)	(0.0178)	(0.0171)	(0.0170)	(0.0163)
GREEN-DIST	-0.0087***	-0.0067**	-0.0081**	-0.0071**	-0.0087***
	(0.0032)	(0.0033)	(0.0035)	(0.0034)	(0.0031)
RIVER-DIST	-0.0048**	-0.0108***	-0.0048**	-0.0072***	-0.0016
	(0.0021)	(0.0024)	(0.0021)	(0.0022)	(0.0020)
PM2.5-BG	0.0399***	0.0345***	0.0359***	0.0325***	0.0375***
	(0.0122)	(0.0114)	(0.0114)	(0.0115)	(0.0116)
AVG-CCI	0.8024***				
	(0.2769)				
LST		-0.0293***			
		(0.0040)			
EVI			1.1427***		
			(0.1458)		
T-CANOPY-BG				0.6746***	
				(0.1179)	
WELL-DENS					0.0014***
					(0.0003)
Constant	12.6760***	14.3927***	12.8927***	12.7933***	12.7851***
	(0.2068)	(0.3402)	(0.2136)	(0.2081)	(0.2059)
R-squared	0.7274	0.7434	0.7400	0.7367	0.7306
VIF >10	No	No	No	No	No

Notes: All models include month-year fixed effects, and robust standard errors clustered by block group.
Significance expressed as: ***p<0.01, **p<0.05, *p<0.1

Table A5: Baseline Models, and Physical Features with lnZEST (N=3,674)

Dependent Variable: lnZEST		
Variables	Model 1	Model 2
BATH	0.0026	0.0027
	(0.0110)	(0.0110)
AREA	0.0003***	0.0003***
	(0.0000)	(0.0000)
LOTSIZE	0.0263***	0.0262***
	(0.0054)	(0.0054)
POOL	0.0517**	0.0516**
	(0.0205)	(0.0205)
WAT-SMART	0.0415***	0.0414***
	(0.0094)	(0.0094)
GARAGE	0.0382**	0.0378**
	(0.0153)	(0.0153)
AGE	-0.0022***	-0.0023***
	(0.0003)	(0.0003)
POP-DENS	-0.0015***	-0.0015***
	(0.0002)	(0.0002)
WHITE-PCT	0.1756***	0.1754***
	(0.0290)	(0.0289)
MED-INC	0.0011***	0.0012***
	(0.0002)	(0.0002)
AVG-UEMP	-0.2740***	-0.2771***
	(0.0457)	(0.0471)
HWAY-DIST	-0.0038	-0.0038
	(0.0034)	(0.0033)
MSCH-RATINGS	0.0476**	0.0479**
	(0.0201)	(0.0201)
GREEN-DIST	-0.0102***	-0.0097***
	(0.0033)	(0.0033)
RIVER-DIST	-0.0035	
	(0.0021)	
PM2.5-BG	0.0421***	0.0434***
	(0.0129)	(0.0129)
DITCH-DIST		-0.0032
		(0.0022)
Constant	12.6070***	12.6043***
	(0.2122)	(0.2155)
R-squared	0.7316	0.7315
VIF > 10	No	No

Notes: All models include month-year fixed effects, and robust standard errors clustered by block group. Significance expressed as: ***p<0.01, **p<0.05, *p<0.1

Table A6: Extended Models with lnZEST (N=3,674)

Dependent Variable: lnZEST					
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0044	0.0075	0.0074	0.0051	0.0050
	(0.0109)	(0.0107)	(0.0107)	(0.0109)	(0.0108)
AREA	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0252***	0.0239***	0.0219***	0.0235***	0.0249***
	(0.0048)	(0.0044)	(0.0043)	(0.0045)	(0.0050)
POOL	0.0510**	0.0460**	0.0431**	0.0495**	0.0522**
	(0.0203)	(0.0197)	(0.0200)	(0.0201)	(0.0206)
WAT-SMART	0.0453***	0.0471***	0.0516***	0.0460***	0.0437***
	(0.0094)	(0.0094)	(0.0094)	(0.0093)	(0.0092)
GARAGE	0.0400***	0.0425***	0.0378**	0.0442***	0.0476***
	(0.0154)	(0.0155)	(0.0152)	(0.0154)	(0.0150)
AGE	-0.0025***	-0.0031***	-0.0034***	-0.0031***	-0.0024***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
POP-DENS	-0.0015***	-0.0013***	-0.0014***	-0.0015***	-0.0014***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
WHITE-PCT	0.1787***	0.1572***	0.1736***	0.1604***	0.1802***
	(0.0292)	(0.0274)	(0.0282)	(0.0278)	(0.0289)
MED-INC	0.0011***	0.0010***	0.0010***	0.0011***	0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
AVG-UEMP	-0.2867***	-0.2905***	-0.3499***	-0.2831***	-0.2871***
	(0.0430)	(0.0481)	(0.0458)	(0.0427)	(0.0434)
HWAY-DIST	-0.0030	0.0023	-0.0012	0.0000	-0.0040
	(0.0034)	(0.0034)	(0.0033)	(0.0033)	(0.0033)
MSCH-RATINGS	0.0464**	0.0315	0.0474**	0.0457**	0.0455**
	(0.0206)	(0.0206)	(0.0205)	(0.0205)	(0.0196)
GREEN-DIST	-0.0096***	-0.0071**	-0.0083**	-0.0077**	-0.0096***
	(0.0033)	(0.0034)	(0.0036)	(0.0035)	(0.0033)
RIVER-DIST	-0.0043*	-0.0102***	-0.0045**	-0.0069***	-0.0015
	(0.0022)	(0.0025)	(0.0022)	(0.0023)	(0.0021)
PM2.5-BG	0.0429***	0.0381***	0.0395***	0.0360***	0.0414***
	(0.0126)	(0.0119)	(0.0117)	(0.0119)	(0.0122)
AVG-CCI	0.7569**				
	(0.3082)				
LST		-0.0281***			
		(0.0043)			
EVI			1.1739***		
			(0.1530)		
T-CANOPY-BG				0.6916***	
				(0.1286)	
WELL-DENS					0.0012***
					(0.0003)
Constant	12.5421***	14.2281***	12.8052***	12.6695***	12.6470***
	(0.2073)	(0.3675)	(0.2164)	(0.2095)	(0.2080)
R-squared	0.7340	0.7492	0.7484	0.7446	0.7366
VIF>10	No	No	No	No	No

Notes: All models include month-year fixed effects, and robust standard errors clustered by block group.
Significance expressed as: ***p<0.01, **p<0.05, *p<0.1

Table A7: Baseline Models, and Physical Features with Conley Standard Errors (N=5,113)

Dependent Variable: lnLP		
Variables	Model 1	Model 2
BATH	0.0166	0.0167
	(0.0107)	(0.0107)
AREA	0.0003***	0.0003***
	(0.0000)	(0.0000)
LOTSIZE	0.0263***	0.0261***
	(0.0057)	(0.0057)
POOL	0.0608***	0.0607***
	(0.0187)	(0.0188)
WAT-SMART	0.0460***	0.0459***
	(0.0073)	(0.0073)
GARAGE	0.0461***	0.0456***
	(0.0134)	(0.0134)
AGE	-0.0022***	-0.0022***
	(0.0003)	(0.0003)
POP-DENS	-0.0016***	-0.0016***
	(0.0001)	(0.0001)
WHITE-PCT	0.1535***	0.1536***
	(0.0213)	(0.0213)
MED-INC	0.0012***	0.0012***
	(0.0001)	(0.0001)
AVG-UEMP	-0.2868***	-0.2879***
	(0.0303)	(0.0312)
HWAY-DIST	-0.0075***	-0.0075***
	(0.0021)	(0.0021)
MSCH-RATINGS	0.0322**	0.0324**
	(0.0147)	(0.0147)
GREEN-DIST	-0.0093***	-0.0089***
	(0.0023)	(0.0023)
RIVER-DIST	-0.0037**	
	(0.0016)	
PM2.5-BG	0.0386***	0.0412***
	(0.0103)	(0.0102)
DITCH-DIST		-0.0032*
		(0.0016)
R-squared	0.7230	0.7229
Distance-cutoff	1 km	1km

Notes: All models include month-year-fixed effects, and Conley standard errors. Significance expressed as: ***p<0.01, **p<0.05, *p<0.1

Table A8: Extended Models with Conley Standard Errors (N=5,113)

Dependent Variable: lnLP					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0182*	0.0200**	0.0201*	0.0186*	0.0188*
	(0.0105)	(0.0101)	(0.0103)	(0.0104)	(0.0105)
AREA	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0246***	0.0233***	0.0219***	0.0235***	0.0245***
	(0.0051)	(0.0044)	(0.0047)	(0.0050)	(0.0053)
POOL	0.0612***	0.0558***	0.0547***	0.0585***	0.0614***
	(0.0186)	(0.0178)	(0.0179)	(0.0183)	(0.0186)
WAT-SMART	0.0496***	0.0517***	0.0544***	0.0505***	0.0484***
	(0.0073)	(0.0070)	(0.0071)	(0.0071)	(0.0072)
GARAGE	0.0480***	0.0525***	0.0460***	0.0503***	0.0552***
	(0.0134)	(0.0132)	(0.0132)	(0.0133)	(0.0133)
AGE	-0.0024***	-0.0031***	-0.0034***	-0.0030***	-0.0023***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
POP-DENS	-0.0016***	-0.0014***	-0.0015***	-0.0016***	-0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
WHITE-PCT	0.1579***	0.1396***	0.1534***	0.1415***	0.1588***
	(0.0215)	(0.0203)	(0.0208)	(0.0209)	(0.0212)
MED-INC	0.0012***	0.0010***	0.0011***	0.0012***	0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AVG-UEMP	-0.2971***	-0.2895***	-0.3485***	-0.2904***	-0.3004***
	(0.0299)	(0.0311)	(0.0310)	(0.0293)	(0.0297)
HWAY-DIST	-0.0066***	-0.0013	-0.0049**	-0.0036*	-0.0075***
	(0.0021)	(0.0022)	(0.0021)	(0.0021)	(0.0021)
MSCH-RATINGS	0.0287*	0.0129	0.0325**	0.0295*	0.0312**
	(0.0151)	(0.0154)	(0.0153)	(0.0151)	(0.0148)
GREEN-DIST	-0.0087***	-0.0067***	-0.0081***	-0.0071***	-0.0087***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
RIVER-DIST	-0.0048***	-0.0108***	-0.0048***	-0.0072***	-0.0016
	(0.0016)	(0.0017)	(0.0016)	(0.0016)	(0.0016)
PM25-BG	0.0399***	0.0345***	0.0359***	0.0325***	0.0375***
	(0.0102)	(0.0096)	(0.0097)	(0.0097)	(0.0100)
AVG-CCI	0.8024***				
	(0.1810)				
LST		-0.0293***			
		(0.0026)			
EVI			1.1427***		
			(0.1034)		
T-CANOPY-BG				0.6746***	
				(0.0737)	
WELL-DENS					0.0014***
					(0.0002)
R-squared	0.7256	0.7418	0.7383	0.7350	0.7289
Distance cutoff	1 km	1 km	1 km	1 km	1 km

Notes: All models include month-year fixed effects and Conley standard errors. Significance expressed as: ***p<0.01, **p<0.05, *p<0.1

Table A9: Baseline Models, and Physical Features with lnZEST; Classical OLS Results (N=3,674)

Dependent Variable: lnZEST		
Variables	Model 1	Model 2
BATH	0.0023	0.0024
	(0.0073)	(0.0073)
AREA	0.0003***	0.0003***
	(0.0000)	(0.0000)
LOTSIZE	0.0264***	0.0263***
	(0.0022)	(0.0022)
POOL	0.0466**	0.0465**
	(0.0181)	(0.0181)
WAT-SMART	0.0419***	0.0418***
	(0.0085)	(0.0085)
GARAGE	0.0402***	0.0398***
	(0.0116)	(0.0116)
AGE	-0.0023***	-0.0023***
	(0.0002)	(0.0002)
POP-DENS	-0.0015***	-0.0015***
	(0.0001)	(0.0001)
WHITE-PCT	0.1746***	0.1745***
	(0.0186)	(0.0186)
MED-INC	0.0011***	0.0011***
	(0.0001)	(0.0001)
AVG-UEMP	-0.2763***	-0.2776***
	(0.0263)	(0.0273)
HWAY-DIST	-0.0041**	-0.0041**
	(0.0017)	(0.0017)
MSCH-RATINGS	0.0494***	0.0496***
	(0.0165)	(0.0165)
GREEN-DIST	-0.0100***	-0.0097***
	(0.0018)	(0.0018)
RIVER-DIST	-0.0025*	
	(0.0014)	
PM2.5-BG	0.0435***	0.0448***
	(0.0095)	(0.0095)
DITCH-DIST		-0.0023
		(0.0014)
Constant	12.6556***	12.6486***
	(0.1445)	(0.1471)
R-squared	0.7253	0.7252
AIC	-571.422	-570.503
VIF > 10	No	No

Notes: Significance expressed as *** p<0.01, ** p<0.05, * p<0.1

Table A10: Extended Models with lnZEST: Classical OLS Results (N=5,113)

Dependent Variable: lnZEST					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0043	0.0075	0.0073	0.0050	0.0048
	(0.0073)	(0.0071)	(0.0071)	(0.0072)	(0.0073)
AREA	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0252***	0.0239***	0.0220***	0.0235***	0.0250***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
POOL	0.0459**	0.0411**	0.0380**	0.0446**	0.0472***
	(0.0180)	(0.0175)	(0.0175)	(0.0176)	(0.0179)
WAT-SMART	0.0462***	0.0477***	0.0521***	0.0468***	0.0441***
	(0.0085)	(0.0082)	(0.0083)	(0.0083)	(0.0084)
GARAGE	0.0422***	0.0444***	0.0395***	0.0461***	0.0498***
	(0.0116)	(0.0112)	(0.0113)	(0.0113)	(0.0116)
AGE	-0.0025***	-0.0032***	-0.0035***	-0.0032***	-0.0024***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
POP-DENS	-0.0015***	-0.0013***	-0.0014***	-0.0015***	-0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
WHITE-PCT	0.1779***	0.1551***	0.1721***	0.1587***	0.1792***
	(0.0185)	(0.0180)	(0.0180)	(0.0182)	(0.0185)
MED-INC	0.0011***	0.0009***	0.0010***	0.0011***	0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AVG-UEMP	-0.2901***	-0.2921***	-0.3518***	-0.2853***	-0.2895***
	(0.0263)	(0.0254)	(0.0260)	(0.0257)	(0.0261)
HWAY-DIST	-0.0032*	0.0022	-0.0015	-0.0001	-0.0043***
	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
MSCH-RATINGS	0.0480***	0.0323**	0.0487***	0.0469***	0.0471***
	(0.0164)	(0.0160)	(0.0160)	(0.0161)	(0.0163)
GREEN-DIST	-0.0094***	-0.0069***	-0.0081***	-0.0075***	-0.0095***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
RIVER-DIST	-0.0035***	-0.0096***	-0.0037***	-0.0063***	-0.0006
	(0.0014)	(0.0014)	(0.0013)	(0.0014)	(0.0014)
PM2.5-BG	0.0443***	0.0391***	0.0407***	0.0370***	0.0427***
	(0.0094)	(0.0092)	(0.0092)	(0.0093)	(0.0094)
AVG-CCI	0.8325***				
	(0.1331)				
LST		-0.0289***			
		(0.0018)			
EVI			1.1913***		
			(0.0759)		
T-CANOPY-BG				0.7159***	
				(0.0511)	
WELL-DENS					0.0012***
					(0.0001)
Constant	12.5829***	14.3196***	12.8533***	12.7195***	12.6958***
	(0.1442)	(0.1726)	(0.1405)	(0.1409)	(0.1432)
R-squared	0.7282	0.7440	0.7426	0.7393	0.7305
AIC	-608.532	-829.019	-808.757	-761.86	-639.684
VIF > 10	No	No	No	No	No

Notes: Significance expressed as *** p<0.01, ** p<0.05, * p<0.1

Table A11: Spatial Dependence Diagnostics for Extended Models with lnZEST

Dependent Variable: lnZEST			
Models	Test	MI/DF	Value
Model 1	Moran's I (error)	0.3314	28.9408***
	LM (lag)	1	105.6125***
	Robust LM (lag)	1	28.0373***
	LM (error)	1	820.8112***
	Robust LM (error)	1	743.2360***
Model 2	Moran's I (error)	0.3232	28.2260***
	LM (lag)	1	82.0564***
	Robust LM (lag)	1	18.5545***
	LM (error)	1	780.4817***
	Robust LM (error)	1	716.9799***
Model 3	Moran's I (error)	0.3185	27.8224***
	LM (lag)	1	91.1241***
	Robust LM (lag)	1	23.7987***
	LM (error)	1	758.1953***
	Robust LM (error)	1	690.87***
Model 4	Moran's I (error)	0.3132	27.3572***
	LM (lag)	1	91.9486***
	Robust LM (lag)	1	24.7416***
	LM (error)	1	732.8643***
	Robust LM (error)	1	665.6574***
Model 5	Moran's I (error)	0.3223	28.1439***
	LM (lag)	1	105.3941***
	Robust LM (lag)	1	29.7804***
	LM (error)	1	776.3127***
	Robust LM (error)	1	700.669***

Notes: MI indicates the Moran's I score; DF indicates the degrees of freedom in the LM test. Significance is expressed as; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A12: Extended Classical OLS Results; Within MRGCD Boundaries (N=962)

Dependent variable: lnLP					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0969***	0.0947***	0.0951***	0.0974***	0.0975***
	(0.0163)	(0.016)	(0.0161)	(0.0161)	(0.0163)
AREA	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0644***	0.0602***	0.0603***	0.0661***	0.0681***
	(0.0068)	(0.0066)	(0.0067)	(0.0066)	(0.0066)
POOL	0.0860*	0.0701	0.0832*	0.0829*	0.1054**
	(0.0483)	(0.0475)	(0.0478)	(0.0479)	(0.0483)
WAT-SMART	0.0269	0.0357	0.0365	0.0268	0.0215
	(0.0253)	(0.0248)	(0.0251)	(0.0250)	(0.0252)
GARAGE	0.0947***	0.0955***	0.0926***	0.0961***	0.1018***
	(0.0245)	(0.0241)	(0.0243)	(0.0243)	(0.0246)
AGE	-0.0026***	-0.0028***	-0.0029***	-0.0029***	-0.0026***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
POP-DENS	-0.0029***	-0.0026***	-0.0025***	-0.0029***	-0.0028***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
WHITE-PCT	0.1093**	0.1005**	0.1108**	0.1025**	0.117**
	(0.052)	(0.051)	(0.0514)	(0.0516)	(0.0521)
MED-INC	0.0016***	0.0015***	0.0015***	0.0015***	0.0014***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
AVG-UEMP	-0.2126***	-0.2544***	-0.2552***	-0.2017***	-0.1795***
	(0.0544)	(0.0532)	(0.0544)	(0.0527)	(0.0529)
HWAY-DIST	0.0231***	0.0204**	0.022***	0.0235**	0.0255***
	(0.0085)	(0.0082)	(0.0082)	(0.0082)	(0.0083)
MSCH-RATINGS	-0.0336	-0.035	-0.0277	-0.0315	-0.0404
	(0.0437)	(0.0427)	(0.0432)	(0.0432)	(0.0436)
GREEN-DIST	-0.0154***	-0.0113***	-0.0134***	-0.0131***	-0.0156***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
RIVER-DIST	0.0087	0.0236**	0.0117	0.0127	-0.0011
	(0.0116)	(0.0115)	(0.0112)	(0.0113)	(0.011)
PM2.5-BG	0.1217***	0.1025***	0.1153***	0.1062***	0.1271***
	(0.0245)	(0.0242)	(0.0242)	(0.0245)	(0.0245)
AVG-CCI	1.0801***				
	(0.3216)				
LST		-0.0302***			
		(0.0045)			
EVI			0.8316***		
			(0.1528)		
T-CANOPY-BG				0.5565***	
				(0.1104)	
WELL-DENS					0.0006***
					(0.0002)
Constant	12.0522***	13.9799***	12.2748***	12.2124***	12.1***
	(0.3377)	(0.4279)	(0.3340)	(0.3341)	(0.3369)
R-squared	0.7467	0.7561	0.752	0.7509	0.7466
AIC	438.494	402.245	418.204	422.365	439.007
VIF > 10	No	No	No	No	No

Notes: AIC denotes the Akaike Information Criterion. Significance expressed as *** p<0.01, ** p<0.05, * p<0.1

Table A13: Spatial Dependence Diagnostics for Extended Classical OLS Results; Within MRGCD boundaries

Dependent Variable: lnLP			
Models	Test	MI/DF	Value
Model 1	Moran's I (error)	0.1934	10.7204***
	LM (lag)	1	197.3398***
	Robust LM (lag)	1	100.3525***
	LM (error)	1	103.3486***
	Robust LM (error)	1	6.3613**
Model 2	Moran's I (error)	0.1915	10.6171***
	LM (lag)	1	174.5757 ***
	Robust LM (lag)	1	82.0362***
	LM (error)	1	101.3026***
	Robust LM (error)	1	8.7631***
Model 3	Moran's I (error)	0.1957	10.8427***
	LM (lag)	1	182.4314***
	Robust LM (lag)	1	85.2931***
	LM (error)	1	105.7566***
	Robust LM (error)	1	8.6183***
Model 4	Moran's I (error)	0.1890	10.4852***
	LM (lag)	1	184.3313***
	Robust LM (lag)	1	92.1989***
	LM (error)	1	98.6160***
	Robust LM (error)	1	6.4836**
Model 5	Moran's I (error)	0.1878	10.3979***
	LM (lag)	1	193.7616***
	Robust LM (lag)	1	101.2442***
	LM (error)	1	97.4301***
	Robust LM (error)	1	4.9128**

Notes: MI indicates the Moran's I score; DF indicates the degrees of freedom in the LM test. Significance is expressed as; *** p<0.01, ** p<0.05, * p<0.1

Table A14: Extended Classical OLS Results with Ditches; Within MRGCD Boundaries (N=962)

Dependent Variable: lnLP					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	0.0949***	0.0920***	0.0925***	0.0952***	0.0961***
	(0.0162)	(0.0159)	(0.0160)	(0.0161)	(0.0162)
AREA	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0662***	0.0628***	0.0623***	0.0685***	0.0704***
	(0.0068)	(0.0066)	(0.0067)	(0.0066)	(0.0067)
POOL	0.0844*	0.0695	0.0816*	0.0821*	0.1071**
	(0.0481)	(0.0472)	(0.0474)	(0.0476)	(0.0481)
WAT-SMART	0.0305	0.0384	0.0413*	0.0297	0.0236
	(0.0252)	(0.0247)	(0.0250)	(0.0249)	(0.0251)
GARAGE	0.0964***	0.0977***	0.0943***	0.0980***	0.1038***
	(0.0244)	(0.0239)	(0.0241)	(0.0242)	(0.0245)
AGE	-0.0026***	-0.0027***	-0.0028***	-0.0027***	-0.0025***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
POP-DENS	-0.0030***	-0.0027***	-0.0026***	-0.0029***	-0.0029***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
WHITE-PCT	0.1045**	0.0988*	0.1055**	0.0978*	0.1103**
	(0.0517)	(0.0507)	(0.0510)	(0.0512)	(0.0518)
MED-INC	0.0015***	0.0014***	0.0014***	0.0014***	0.0014***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
AVG-UEMP	-0.1827***	-0.2090***	-0.2218***	-0.1650***	-0.1530***
	(0.0541)	(0.0531)	(0.0540)	(0.0531)	(0.0536)
HWAY-DIST	0.0099	0.0087	0.0066	0.0109	0.0124
	(0.0094)	(0.0090)	(0.0092)	(0.0091)	(0.0093)
MSCH-RATINGS	-0.0424	-0.0477	-0.0383	-0.0418	-0.0484
	(0.0435)	(0.0426)	(0.0429)	(0.0431)	(0.0435)
GREEN-DIST	-0.0182***	-0.0148***	-0.0166***	-0.0161***	-0.0180***
	(0.0039)	(0.0038)	(0.0038)	(0.0039)	(0.0039)
DITCH-DIST	0.0482***	0.0557***	0.0579***	0.0507***	0.0413***
	(0.0158)	(0.0153)	(0.0156)	(0.0155)	(0.0155)
PM2.5-BG	0.1244***	0.1070***	0.1180***	0.1085***	0.1293***
	(0.0243)	(0.0240)	(0.0241)	(0.0243)	(0.0244)
AVG-CCI	1.2421***				
	(0.3422)				
LST		-0.0301***			
		(0.0043)			
EVI			0.9301***		
			(0.1518)		
T-CANOPY-BG				0.5893***	
				(0.1075)	
WELL-DENS					0.0007***
					(0.0002)
Constant	11.9671***	13.8799***	12.2035***	12.1387***	12.0410***
	(0.3373)	(0.4149)	(0.3318)	(0.3327)	(0.3363)
R-squared	0.7490	0.7584	0.7553	0.7534	0.7485
VIF > 10	No	No	No	No	No
AIC	429.616	393.183	405.434	412.796	431.784

Notes: AIC denotes the Akaike Information Criterion. Significance expressed as *** p<0.01, ** p<0.05, * p<0.1

Table A15: Spatial Dependence Diagnostics for Extended Classical OLS Results with Ditches; Within MRGCD boundaries

Dependent Variable: lnLP			
Models	Test	MI/DF	Value
Model 1	Moran's I (error)	0.1869	10.3533***
	LM (lag)	1	196.0368***
	Robust LM (lag)	1	104.3864***
	LM (error)	1	96.4372***
	Robust LM (error)	1	4.7868**
Model 2	Moran's I (error)	0.1821	10.1001***
	LM (lag)	1	172.0850***
	Robust LM (lag)	1	86.5391***
	LM (error)	1	91.5743***
	Robust LM (error)	1	6.0285**
Model 3	Moran's I (error)	0.1857	10.2911***
	LM (lag)	1	178.1170***
	Robust LM (lag)	1	89.0193***
	LM (error)	1	95.2494***
	Robust LM (error)	1	6.1517**
Model 4	Moran's I (error)	0.1802	10.0025***
	LM (lag)	1	182.0227***
	Robust LM (lag)	1	96.7389***
	LM (error)	1	89.6943***
	Robust LM (error)	1	4.4105**
Model 5	Moran's I (error)	0.1826	10.1042***
	LM (lag)	1	193.9129***
	Robust LM (lag)	1	105.5833***
	LM (error)	1	92.1390***
	Robust LM (error)	1	3.8094*

Notes: MI indicates the Moran's I score; DF indicates the degrees of freedom in the LM test.
Significance is expressed as; *** p<0.01, ** p<0.05, * p<0.1

Table A16: Extended Classical OLS Results; Outside MRGCD Boundaries (N=4,151)

Dependent variable: lnLP					
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
BATH	-0.0074	-0.0064	-0.0070	-0.0090	-0.0065
	(0.0067)	(0.0065)	(0.0066)	(0.0066)	(0.0066)
AREA	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LOTSIZE	0.0160***	0.0165***	0.0155***	0.0151***	0.0146***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
POOL	0.0486***	0.0487***	0.0452***	0.0511***	0.0365**
	(0.0156)	(0.0152)	(0.0154)	(0.0154)	(0.0154)
WAT-SMART	0.0548***	0.0551***	0.0568***	0.0560***	0.0563***
	(0.0071)	(0.0069)	(0.0069)	(0.0069)	(0.0069)
GARAGE	0.0261**	0.0273***	0.0204*	0.0240**	0.0292***
	(0.0108)	(0.0105)	(0.0106)	(0.0106)	(0.0106)
AGE	-0.0024***	-0.0034***	-0.0037***	-0.0033***	-0.0024***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
POP-DENS	-0.0014***	-0.0013***	-0.0014***	-0.0015***	-0.0013***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
WHITE-PCT	0.1486***	0.1262***	0.1409***	0.1335***	0.1476***
	(0.0154)	(0.0150)	(0.0151)	(0.0152)	(0.0152)
MED-INC	0.0011***	0.0008***	0.0009***	0.0010***	0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
AVG-UEMP	-0.3735***	-0.3122***	-0.3731***	-0.3476***	-0.3666***
	(0.0252)	(0.0248)	(0.0247)	(0.0248)	(0.0248)
HWAY-DIST	-0.0092***	-0.0048***	-0.0080***	-0.0066***	-0.0086***
	(0.0014)	(0.0014)	(0.0013)	(0.0014)	(0.0013)
MSCH-RATINGS	0.0419***	0.0243*	0.0450***	0.0402***	0.0419***
	(0.0143)	(0.0140)	(0.0141)	(0.0141)	(0.0141)
GREEN-DIST	-0.0064***	-0.0034**	-0.0051***	-0.0040**	-0.0072***
	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
RIVER-DIST	-0.0008	-0.0111***	-0.0056***	-0.0069***	0.0003
	(0.0013)	(0.0013)	(0.0012)	(0.0013)	(0.0012)
PM2.5-BG	0.0209**	0.0188**	0.0199**	0.0211**	0.0184**
	(0.0084)	(0.0082)	(0.0083)	(0.0083)	(0.0083)
AVG-CCI	0.0671				
	(0.1403)				
LST		-0.0292***			
		(0.0019)			
EVI			1.2542***		
			(0.1049)		
T-CANOPY-BG				0.6981***	
				(0.0593)	
WELL-DENS					0.0043***
					(0.0004)
Constant	13.1885***	14.6394***	13.1412***	13.1354***	13.1801***
	(0.1354)	(0.1600)	(0.1311)	(0.1311)	(0.1312)
R-squared	0.7308	0.7453	0.7398	0.7395	0.7388
VIF > 10	No	No	No	No	No
AIC	-1456	-1685.68	-1596.88	-1592.67	-1581.07

Notes: AIC denotes Akaike Information Criterion. Significance expressed as; *** p<0.01, ** p<0.05, * p<0.1

Table A17: Spatial Dependence Diagnostics for Extended Classical OLS Results; Outside MRGCD Boundaries

Dependent Variable: lnLP			
Models	Test	MI/DF	Value
Model 1	Moran's I (error)	0.3678	40.9891***
	LM (lag)	1	586.2489***
	Robust LM (lag)	1	122.5329***
	LM (error)	1	1644.8126***
	Robust LM (error)	1	1181.0966***
Model 2	Moran's I (error)	0.3649	40.6772***
	LM (lag)	1	484.1017***
	Robust LM (lag)	1	80.1424***
	LM (error)	1	1619.6574***
	Robust LM (error)	1	1215.6981***
Model 3	Moran's I (error)	0.3615	40.2922***
	LM (lag)	1	523.5872***
	Robust LM (lag)	1	100.5993***
	LM (error)	1	1589.2690***
	Robust LM (error)	1	1166.2811***
Model 4	Moran's I (error)	0.3570	39.7985***
	LM (lag)	1	533.6786***
	Robust LM (lag)	1	109.8216***
	LM (error)	1	1550.0611***
	Robust LM (error)	1	1126.2041***
Model 5	Moran's I (error)	0.3608	40.2166***
	LM (lag)	1	534.8977***
	Robust LM (lag)	1	106.2666***
	LM (error)	1	1582.9872***
	Robust LM (error)	1	1154.3560***

Notes: MI indicates the Moran's I score; DF indicates the degrees of freedom in the LM test.
Significance is expressed as; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A18: Summary Statistics for Price Variables; Within MRGCD Boundaries

Variable	N	Mean	Median	Std. Dev.
LIST-PRICE	1,024	535,241	415,000	432,630
ZEST	738	518,100	397,350	443,000

Table A19: Summary Statistics for Structural Characteristics; Within MRGCD Boundaries

Variable	N	Mean	Median	Std. Dev.
BED	992	3.3145	3	0.9007
BATH	992	2.5176	2	1.0573
AGE	1,024	38.7832	33.5	32.215
GARAGE	1,024	0.707	1	0.4553
POOL	1,024	0.0459	0	0.2094
AREA	1,024	2,315.594	2,013	1243.52
LOTSIZE	986	0.7676	0.26	1.7243
WAT-SMART	1,024	0.1992	0	0.3996

Table A20: Summary Statistics for Neighborhood Characteristics; Within MRGCD Boundaries

Variable	N	Mean	Median	Std. Dev.
MED-INC	1,018	66.99423	60.917	28.01582
HWAY-DIST	1,024	2.007107	1.871141	1.355519
AVG-UEMP	1,024	3.598482	3.4	0.2653624
ELM-SCH	1,024	1.031445	0.8	1.08913
MID-SCH	1,024	2.05791	1.5	1.69543
HIGH-SCH	1,024	3.146777	2.5	2.440184
ESCH-RATINGS	1,024	4.290039	4	1.333404
MSCH-RATINGS	1,024	4.055664	4	0.2293839
HSCH-RATINGS	1,024	4	4	0
POP-DENS	1,021	21.52578	15.83219	20.78235
WHITE-PCT	1,021	0.5670486	0.5498155	0.2128149

Table A21: Summary Statistics for Environmental Quality Characteristics; Within MRGCD Boundaries

Variable	N	Mean	Median	Std. Dev.
LST	1024	48.10884	48.37794	2.622131
LST-BG	1022	48.67563	49.20567	3.158348
AVE-CCI	1024	0.1787144	0.1710557	0.0334133
AVE-CCI-BG	1022	0.1717972	0.1663018	0.0419922
T-CANOPY	1024	0.1204089	0.1001364	0.0931841
T-CANOPY-BG	1024	0.1529177	0.1357409	0.1002608
EVI	1024	0.1879539	0.1721455	0.0779858
EVI-BG	1022	0.1700161	0.153796	0.0759995
RIVER-DIST	1024	1.254738	1.038765	0.9327525
DITCH-DIST	1024	0.3406909	0.1100228	0.790991
GREEN-DIST	1024	2.39828	0.8463617	3.308993
WELL-DIST	1024	0.1277581	0.0796394	0.1726955
WELL-DENS	1024	29.82324	14	46.95497
PM-2.5	1024	6.188833	6.367662	0.5004595
PM2.5-BG	1022	6.018324	6.158079	0.5564317

Table A22: Summary Statistics for Price Variables; Outside MRGCD Boundaries

Variable	N	Mean	Median	Std. Dev.
LIST-PRICE	4,519	451,915	395,000	248,004
ZEST	3,221	445,255	390,000	227,230

Table A23: Summary Statistics for Structural Characteristics; Outside MRGCD Boundaries

Variable	N	Mean	Median	Std. Dev.
BED	4,388	3.440064	3	0.7511463
BATH	4,389	2.534233	2	0.7868737
AGE	4,519	26.98539	21	23.68638
GARAGE	4,519	0.8599248	1	0.3471035
POOL	4,519	0.0431511	0	0.2032197
AREA	4,391	2,169.652	2018	840.9278
LOTSIZE	4,252	0.441224	0.17	1.749355
WAT-SMART	4,519	0.2980748	0	0.4574631

Table A24: Summary Statistics for Neighborhood Characteristics; Outside MRGCD Boundaries

Variable	N	Mean	Median	Std. Dev.
MED-INC	4,468	78.90401	75.886	30.21965
HWAY-DIST	4,519	3.69789	3.020127	2.711255
AVG-UEMP	4,519	3.478646	3.4	0.1640493
ELM-SCH	4,519	1.603209	.8	3.0059
MID-SCH	4,519	2.622593	1.5	3.181293
HIGH-SCH	4,519	3.660943	2.6	3.433932
ESCH-RATINGS	4,519	4.338792	4	1.315814
MSCH-RATINGS	4,519	4.050454	4	0.2189033
HSCH-RATINGS	4,519	4	4	0
POP-DENS	4,477	40.178	33.61749	38.60767
WHITE-PCT	4,489	0.6257602	0.6034381	0.2375674

Table A25: Summary Statistics for Environmental Quality Characteristics: Outside MRGCD Boundaries

Variable	N	Mean	Median	Std. Dev.
LST	4,519	49.88647	50.32171	2.549072
LST-BG	4,507	49.80841	50.25502	2.904255
AVE-CCI	4,519	0.1485891	0.1484688	0.027966
AVE-CCI-BG	4,507	0.1507385	0.1473665	0.0331854
T-CANOPY	4,519	0.0884024	0.0686518	0.082897
T-CANOPY-BG	4,519	0.0804969	0.0597285	0.0773494
EVI	4,519	0.1197041	0.1119242	0.0434166
EVI-BG	4,507	0.1272183	0.1142914	0.0486762
RIVER-DIST	4,519	4.943982	4.271362	3.481525
DITCH-DIST	4,519	3.928408	3.090774	3.496587
GREEN-DIST	4,519	1.54045	0.3598519	2.43433
WELL-DIST	4,519	0.6838523	0.522562	0.5873063
WELL-DENS	4,519	2.105776	0	8.189589
PM-2.5	4,519	5.715949	5.740188	0.4888926
PM2.5-BG	4,507	5.714367	5.736777	0.4990215