Title: Do Energy Savings Grow On (Shade) Trees?

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ABSTRACT

This study presents the first causal evidence that trees have a major impact on consumer demand—with large shade trees reducing household electricity use by more than 20 percent. This work contributes to the existing literature on the energy saving potential of urban forests by implementing a quasi-experimental design to identify a causal link between tree shade and energy use. Results suggest that the energy savings from tree shade are an order of magnitude greater than other energy-efficiency policy measures, providing new evidence that tree ordinances may serve as effective demand-side management policies.

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DO ENERGY SAVINGS GROW ON (SHADE) TREES?

Buildings account for 42 percent of energy use and 38 percent of CO_2 emissions in the United States, making building energy efficiency a key component of broader energy and climate goals (US Green Building Council, 2011). In recent years, state and federal governments have adopted stringent building code regulations and invested billions of dollars into demand side management (DSM) programs that subsidize energy-saving building improvements for homes and businesses. This surge in public investment has spurred a renewed interest in evaluations conventional policies, such as building codes, DSM policies, and behavioral interventions; with studies typically showing these conventional approaches have limited demand-reduction effects and fail cost-benefit tests (e.g. Jacobsen and Kotchen 2012; Davis et al., 2014; Alcott, 2011). Despite the well-established limitations of conventional DSM approaches, empirical research continues to overlook the role of environmental factors known to affect energy consumption. For example, sun exposure, a key environmental factor determining building energy performance, drives numerous engineering decisions about building design, such as building orientation, roof reflectance, heat ventilation, and shade.

Considering the widespread role that environmental factors play in energy efficiency, surprisingly little empirical research considers how the environmental factors, such as green infrastructure, can play a role in energy-conservation. Trees shade buildings during summer months, reducing air-conditioning usage, and can also serve as windbreaks during winter months, reducing heating requirements for buildings. Today, more than 3,400 U.S. cities have tree-ordinances to protect urban tree canopies, which

may offer effective DSM policies if shade trees and windbreak trees could substantially improve building energy efficiency (Tree City USA, 2015).

Conventional wisdom suggests that trees have little effect on consumer electricity consumption; however, these studies fail to demonstrate any causal connections. Current empirical research suggests a correlation between tree cover and slightly lower summer energy consumption, but fails to find effects large enough to attract policy attention. Donovan and Butry (2009) use monthly billing data from 460 homes in Sacramento, California, and find that homes with south and west facing trees have lower summertime energy bills. Pandit and Laband (2010) present a similar model for 160 homes in Auburn, Alabama, and find that a 20 percent increase in tree shade reduces summertime electricity bills between 3 and 9 percent, but also substantially increases winter electricity bills.

These studies identify effects based on cross-sectional comparisons of energy use between houses with varying levels of tree shade. Both papers include only basic controls for home characteristics (house square footage and presence of a pool) and rely almost entirely on average early-spring energy to serve as a proxy of baseline energy use without shade. However, these cross-sectional estimators will be biased if tree size is correlated with other variables that affect energy efficiency, such as home age. Pandit and Laband (2010) also require participant permission to read electricity meters, introducing selection bias into the estimates. Endogeneity problems are also likely if homeowners who prefer trees also practice energy conservation.

This essay presents the first causal evidence that trees have a major impact on consumer demand—with large shade trees reducing household electricity use by more than 20 percent. My work contributes to the existing literature on the energy saving

potential of urban forests in four ways. First, I use a quasi-experimental design to identify a causal link between tree shade and energy use. Estimates are identified by electricity variation "within" households, reducing omitted variable bias and endogeneity problems of cross-sectional "between" estimators. Second, my study draws from a full census of 30,000 households within the GRU service area, improving the consistency of estimates compared to previous studies with small samples and selection biases. Third, given the context of a city-wide tree ordinance, these estimates have direct policy relevance. Fourth, my estimates suggest that energy savings from tree shade coincide with seasons of peak electricity demand, providing new evidence that tree ordinances may serve as effective demand-side management policies. Results suggest that the energy savings from tree shade are on an order of magnitude greater than other energy-efficiency policy measures, such as a 2006 Florida state law increasing the stringency of building codes (Jacobsen and Kotchen, 2013).

EMPIRICAL SETTING AND DATA COLLECTION

Over the past decade of growing energy demand, Gainesville, Florida, has prioritized demand-side management programs designed to avert or delay major infrastructure upgrades. Since 2005, Gainesville Regional Utilities (GRU) has invested $27.8 million in energy conservation initiatives, including subsidies for energy-efficient retrofits and incentives for solar technology adoption (GRU, 2008). Despite aggressive efforts to slow demand growth, GRU's existing infrastructure will be unable to supply Gainesville's energy needs in the near-future. As a result, GRU commissioned a third-party to build and operate a 100-MW power plant that became operational in 2013. Under the 30-year contract, GRU must purchase all electricity output from the facility—a

cost of $3.1 billion over the contract lifetime. Ultimately, these costs will be passed onto consumers: average electricity prices already increased by 1.9 cents per kWh in 2013, for an increase of 15 percent in one year.[7] The high cost of supply-side solutions has spurred new interest in cost-effective demand-side solutions—specifically, policies that reduce energy demand more cheaply than the marginal cost of increasing energy supply.

In contrast, tree ordinances are not designed for demand-side management; rather the central aim of tree ordinances is to preserve the character, heritage, and beauty of Gainesville. Removing trees on private property has been regulated in Gainesville under a city-wide tree ordinance since 1999.[8] Like tree ordinances in hundreds of other U.S. cities, Gainesville's ordinance requires residents to apply for permits approved by a city arborist prior to the removal of any mature tree within the city limits (Treiman and Gartner, 2004; Kielbaso, 1989; U.S. Conference of Mayors, 2008).[9] Tree ordinance measures are strictly enforced and apply to all large trees on private property.[10] Since the energy savings from trees are largely anecdotal, the Gainesville tree ordinance is not recognized as part of city energy-efficiency efforts. In fact, like most cities, the

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[7] This calculations compares September 2012 and October 2013 based on GRU electricity rates. Average rates are total utility bills divided by total electricity consumption for a household consuming 700 kWh per month. Monthly bills were $88.36 in 2012 and $101.34 in 2013. A majority of the utility bill increase is due to an additional 2-cent per kWh fuel surcharge directly attributed to capital costs of the new power plant.

[8] Tree removal permitting regulations established under Gainesville City Ordinance Sec. 30-254 (Gainesville Land Development Code, Article VIII). A summary of regulations is available online at http://www.cityofgainesville.org/Portals/0/nod/UF-TreeRemovalRegulations-1.pdf.

[9] The exact number of U.S. cities that protect trees on private property is unknown. Multiple surveys confirm that over 130 cities have private property regulations, no comprehensive survey of all cities with tree ordinances exists. Two surveys suggest that private property restrictions apply to about 13% of U.S. cities (Treiman and Gartner 2004, Kielbaso 1989), while an informal survey of tree ordinances in 135 large cities reports that 68% of tree protection laws cover private properties (U.S. Conference of Mayors, 2008).

[10] During the period of this study, permits were required for any tree over 20-inches in diameter for single-family residences, and 8-inches in diameter for multi-family residences and planned single-family developments. However, regulations began at a 30-inch diameter for four specific tree species: Water Oaks, Laurel Oaks, Sweetgums, and Loblolly Pines.

Gainesville tree ordinance is void of any energy-conservation criteria to assess eligibility for tree removals or mitigation plantings. Moreover, Gainesville lacks any system to monitor energy savings from tree-related programs, which is information required for all traditional demand-side management programs operated by GRU.

The essay focuses on how changes in residential tree shade translate into changes in actual energy consumption. In particular, this essay focuses on changes in tree shade in a region of the southern United States with a humid tropical climate. The study uses residential utility data for households in the city of Gainesville, Florida. The data were downloaded from Gainesville-Green.com, which is a website designed to encourage energy conservation through the provision of publicly-available information on household energy consumption. The dataset includes monthly billing records for electricity and natural gas consumption for residential households. Monthly billing data spans from 2000 through 2012. Also included in the billing data are residence-specific identifier codes that correspond to unique street addresses. Based on street address, billing data are linked to several other datasets, including datasets of housing characteristics, renovation projects, and tree removals.

Tree Removal Permit Data

The data on tree removal permits are of primary interest because they record which residences have removed trees and, in particular, when the trees were removed. Information on the location and timing of tree removals, combined with billing data, allow a comparison of energy consumption before and after a change in tree cover. Permit data were acquired from the Gainesville city arborist, who enforces ordinances by visiting the residence of each applicant to assess whether trees are eligible for removal.

The dataset includes the street address of residents who were issued permits, the number of trees approved for removal by each permit, and the issue date for each permit.

The key characteristic is the issue date because it can be used to determine when a tree removal occurred and, in particular, whether a monthly energy bill is subject to shade conditions before or after the change in tree canopy.

Using permit issue dates to categorize monthly energy bills as occurring pre- or post-tree removal, one must also take account of the fact that permits are issued prior to tree removal and not on the actual date a tree is removed. According to tree ordinances, a tree removal permit is valid for a six-month period after the issue date, after which the permit expires. Thus, for tree-removal residences, monthly energy bills are categorized as pre- or post-tree removal, as follows: a billing-month earlier than the issue date designates a billing record as pre-tree removal; a billing-month occurring six-months after the issue date or later designates a bill as post-tree removal; and a billing-month that occurred less than six-months after the issue date designates a bill as indeterminate because the corresponding tree-cover of the residence is unclear. Thus, all bills occurring within the six-month period following a permit issue date are dropped from the analysis.

While the complete set of permits spans from 1999 through 2012, the analysis only includes permits issued from 2001 through 2011, the period that includes tree-removing residences with a full 12-months of billing data both before and after the permit issue date. Importantly, this essay's empirical strategy is based on a comparison of energy bills before and after a change in tree cover. The best comparison is based on residences with adequate billing information in both tree cover regimes. Thus, for this analysis, treated residents were excluded if they had fewer than 12-monthly billing

observations in either the pre-permit period or the post-permit period.[11] Even without this restriction, most treated residences have multiple years of pre-and-post treatment observations for each season. For example, the median treatment date of June 2007 includes 7.5 years (90 months) of billing data in the pre-permit period, and 4.5 years (54 months) of billing data in the post-permit period. Among the final treatment sample, 94-percent of residences have more than 18-months of billing data after the permit issue date, which guarantees at least one observation in each month-of-the-year for both the pre-treatment period and the post-treatment period.

To quantify the size and location of removed trees, an additional dataset is created from aerial imagery. Using two sets of 1-foot resolution aerial imagery taken in 2001 and 2011, a map of tree canopy loss was generated over 7,417 properties, including all tree removal sites and adjacent residences.[12] The resulting map classifies changes in tree cover during the 10-year period between 2001 and 2011, with tree canopy area mapped at a 1-meter resolution. Combining the tree loss map with data on property boundaries, provided by the Alachua County Property Appraiser, the owners of each tree canopy area are then identified.

[11] Results are robust to an alternate treatment definition that requires 24-monthly billing observations in both the periods leading up to and following the permit issue date.
[12] See Appendix 2.1 for additional details about input data and methods used to classify tree canopy loss.

Sun Position and Tree Shade

Additional data are also considered to measure the loss of shade associated with a tree removal. Tree shade can be determined from three metrics: tree size, tree location, and sun position. The first two factors—tree size and location—are quantified by mapping tree loss from aerial imagery. Specifically, a map of tree loss is created at the 1-meter pixel resolution.

In addition to quantifying tree position, a full characterization of shade coverage must also consider information about sun position. Sun position is defined by two angles: aspect angle (north, east, south and west) determines shadow direction; and altitude angle (0 to 90 degrees) determines shadow length. Sun movement describes temporal changes the sun position, which varies based on time-of-day and by season-of-year. Short shadows occur when sun reaches high altitudes, which reach a daily-maximum at solar noon, and an annual-maximum during the summer solstice. Conversely, longer shadows occur at low altitude angles, which occur near sunrise and sunset, and during winter months.

Figure 2 is a three-dimensional diagram of seasonal sun paths over Gainesville that conveys temporal changes in sun position relative to a house.[13] During the equinox, marking the first days of spring and autumn, the sun rises due east, sets due west, and arcs across the south reaching a maximum altitude of 60-degrees (the center arch in figure 2). On the winter solstice, with a brief 10-hours between sunrise (southeast) and sunset (southwest), the sun traverses the southern horizon at a low-altitude, reaching a

[13] The geographic coordinates at the center of Gainesville, Florida, are used to simulate sun paths and shadow position. Gainesville is located at latitude 29°39.0978′ N and longitude 82°19.4898′ W.

maximum angle of 35-degrees (the right arch in figure 2). In contrast, the summer solstice marks a 14-hour day, with sunrise in the northeast, sunrise in the northwest, and a mid-day sun passing overhead at a maximum altitude of 84-degrees (the left arch in figure 2).

Figure 3 illustrates the shadows of a 50-foot tree at various times of the day and various seasons. In the summer, western trees set back as far as 75 feet provide cooling shade in late afternoon, leading to our prior expectation that west-side trees may reduce summer electricity use from air conditioning. Interestingly, despite providing cooling shade during mid-afternoon, south-side trees may only reduce electricity consumption at distances of less than 25-feet from a house. This follows because south-side trees cast very short shadows during the Gainesville summer, as the mid-afternoon sun is positioned overhead at a high angle in the sky. In the winter, on the other hand, south-side trees provide almost all shading. In fact, due to the low altitude sun position, south-side trees set back as far as 100-feet can provide cooling shade that may increase heating demand for homes. Since most homes use natural gas during the winter, one could expect that south-side trees may increase natural gas used for heating.

Mapping Canopy Loss

Given that the amount of shade a tree provides depends upon its location, it is critical to develop a measure of tree cover loss that encompasses both tree size and tree position around houses. To do so, data from aerial imagery is used to construct a single measure of tree cover change for the decade-epoch spanning 2001-2011. The resulting dataset traces, at a spatial resolution of 1 meter by 1 meter, the patterns of tree cover loss across Gainesville that spans the time period of permit data for tree removals. This

section describes how the tree cover change dataset is constructed from raw aerial images.

There are two main challenges in constructing aerial images of tree loss. First, urban regions like Gainesville are composed of tightly interwoven land-uses, which are peppered with low-density tree cover. This makes it difficult to use satellite sensors, like Landsat, which have been used to measure annual tree loss in higher-density tree cover landscapes. Since these satellites have a coarse spatial resolution of 30 meters by 30 meters, satellite-derived images are too blurry to distinguish individual trees, measure canopy size, or identify tree location on residential properties. An alternative is to draw on sensors attached to low-flying aircraft, which are infrequently commissioned to photograph cities at an ultra-fine spatial resolution as detailed as 1 foot by 1 foot. This aerial imagery dramatic increases the spatial resolution and accuracy of classifications, but identifies tree loss over a longer 10-year interval instead of the annual time-interval possible with Landsat.

To generate the data used in this essay, two sets of aerial imagery are used as inputs. Images from 2001, used to characterize initial tree cover before tree removals, have a spatial resolution of 1 foot by 1 foot and include spectral signals for three bands, which are collectively known as the "visible bands" that can be seen with the human eye (blue [459-479 nm], green [545-565 nm], red [620-670 nm]). Images from 2011, used to characterize final tree cover after tree removals, also have a spatial resolution of 1 foot by 1 foot and include spectral signals for four bands, including the three visible bands, and a fourth band of near-infrared signals [841-876 nm]. Images were acquired separately, with the 2001 data purchased from the office of the Alachua County Property Assessor

(ACPA), and the 2011 data was provided by Florida State University. Both data sets were collected during summer months, during leaf-on seasons. Despite attempts to enhance 2001 images with an available band of 1999 near-infrared imagery, the data fusion was unsuccessful because the 1999 data were collected during a leaf-off season. Auxiliary data available on the ACPA website, including GIS building footprints and property boundaries, were used to define a study area and guide classifications.

Combining aerial images across time presents several challenges. Unlike satellites, which collect data over time with the same sensor, aircraft often collect data with different sensors over time, and these instrument changes introduce spectral differences in images across time. Moreover, spectral differences can also occur when images are collected from different altitudes, lens angles, or time-of-day images. Image post-processing corrects most distortions caused by flight patterns, but comparisons between aerial imagery are not consistently reliable at a spatial resolution of 1 foot by 1 foot. To enable comparison of spectral signals across time, both datasets are aggregated from a resolution of 1 foot by 1 to a resolution of 1 meter by 1 meter. Aggregating spatial resolution, in this case by an order of magnitude, has been shown to minimize error in spectral signals and improve the accuracy of change (Wulder et al., 2000). Despite loss of spatial detail, a final resolution of 1 meter by 1 meter permits a suitably precise measure of tree cover area and tree position.

For each 1 meter by 1 meter observation, a total of 129 image inputs is used (43 individual 1 foot by 1 foot single-band spectral observations for each year, plus their calculated differences). This amount of information, which adds 129 dimensions for each 1 meter by 1 meter pixel, is used to estimate a likelihood of tree cover loss for each pixel.

The next step is to take aerial image inputs and implement a computer algorithm to discriminate between tree and non-tree land cover. The purpose of remote sensing is to develop an algorithm that identifies what spectral signatures or set of signatures—in other words, what combinations of spectral and temporal information—best discriminate tree cover and its loss. For example, plants strongly absorb wavelengths of light in the visible spectrum, but also strongly reflect wavelengths in the near-infrared spectrum. Aerial sensors, which measure light reflected from the ground, will record weak visible (red) signals and strong near-infrared signals from green plant cover. One common metric for determining the density of green vegetation on a patch of land is the normalized difference vegetation index (NDVI), which captures differences in the reflectance of near-infrared and visible (red) light spectrum, and is a useful spectral signature for discerning the presence of vegetation.

In practice, however, one can do much better than using the NDVI alone by exploiting additional dimensions of the data. For example, trees have different spectral signatures than other types of green vegetation. These metrics help discriminate between trees and other bright green vegetation—such as lawns, bushes, and gardens—which remain green year-round in Florida. Several methods for change detection can exploit multi-dimensional data, including the popular Classification and Regression Tree; however, such objective methods are most effective when using two images recoded from the same sensor. For classification of aerial imagery taken at different altitudes and angles using different sensors, subjective methods like the pixel-based change detection method and unsupervised classification permit greater flexibility in identifying signals of land use change (see the Appendix for details on selecting the change detection method).

To take maximal advantage of the richness of spectral signals in the imagery data, a statistical learning procedure known as the iterative self-organizing data analysis technique (ISODATA) is used to identify tree loss. This is a change detection model used to determine which spectral signals best correspond to tree cover and its loss (Tou and Gonzalez 1974). The resulting map classifies changes in tree cover during the 10-year period between 2001 and 2011, with the tree canopy area mapped at a 1-meter resolution.

Shade Intensity Variables

After mapping tree canopy loss, some additional data analysis is needed prior to defining variables of treatment intensity. For the identification strategy employed in this essay, areas of tree canopy loss require details about the date of tree removal, and the tree location relative to nearby buildings—details that require auxiliary datasets. To assign a specific date of tree loss, each canopy area is linked to city tree removal permits based on the property address. As a preliminary step, a property address was first assigned to each area of canopy loss based on GIS property boundary data provided by the office of the ACPA. To characterize tree position around nearby buildings, two variables are calculated: the minimum distance between each tree and the house, and the aspect-angle (north, east, south, west) from the house to each tree. As a location reference for calculations, a GIS map of building footprints was downloaded from the ACPA website. Figure 3 provides a visual illustration of the three main GIS datasets, including tree canopy loss, property boundaries, and building footprints. Thus, maps of tree loss and building locations characterize tree position using two metrics: distance from house, and aspect angle to house.

To quantify the position of tree loss, each tree removal is grouped into one of sixteen regions around each house, as shown in Figure 4. For example, the northern quadrant canopy-loss variables measure the loss area within 25-feet of a house (N-1), loss area within 50-feet of a house (N-1,2), and loss area within 100-feet of a house (N-1,2,3,4). Distance cutoffs are identical for remaining quadrants to the east, south, and west of houses. If a tree canopy spans two or more regions, then the entire canopy area is assigned to the region nearest to the house. For example, in Figure 1, the dark green tree is assigned to region N-1. These canopy-loss variables permit flexible tests of how energy savings vary with differences in the canopy area, proximity to residences, and aspect-angle relative to residences.

To simplify interference, sun path information is use to define three levels of change in shade-intensity caused by tree-removals: heavy shade loss, light shade loss, and no shade loss. Figure 3 panel (b) illustrates how trees are assigned shade-intensity based on position around a house. Heavy shade trees are positioned within 50 feet of a house along the south, west, or east sides of the house (S-1,2; W-1,2; E-1,2). Light shade trees are set back further than 50 feet from the house on the south, west, or east sides; or within 25 feet of the house on the north side (S-3,4; W-3,4; E-3,4; N-1). Non-shade trees are on the north side of the house set back further than 25 feet from the house (N-2,3,4).

To complement shade-intensity variables, a less-parametric grouping of tree position and size helps to identify marginal treatment effects, such as increasing the area of canopy removed. For each house, twelve canopy-area variables are calculated. These correspond to the area of canopy loss, measured in square meters, contained within each of the sixteen regions around the house.

Matching and Sample Selection

Additional datasets are used to select appropriate control residences through covariate matching methods. Coarsened exact matching is used to identify a single control home for each treatment home based on housing characteristics and baseline energy use patterns (Blackwell et al., 2010). Matching serves to restrict the sample to improve estimate precision. If this ideal is met, then the tree-removal effect can be measured without bias. This is because controls estimate counterfactual outcomes for what the treated energy consumption would have been absent the tree removal treatment.

The goal of covariate matching is to select observable characteristics so that any two residents with the same value for these characteristics will display homogeneous responses to the tree-removal treatment. Ideally, matched treatment and control homes should be "statistical twins" concerning time-varying characteristics related to energy consumption and pre-treatment baseline energy consumption. To achieve this ideal, pre-treatment data on energy consumption are used to match houses with similar energy consumption profiles. Since the earliest tree removals occur in year 2001, baseline electricity and natural gas data from year 2000 are used to match homes with similar levels of summer electricity consumption and winter natural gas consumption. In addition, houses are matched on the increase in electricity consumption between spring and summer, which serves as a proxy for air-conditioning demand.

Time invariant structural characteristics correlated with unobserved time-varying characteristics are also useful matching parameters. The primary motivation for matching in the context of this study is to control for unobserved time-varying

characteristics that affect the energy-savings from tree removals. A priori, energy savings from tree shade are presumed to be dominated by climate-related energy consumption. Thus, treatment and control houses should share characteristics that affect climate-related responses in energy consumption. In this study, structural characteristics are used to match houses with similar heating and cooling requirements and construction quality. Data come from the ACPA property sale database, and include information on house age, square footage, number of stories, number of bedrooms, type of air-conditioning system, heating fuel, and type of roof. Building age is correlated with building energy-efficiency and with the age and size of neighborhood trees. Characteristics of house size are correlated with the heating and cooling requirements of a house. Air conditioning (represented by a central air-conditioning dummy) and heating fuel (electricity, gas, or oil) relate to seasonal variation in electricity and natural gas consumption, while type of roof (shingle, tile, wood, metal) may affect heat transfer from solar radiation.

Exact matching is possible for categorical variables, such as heating fuel type and roof type. For continuous variables, such as energy consumption and square footage, exact matching is applied to coarsened data. In this analysis, each continuous variable is disaggregated into 10-strata that correspond to deciles in the distribution of the treated residences. Exact matching is then applied to minimize the multivariate distance between two residences across all coarsened variables.

To select controls based on a coarsened exact matching distance measure, the method of nearest neighbor matching is most common. In particular, 1:1 nearest neighbor matching selects for each tree-removal resident *i* the control resident with the

smallest distance from resident *i*. One concern of 1:1 matching is the possible reduction in power from discarding unmatched observations. However, the reduction in power is minimal for two reasons. First, in a two-sample comparison of means, the precision is driven by the smaller group size. Because the treatment group stays the same size, and only the control group decreases in size, the overall power should not be greatly reduced (Ho et al. 2007). Second, power increases when groups are more similar because of higher precision and reduced extrapolation (Snedecor and Cochran, 1980). Given the vast number of control residents available in the sample, matching is conducted without replacement and without imposing calipers, simplifications that also lead to easier interpretation of effects. For estimation, matches are pooled into matched treated and control groups and analyses use the groups as a whole, rather than individual matched pairs.

Estimating effects without bias requires that, given a vector of covariates, the non-treated outcomes are what the treated outcomes would have been had they not been treated (i.e. tree-removal is independent of changes in energy use for "similar" residents). Internal validity of estimates relies on the assumption that, after matching on observable characteristics, tree removal is as-good-as random across the sample. One potential concern is self-selection bias, which could arise if all residents have the option to remove trees, and if those residents electing to remove trees differ in terms of potential energy-use outcomes from other residents.

In this study, tree ordinance laws minimize self-selection concerns because, for most residents, removing trees is not a legal option. In particular, the city arborist only approves permits for trees that are dying, diseased, or damaging property; the arborist

denies permits for unnecessary tree removals. The permit vetting process, enforced through site visits, prevents residents from electing to remove trees that are healthy and innocuous. Thus, residents are not in control of whether, or when, they can remove a tree. This follows because the timing of tree death, disease and property damage is unpredictable and determined by natural processes.

In practice, the residents obey tree removal ordinances with near-perfect compliance, as regulations are well-known and permit violations result in expensive penalties. For example, removal of a non-permitted tree with a 30-inch diameter trunk would incur a penalty of $2,500—a cost that is an order of magnitude greater than the same tree removal with an approved permit.[14] To further protect healthy tree canopies, ordinances also prohibit actions that degrade tree health, such as over-pruning or tree-top removal.

EMPIRICAL ANALYSIS

City permits for tree removals, combined with Gainesville data on residential characteristics and utility consumption, provide an opportunity to examine the effect of tree shade on actual electricity and natural gas consumption. This section describes the empirical strategy and results. The first analysis applies a difference-in-difference model to compare changes in energy consumption between residences with and without tree removals. The second analysis tests whether or not the effect of tree removals is greater for trees positioned to provide building shade. The third analysis applies a continuous

[14] Tree ordinance rules mandate that an eligible tree removed without a permit must be replaced on an inch-by-inch basis with 3-inch diameter nursery trees, which cost approximately $250 apiece. Therefore, the example of a 30-inch diameter tree, if removed without a permit, would require on-site mitigation planting of 10 trees with 3-inch diameters, at a total cost of $2,500. In contrast, removal of any size tree with a valid permit only requires on-site planting of two trees with 1.5-inch diameter, at a total cost of approximately $250.

difference-in-differences model to examine how the effect of tree removals increases with tree size.

Because tree shade only affects energy consumption related to space cooling or space heating, the effect of tree removal, if it exists, will be greater during seasons when cooling and heating make up a larger share of a household's energy demand. For electricity, the effect of tree removals should be greatest during summer months when electricity demand for air conditioning is at its peak, and when solar radiation is most intense. For natural gas, the effect of the code change is expected to be greatest in winter months when demand for natural gas-based heating is at its peak. Given the tropical climate of Gainesville, coupled with longer, more intense sun exposure during summer months, tree shade should have a greater effect on summer electricity demand, and a smaller effect on winter natural gas demand.

Tree Removal Treatment

The average effect of tree removal on energy consumption can be estimated without using information about tree size and location relative to a house. I begin with this simple approach to establish a baseline treatment effect. Using only tree removal permits and billing data, I estimate difference-in-differences models for both electricity and natural gas of the form

$$Y_{it} = \tau w_{it} + \lambda_t + c_i + \varepsilon_{it} \tag{1}$$

where the dependent variable Y_{it} is either monthly electricity consumption (kWh) or monthly natural gas consumption (therms), depending on the model; i indexes residences; t indexes the month-year of the billing record; w_{it} is an indicator variable

equal to one for billing months after a tree removal for those residences that remove a tree; λ_t is a month-year specific intercept that controls from month-to-month effects common to all residences, such as weather fluctuations or changes in the price of electricity or natural gas; c_i is a residence-specific intercept; and ε_{it} is assumed to be a normally distributed error term.

Equation (1) is estimated with a fixed-effects estimator and clustered standard errors at the residence level. The coefficients of interest, contained in the vector τ, are difference-in-differences estimates of how changes in energy consumption differ between residents with tree removals and residents without tree removals. If trees removals do, in fact, affect energy consumption, then, around the timing of tree removal, residences should experience changes in energy consumption that differ from changes experienced by other residences. With respect to electricity, if tree shade has the expected effect, residences should have increased electricity consumption after a tree removal. This follows because air conditioning demand, the primary determinant of residential electricity usage, should increase as additional summer sun exposure heats homes after a tree removal. With respect to natural gas, after-tree-removal residences should have decreased natural gas consumption. This follows because heating demand, the primary residential end-use of natural gas, should decrease as additional winter sun exposure naturally warms homes after a tree removal.

Table 1 reports the estimates of specification (1) for electricity and natural gas (columns 1 and 2). Focusing first on electricity, results suggest that after a tree removal, households consume approximately 29 kWh per month more than households without tree removals. The result is statistically significant at the 1-percent level. In terms of

percentage difference, the estimates suggest that the average tree removal results in a 2.5-percent increase in residential electricity consumption. Focusing instead on the electricity saved by trees, these findings suggest that a residential tree in Gainesville reduces household electricity consumption by almost 2.5-percent, assuming that trees targeted for removal provide shade that is similar to other residential trees.

As expected, results for natural gas have a negative coefficient, consistent with the hypothesis that winter heating demand decreases after a loss of tree shade. Although the negative sign is expected, the coefficient estimate for tree removals is not different from zero at any conventional level of statistical significance. Furthermore, the natural gas effect is smaller in magnitude than the electricity effect, as the natural gas estimate suggests that tree removal households consume 0.5 therms per month less than households without tree removals, a change in energy equivalent to about 15 kWh. Hence, a comparison of electricity and natural gas coefficients is consistent with the expectation that, in Gainesville, tree shade has a greater effect on summer electricity demand than winter natural gas demand.

Tree Shade Treatment

While the models presented in Table 1 provide an estimate of the energy effects for average tree removal, the effects may differ in important ways depending on tree size and tree location. In fact, the estimates from specification (1) should be interpreted as a lower-bound of the true energy savings from tree shade. This follows because tree removal is an imperfect proxy for change in tree shade, which contains measurement error. For example, some trees are not originally positioned to shade houses, and these no-shade tree removals would not affect energy use. Such measurement error in the

treatment should, in theory, attenuate estimates towards zero and under-predict the true effect of shade on energy use. The magnitude of this bias will depend upon whether or not the average tree was positioned to shade a home prior to removal. To address these concerns subsequent models account for heterogeneity in shade changes across tree removals to achieve more precise estimates of the energy savings from tree shade.

As discussed previously, tree removal permits are combined with aerial data on tree cover change and building location to determine how much shade a tree provided the residence before a tree removal. For simplicity, based on tree position relative to buildings, tree removals are assigned to one of three groups: heavy-shade, light-shade, or no-shade. With these definitions of shade-intensity, I estimate expanded versions of specification (1) for electricity and natural gas as follows:

$$Y_{it} = w_{it}[Heavy_i,\ Light_i,\ NoShade_i]\tau + \lambda_t + c_i + \varepsilon_{it} \qquad (2)$$

where the indicator variable for billing months after a property-specific tree removal is interacted with each of the shade-intensity variables. Following the same estimation strategy, equation (2) is estimated with a fixed-effects estimator, and standard errors are clustered at the residence level.

The parameters of interest, contained in the vector τ, are shade-intensity treatment effect coefficients that represent the average monthly energy change caused by the loss of shade from a tree removal. Earlier results and intuition can guide expectations about the direction and magnitude of energy across shade-intensities. With respect to electricity, if the loss of tree shade is a key driver of tree removal effects, one would expect greater increases in electricity consumption for residences that remove trees providing heavy shade on a house. This follows because air conditioning, which is used more intensively

with higher outdoor temperatures, should increase demand as residences experience a greater loss of house shade. With respect to natural gas, previous results are not statistically significant and provide limited guidance; however, intuition suggests that natural gas heating, which is used less intensively with higher indoor temperatures, should decrease in demand as houses experience a greater loss of house shade. This follows because natural gas heating, which is used more intensively with lower indoor temperatures, should decrease in demand with a greater loss of house shade; however, because sun exposure is less intense during winter months, and some trees drop foliage, shade loss should affect natural gas consumption less than summer electricity consumption.

The first column of Table 2 reports the electricity estimates of specification (2). Focusing on the interacted shade intensity variables, which identify the amount of shade loss experienced by residences, coefficients have the expected signs and expected pattern of effects that increase with shade intensity. Electricity consumption is increasing with the intensity of shade lost, and these results are consistent with electricity being the primary energy source for cooling of Florida residences.

While the sign and trend of shade intensity coefficients are predictable, the magnitude of effects is unexpected. Surprisingly, based on the interaction with $Heavy$ shade, estimates suggest that electricity consumption increases dramatically after residences remove heavy-shade trees. In particular, residences increase electricity consumption by an average of 203 kWh per month after the removal of a heavy-shade tree, a result that is significant at the 1-percent level. In terms of percentage difference, the estimates suggest that removal of a heavy-shade tree results in a 17.7-percent increase

in residential electricity consumption. The coefficient for heavy shade tree removals represents the potential role of specific shade trees in regulating residential energy consumption, rather than the average role of trees estimated in specification (1). By comparison, the coefficient for light shade tree removals suggests a more modest increase in electricity consumption, averaging 48 kWh per month, or an increase of 4.2-percent, a result of an unassuming magnitude that is also significant at the 1-percent level.

The coefficient estimate for no-shade tree removals provides a falsification test, which can address concerns about potential self-selection of tree removing residents. My analysis shows little evidence of observable differences between residents with tree removals compared to residences without tree removals.

It is theoretically possible, however, that an increase in electricity consumption after a tree removal is driven by a trend in energy usage that is related to the self-selection of a resident choosing to remove a tree. For example, if residences that remove private trees were experiencing faster growth in electricity demand, this could lead to a spurious positive "effect" from tree removals. On the other hand, if electricity increases occur through the causal channel of shade change, then one would expect a zero effect from tree removals without any change in shade. Trees that never shaded a home, or no-shade trees, serve as a test case of tree removals without any change in shade on the house. Results of specification (2) lack any evidence of a spurious effect for electricity usage, since the coefficient for no-shade tree removals is not different from zero at any relevant level of statistical significance, nor of a magnitude similar to cases of trees providing some shade for the house.

Given the identifying assumption that households removing no-shade trees are no different than households removing shade trees, the estimates presented in table 2 represent the effects of tree shade on energy use, rather than other confounding factors related to self-selection into treatment.. In addition, since Gainesville arborists reject permits for healthy, non-hazardous trees, homeowners are often removing diseased or damaged trees, rather than removing trees because they attach a low value to trees.

Turning to the natural gas results, the interacted shade-intensity variables in column (2) reveal a nuanced relationship between trees and natural gas consumption. The largest source of variability in natural case consumption, among homes with access to natural gas, would be due to its use in heating during winter months. As expected, the coefficient on heavy-shade tree removals has a negative sign, suggesting that a large increase in sun exposure following a tree removal leads to lower natural gas consumption for heating. While the sign of effects is predictable, as in the case of electricity results, the large magnitude of effects on natural gas is also somewhat surprising. In particular, residences reduce natural gas consumption by an average of about 5 therms per month after the removal of a heavy shade tree, which amounts to a 14-percent decrease in natural gas consumption. Further, this result that is significant at the 1-percent level.

In contrast, and contrary to expectations, light-tree shade removals have the exact opposite effect of heavy tree shade removals. Unlike heavy-shade results, the coefficient for light-shade removals suggests that residences increase natural gas consumption by 4.7 therms per month after the removal of a light shade tree. This result is significant only at the 5-percent level.

One possible explanation for a positive coefficient is straightforward: the effect of light-shade tree removals is unrelated to shade, but, instead, operates through another causal channel, which is the well-known service trees provide as windbreaks, or barriers that insulate houses from cold winter winds. Windbreak trees reduce wind-chill most effectively when set back from buildings by 50 to 100 feet, a distance that corresponds closely with the outer-ring buffer zones used in this study to define light-shade trees (see Figure 4).

Although windbreaks are most common in colder climates, natural gas results provide compelling evidence that trees set back from properties, or de-facto windbreaks, can provide energy-efficiency services during winter. Focusing now on the falsification test, the coefficient for non-shade tree removals is not statistically significant at any relevant level for natural gas, a finding that is consistent with the falsification test for electricity. Overall, natural gas results suggest that trees have a complex effect on winter energy consumption, with opposing effects depending on location: trees providing shade increase natural gas consumption, while trees serving as windbreaks decrease natural gas consumption.

Continuous Tree Canopy Loss Treatment

The analysis thus far builds a case that tree removals increase electricity consumption, due to change in shade, and also affect natural gas consumption, both due to changes in shade and windbreaks. The empirical strategy identifies effects based on both the timing of tree removals, from billing data, and the location of tree removals from satellite data used to classify shade density. Although proxy metrics for shade density refine inferences from models, nonparametric measures of tree location may help identify

more specific information about how effects change with tree orientation and proximity to houses. In addition, while specification (2) provides estimates of average energy effects based on shade density, as defined by tree location, the effects may also differ in important ways depending on the size and number of trees removed. To test how tree size influences energy effects, and to further examine tree location affects, subsequent models include continuous variables of the size of trees removed, defined in terms of tree canopy area.

Two groups of four tree canopy variables are created. The first four variables record the area of tree cover removed in each quadrant within a 25 foot buffer zone around a house, with each variable representing a section to the north, east, south, or west. The second group of four variables records the area of tree cover removed in a ring-shaped buffer zone containing the area from 50 to 100 feet around the house, again divided into quadrants to the north, south, east and west. These two groups of continuous variables of canopy area are estimated separately for both electricity and natural gas, following the form

$$Y_{it} = w_{it}[North,\ East,\ West, South]\theta + \lambda_t + c_i + \varepsilon_{it} \qquad (3)$$

where the indicator variable for post-tree-removal is interacted with the continuous variables of tree canopy area within each of the directional quadrants for either the 0-to-25 foot buffer or the 50-to-100 foot buffer, depending on the model. Consistent with previous models, equation (3) is estimated using a two-way fixed effects estimator with standard errors clustered at the residence level.

The parameters of interest, contained in the vector θ, represent the marginal effect on energy consumption from increasing the canopy area of a tree removal, with separate

estimates for each of the eight areas defined by orientation and proximity to a house. Based on previous shade-density results, and intuition about seasonal changes in sun angle, expected signs of coefficients for specific directional quadrants are straightforward. For electricity, I expect coefficients with a positive sign, representing higher consumption for increases in the canopy area of tree removals, especially for trees located along the west-side of houses. This is because trees on the west provide shade from the afternoon sun during the hottest hours of the day. Furthermore, for electricity, I expect tree cover within 0-to-25-foot buffer areas to have larger effects than tree cover for 50-to-100-foot buffer areas, since the summer sun is positioned high in the sky and casts short shadows.[15]

For natural gas, I expect coefficients with a negative sign, representing lower consumption for increases in the canopy area of tree removals, especially for trees along the east or south sides of houses. This is because sun from these directions is most relevant for winter heating: the eastern sun in the morning warms houses during in the coldest hours of day; and southern sun extends throughout most of the day during winter months. In addition, for natural gas-heating, tree cover in 0-to-25-foot and 50-to-100-foot buffer areas can be expected to have similar effects because winter sun is positioned low in the sky and casts long shadows. However, the potential energy effect of windbreak trees, if it exists, makes expectations about the sign and magnitude of natural gas effects ambiguous.

[15] Additional models were also used to investigate possible seasonal effects from tree removal. However, models including a treatment effects indicator interacted with an indicator variable equal to one for the months of April to November yielded estimates with economic inferences similar to the continuous treatment estimates presented in this section. Thus, they are not included here.

The first two columns of Table 3 report the electricity estimates of specification (3), including results for tree canopy area within 0-to-25-feet (column 1) and 50-to-100-feet (column 2) of houses. For electricity, coefficients have the expected signs for both buffer areas. Focusing first on west-side tree removals, coefficients are positive, suggesting that electricity increases with the removal of larger tree canopy to the west. These results are consistent with the expectation that loss of shade from the west, which occurs during the hottest hours of the afternoon, raises inside temperatures, and increases demand for electricity to cool houses. In addition, comparison between west coefficients reported in column (1) and column (2) suggest that electricity demand increases most from the loss of tree canopy in close proximity to houses, a finding consistent with effects caused by short shadows during summertime.

In particular, marginal effects suggest that removal of an additional 10-square-meters of tree canopy area on the west side of homes increases electricity usage by about 6 kWh per month for trees less than 25-feet from houses, and by 4.7 kWh per month for trees set back 50-to-100 feet from houses, results that are statistically significant at the 1-percent level and 10-percent level, respectively. In contrast, all remaining coefficients for continuous canopy area to the north, east, and south are found to be no different from zero at any conventional level of statistical significance.

Turning to natural gas results, reported in columns (3) and (4) of Table 3, all coefficients have the expected signs. Focusing first on south-side tree removals, coefficients are negative, suggesting that loss of shade from the south, which extends for most of the day during winter, increases inside temperatures, and reduces demand for natural gas-based heating. In addition, comparison between south coefficients reported in

column (3) and column (4) suggests that natural gas demand decreases by similar amounts for the loss of tree canopy area anywhere within 100 feet of a house, a finding consistent with long shadows from the south during wintertime. In particular, marginal effects suggest that increasing the area of tree canopy removal by 10-square-meters along the south-side of homes decreases natural gas demand by 0.13 therms per month for trees less than 25-feet from houses, and by 0.07 therms for trees set back 50-to-100 feet from houses. Focusing on the east, the coefficient for canopy area is positive, as expected for morning sun that warms homes during the coolest parts of the day; however, these results are not different from zero at any conventional level of statistical significance. In contrast coefficients for canopy area to the north and west are negative, perhaps that appear to reflect windbreak effects that insulate houses from cold winter winds. However, again, results are not statistically significant.

In sum, canopy area variables provide evidence that electricity and natural gas effects increase with tree size. Results also confirm that previous tree shade results are robust to nonparametric definitions of tree shade, which verify that tree removal effects for electricity are, in fact, identified in the west, where summer sun is most intense, while tree removal effects for natural gas are identified in the south, where the sun is positioned for most of the winter. Furthermore, the magnitude of marginal effects, when aggregated to reflect the size of a large tree canopy of 350-square-meters are consistent with the magnitudes of electricity and natural gas effects estimated for heavy-shade variables with specification (2).[16]

[16] The most common tree species removed in Gainesville is the live oak, which has a span of 25-meters at full maturity, and a canopy area of approximately 450-square-meters.

CONCLUSIONS

As ecologically-conscious agencies search for effective policies to reduce energy consumption, there is, of course, the hope for a solution arising from nature itself. Intuitively, policymakers wishfully think of shade trees. However, to this point, these possibilities have remained in the realm of idealistic speculation. Taking a quasi-experimental approach to estimate accurate causal impacts, this study establishes that shade trees are, in fact, quite an effective means of reducing energy consumption. Not only are shade trees effective, but the magnitude of effects is surprisingly substantial. Therefore, a policy that both promotes tree shade canopies and also protects existing shade trees can be a powerful demand side management tool. Further, this study compiles significant evidence that can help homeowners locate trees strategically to lower both summer electricity bills and winter natural gas bills. Such recommendations could become an important element of consumer education to reduce future energy use.

APPENDIX FOR ESSAY 2: CHANGE CLASSIFICATION METHODS[17]

Change classification occurs in two stages: change detection and change classification. First, tree cover change between 2001 and 2011 was identified using a change detection model found under the image interpreter tool in Erdas Imagine, version 9.3 (ERDAS, 1999). The pixel-by-pixel algorithm analyzes differences between spectral values of imagery at each time period. The probability of change is determined by a maximum likelihood framework. Probability thresholds used to characterize change are determined subjectively by an iterative process of visual inspection of output in areas of known change. The model is revised to balance errors of omission and errors of commission. The output of the change detection model is a binary indicator map indicating whether or not change occurred for a given pixel location.

Vegetation is best characterized by red and near-infrared (NIR) wavelengths on the electromagnetic spectrum. Input data for the change detection include an NIR band from 2011 aerial imagery and a red band from 2001 imagery. An NIR band is not available for the 2001 imagery, which requires change detection across different spectral bands.

Second, classification of changed pixels into thematic groups begins after change detection has been finalized. Unsupervised classifications were conducted using the 'feature analyst' and 'ISODATA clump' tools in Erdas Imagine. The change classifications fall into three categories: trees, impervious surface, and open space. The 2011 four-band imagery was used to create baseline classifications that include additional

[17] I thank Binesh Maharjan, remote sensing specialist at the Global Ecosystem Center, who conducted this tree cover change analysis using Erdas IMAGINE (version 9.3) software.

categories of bare earth and water. The 2001 classifications were established by reclassifying detected changes from the 2011 baseline. Particular attention was provided to mapping changes in the tree cover class. The 'feature analyst' tool was used for initial classifications; the 'ISODATA clump' tool was used to revise classifications and create spatial cohesion by combining adjacent similar classified areas.

Other input data and classification methods were also attempted but provided problematic results. Classifications based on an NIR band from 1999 imagery proved problematic because of spectral differences between the 1999 and 2011 NIR sensor and differences in the season and time-of-day of imagery. A fusion between 1999 NIR and 2001 red imagery created similar problems. A more objective Classification and Regression Tree (CART) model also produced unreliable results due to spectral differences between 2001 and 2011 imagery. Although CART methods are typically preferred, they are most effective when using two sets of data from the same sensor. For classification of aerial imagery taken at different altitudes and angles using different sensors, subjective methods like the pixel-based change detection model and unsupervised (ISODATA) classification, and feature extraction methods, permit greater flexibility in defining the criterion for land use changes.

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FIGURES

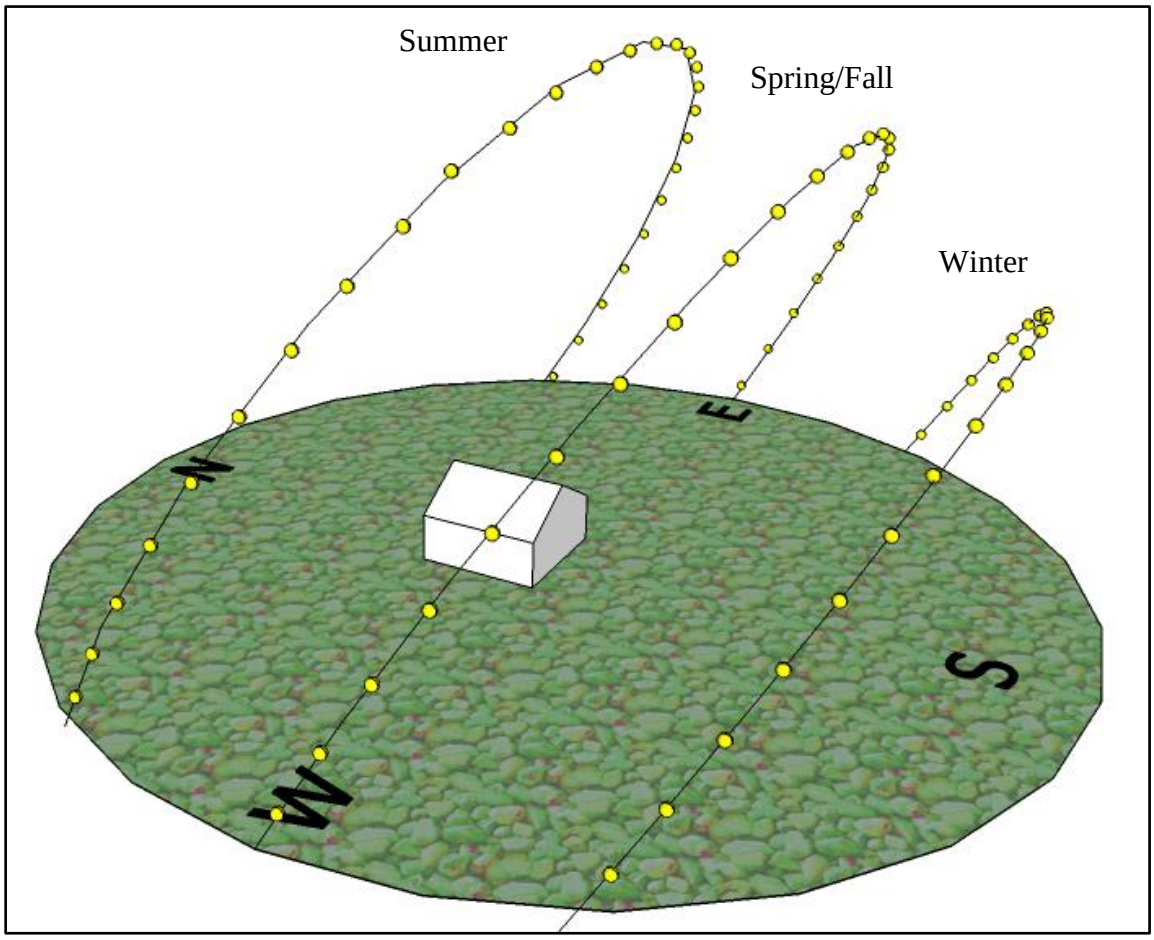
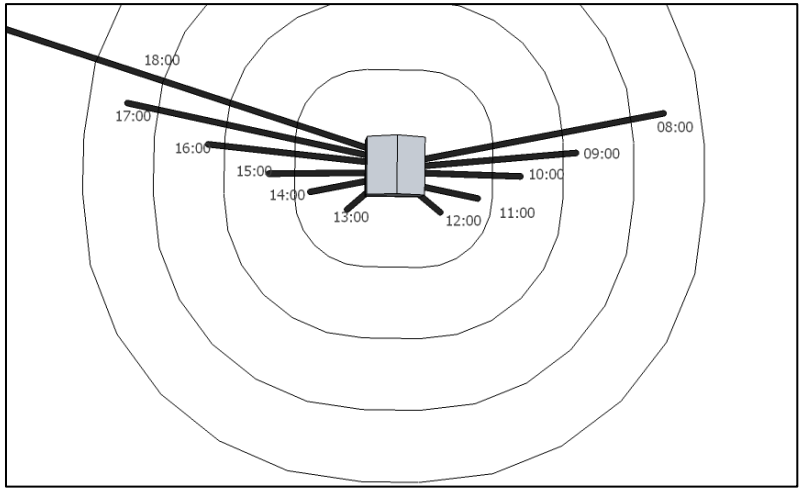


Figure 1 Sun path on the summer solstice (June 21), the spring and fall equinox (March 21 and September 21), and the winter solstice (December 21). Each yellow sphere marks the position of the sun in 30-minute increments between sunrise and sunset. From the house, athmuz angle measures sun direction (north, east, and south, west) around circular plane; altitude angle measured as the degree angle from house foundation to sun.

(a) Summer



(b) Winter

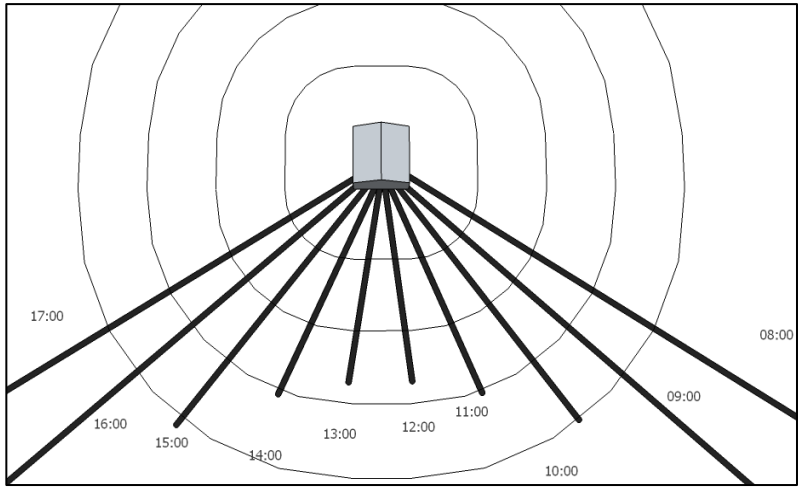


Figure 2 Hourly shadows cast by a 50 foot tree located at the maximum distance to shade the roof of a two-story house (15 foot roof) in Gainesville, Florida. Each black line represents the length and direction of a shadow on the hour during 8am-6pm. Concentric circles represent areas within 25ft, 50ft, 75ft, and 100ft buffers surrounding a square house. Panel (a) conveys the shadows on June 21, 2010 (summer solstice). Panel (b) conveys the shadows on December 21, 2010 (winter solstice).

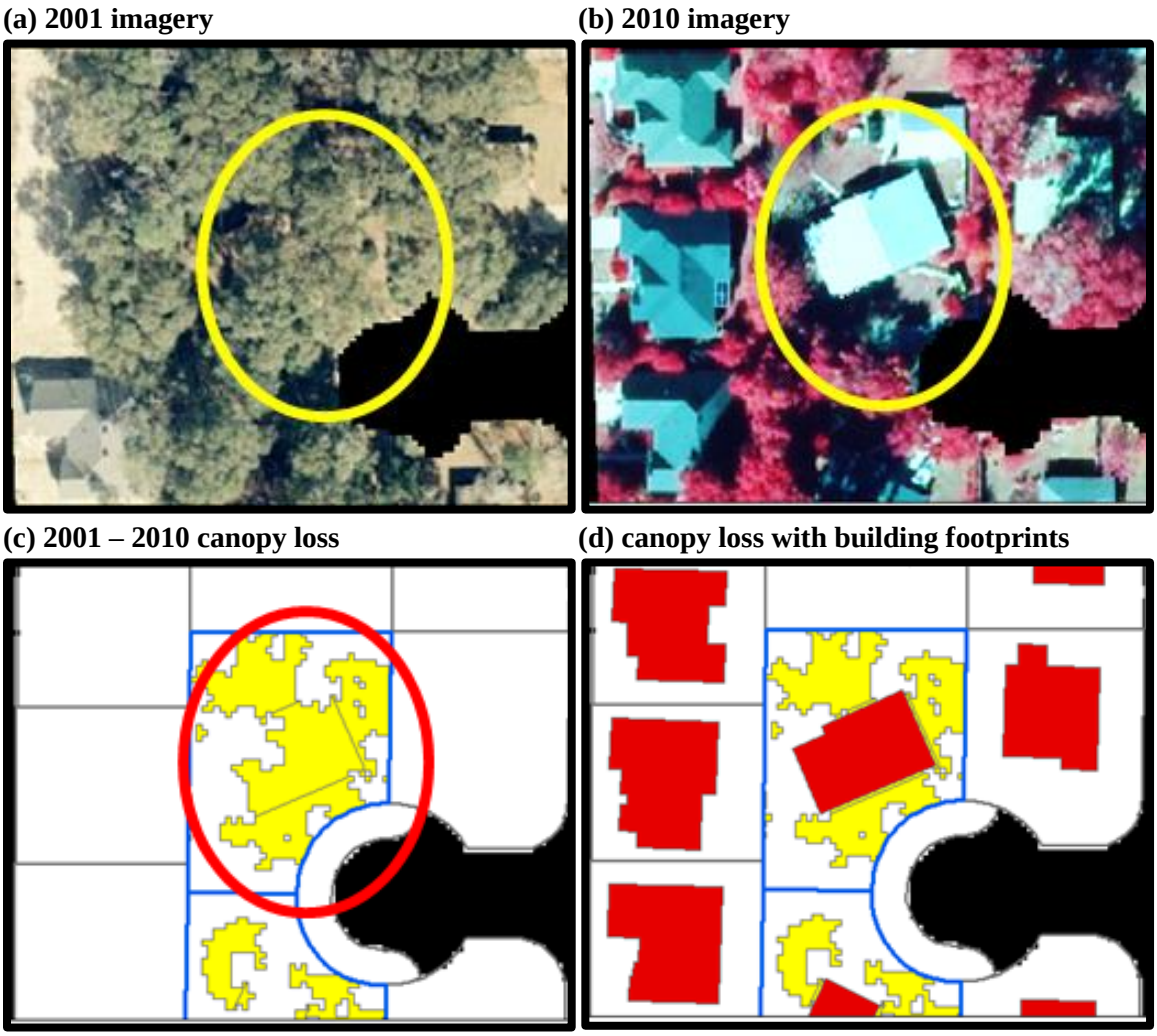


Figure 3 Visual illustrations of inputs and outputs used to create a canopy loss map, as well as auxiliary cadastral data used to define shade-intensity variables. Panels (a)-(d) cover identical spatial extent in a Gainesville neighborhood to illustrate the remote sensing data inputs. Panel (a) shows 2001 color imagery input (1-foot resolution) and panel (b) shows 2010 color infra-red imagery input (1-foot resolution). Panel (c) shows the tree canopy loss map (1-meter resolution) for two properties with tree removal permits (blue polygons). Yellow polygons represent areas of canopy loss during 2001-2010, blue polygons represent property boundaries for residents with tree removals, and gray polygons are neighboring property boundaries. Panel (d) adds cadastral data of building footprints used to determine the position and shade potential of canopy loss on each property.

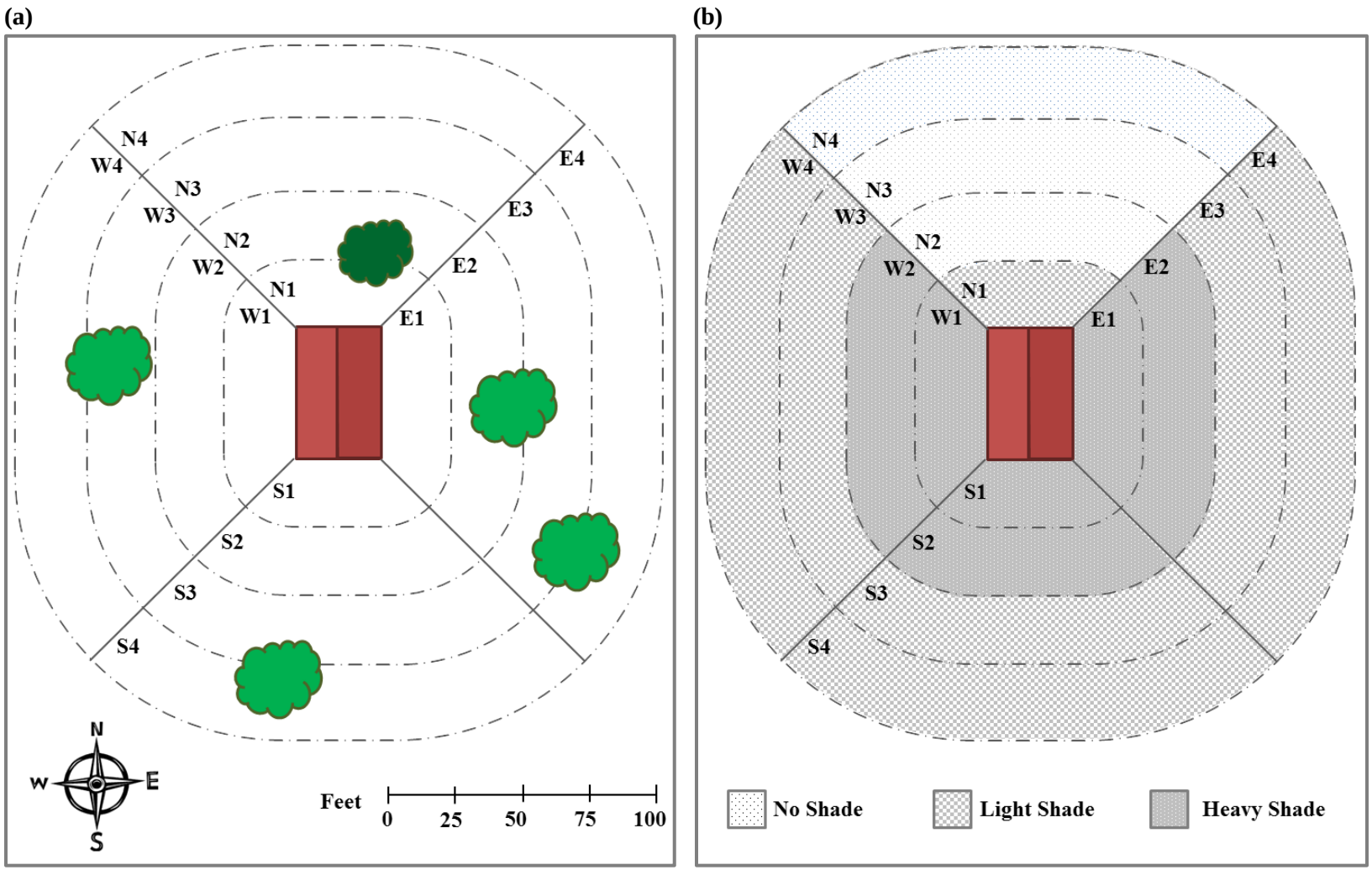


Figure 4 Sixteen concentric zones used to quantify tree position and shade-intensity. Panel (a) illustrates the four directional quadrants (north, east, south, west) and four distance buffers (25ft, 50ft, 75ft, 100ft) that define the sixteen zones of tree position for each house. Panel (b) shows the aggregated zones used to define three levels of shade intensity: no shade (white), light shade (checkered), and heavy shade (gray).

TABLES

Table 1: Effects of Tree Removal on Energy Consumption

Variables	kWh	therms
Tree Removal Effect	29.14 ***	-0.54
	(7.25)	(0.53)
Constant	306.14 ***	75.11 ***
	(33.79)	(1.30)
Number of utility bills	174,268	127,906
Number of residences	1,338	970
R^2	0.267	0.581

All regressions include fixed effects for residence and fixed effects for billing month. Dependent variable is monthly electricity consumption (kWh per month) for model (1) and monthly natural gas consumption (terms per month) for model (2). The independent variable is an indicator for utility bills occurring after a tree removal among residences that remove a tree. All models include standard errors clustered by residence. Asterisks denote statistical significance at levels of 1-percent (***), 5-percent (**), and 10-percent (*).

Table 2: Effects of Shade Intensity on Energy Consumption

Variables	kWh	therms
Removal * Heavy Shade	203.65 ***	-4.98 ***
	(25.19)	(1.87)
Removal * Light Shade	48.15 ***	4.69 **
	(9.59)	(1.87)
Removal * No Shade	-54.28	-1.84
	(55.45)	(1.64)
Constant	307.32	8.89
	(33.86)	(1.78)
Number of utility bills	174,268	126,936
Number of residences	1,338	970
R^2	0.267	0.581

All regressions include fixed effects for residence and fixed effects for billing month. The dependent variable is monthly electricity consumption (kWh per month) for model (1) and monthly natural gas consumption (terms per month) for model (2). Independent variables are tree removal indicators interacted with a measure for intensity of shade provided by removed trees. All models include standard errors clustered by residence. Asterisks denote statistical significance at levels of 1-percent (***), 5-percent (**), and 10-percent (*).

Table 3: Continuous Effects of Tree Canopy Loss on Energy Consumption

Variables	25 feet setback kWh	100 feet setback kWh	25 feet setback therms	100 feet setback therms
Removal * Area North (m²)	0.162	0.142	0.023	0.021
	(0.288)	(0.268)	(0.025)	(0.024)
Removal * Area East (m²)	-0.077	-0.301	-0.014	-0.013
	(0.249)	(0.198)	(0.018)	(0.013)
Removal * Area South (m²)	0.110	-0.044	-0.013 *	-0.007 *
	(0.167)	(0.132)	(0.007)	(0.004)
Removal * Area West (m²)	0.594 ***	0.467 **	0.005	0.001
	(0.195)	(0.227)	(0.007)	(0.009)
Constant	989.079 ***	989.158 ***	74.591 ***	75.109 ***
	(14.976)	(14.973)	(0.986)	(1.300)
Number of utility bills	175,606	175,606	127,906	127,906
Number of residences	1,338	1,338	970	970
R^2	0.267	0.267	0.547	0.581

All regressions include fixed effects for residence and fixed effects for billing month. The dependent variable is monthly electricity consumption (kWh per month) for models (1) and (2), and monthly natural gas consumption (terms per month) for models (3) and (4). Independent variables are tree removal indicators interacted with square-meters of canopy area removed within each directional quadrant. Models (1) and (3) use canopy area within 25 feet of a residence; models (2) and (4) use canopy area setback by 50 feet to 100 feet from a residence. All models include standard errors clustered by residence. Asterisks denote statistical significance at levels of 1-percent (***), 5-percent (**), and 10-percent (*)