Optimization of Residential Green Space for Environmental Sustainability and Property Appreciation in Metropolitan Phoenix, Arizona

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1. Introduction

Urban regions in the United States are dominated by residential land, which creates challenges and opportunities for sustainable land management due to the preponderance of outdoor space in yards. Studies estimated that approximately 65% of all urban land is devoted to single-family residential neighborhoods and it is the most prevalent zoning in areas slated for future development (Burchell & Shad, 1998; Burchell & Mukherji, 2003; Hirt, 2014). Residential land use is often associated with proliferating turf grass in the continental U.S., which in many regions require extensive irrigation to maintain (Milesi et al., 2005; Cook and Faeth, 2006). This is particularly true in the arid U.S. Southwest, where precipitation can be 18 cm or less per year (Sheppard et al., 2002). Nevertheless, irrigated landscaping provides both environmental benefits such as lower temperatures (Wang et al., 2016; Wang, 2018) and economic benefits such as higher home values (Kestens et al., 2004, Mei et al., 2018). Research is therefore needed to better understand both the relationships and tradeoffs between vegetation cover, land surface temperature, water use, and home values.

Generally, green infrastructure contributes to a range of ecosystem services in cities (e.g., habitat provisioning, stormwater regulation, carbon sequestration), though the mix and extent of services depends on vegetative type and management, and homogenous turf landscapes likely provide nominal ecological benefits (Larson et al., 2016; Groffman et al., 2017). Green infrastructure can also provide socioeconomic and health benefits. For illustration, large public green spaces can influence social capital by providing an environmental-friendly gathering place for residents to develop and maintain neighborhood social ties (Kweon et al., 1998; Kuo et al., 1998; Maas et al., 2009). The presence of green vegetation can also significantly contribute to residents' sense of social safety and adjustment (Kuo et al., 1998). In addition, neighborhood parks and views of natural landscapes have positive contributions to home values (Lo and Faber, 1997; Escobedo et al. 2015). From a public health perspective, urban green spaces can not only help maintain physical health, but also improves mental functioning, mental health and wellbeing (Sugiyama et al., 2008).

Despite all the environmental, socioeconomic and health benefits of urban green infrastructure, vegetation requires a significant amount of water for irrigation, adding demand for scarce water resources, especially in hot, arid desert cities. Research has shown that Americans irrigate more acres of turf than its largest three crops—corn, wheat, and soy—combined (Milesi et al., 2005). In desert cities, Myint et al. (2013) studied the impacts of grass fraction and tree fraction on surface temperature for the City of Phoenix and found that trees had a stronger cooling effect than grass. Middel et al. (2015) reported that a targeted 25% tree cover in Phoenix residential neighborhoods would yield a reduction of up to 2 °C at the canopy layer (2 meters above the surface). Moreover, vegetation is correlated with higher property values both at the individual parcel and within the neighborhood (Bark et al., 2011; Escobedo et al., 2015), which provides an economic benefit for property owners, but creates a trade-off with housing affordability and homeownership attainment. Resolving these trade-offs will require better understanding of the interrelationships among vegetation structure, temperature, water use, and property value.

Multiple studies have examined relationships among environmental and economic variables, but never in a single study and without the focus on residential neighborhoods. For instance, several studies examined the relationship between the composition and configuration of urban land use land cover and land surface temperature (LST), finding that the relationship varies depending on land use and region (Connors et al., 2013; Rotem-Mindali et al., 2015, Schwarz and Manceur, 2015; Li et al., 2016; Wang et al., 2019). However, most studies analyzed the cooling effect of vegetation at global or regional scales regardless of various vegetation types, with a few exceptions that examined trees only (Myint et al., 2013, Middel et al., 2015). Similarly, studies have examined relationships between vegetative cover, LST, and outdoor water use (OWU) finding that small decreases in temperature are associated with large increases in water use (Guhathakurta and Gober, 2007; Kaplan et al., 2014; Wang, 2018). These studies do not disambiguate vegetative cover type but have shown that native shrubs are well adapted to the desert climate that can thrive without much rainfall or irrigation (Martin, 2001; Stabler and Martin, 2002). Additionally, vegetation with large canopy and structure, such as mature trees, can also provide shade to reduce temperature for better thermal comfort (Armson et al., 2012; Armson et al., 2013; Middel et al., 2015; Zhao et al., 2018a). Finally, another subset of studies examined relationships between urban vegetation and property sales value (PSV), generally finding a positive relationship, and suggest that trees may have the most positive effect (Kestens et al., 2004, Mei et al., 2018). Given variability in effect of different types of vegetative cover (i.e., trees, shrubs, grass) on urban cooling, water use, and property values, understanding the outcomes associated with different vegetative mixes in arid desert urban residential neighborhoods is essential for minimizing trade-offs and maximizing co-benefits.

To better understand the related dynamics between environmental and economic tradeoffs, this study examines single-family residential neighborhoods with homeowner associations (HOAs) in the Phoenix metropolitan area (PMA), Arizona, USA. HOAs are entities that dictate minimum landscaping requirements and claim to maintain property values over time (McKenzie, 1994; Wentz et al., 2016). The first objective is to examine the impacts of spatial composition of different vegetation cover types on LST, OWU and PSV in major residential communities in the PMA. The second objective is to optimize the spatial composition of residential green spaces in order to achieve a relatively lower LST and OWU and to maintain PSV at the same time. The third objective is to propose residential landscaping strategies for urban sustainability of desert cities in terms of water conservation and urban heat mitigation based on the optimization results.

2. Materials and Methods

2.1 Study Area

The PMA is located in Maricopa County, Arizona, USA. The total population is about 4.67 million residents with nearly 1.66 million households, as estimated by the 2018 American Community Survey (ACS) (U.S. Census Bureau, 2019). As of 2019, the housing stock consists predominantly (~76.2%) of single-family homes with an increasing number of multi-family structures and mobile/manufactured homes (MAG, 2019). The 2018 mean household income of PMA was $87,435, which was lower than the national mean of $87,864 (U.S. Census Bureau, 2019). PMA residents, therefore, need to be conscious of the costs associated with cooling homes, caring for landscaping, and resale values.

The PMA is part of the northeastern Sonoran Desert featuring a subtropical semi-arid hot desert climate (Köppen climate classification: *BWh*) (Figure 1). It is characterized by long, hot summers, but short, mild winters. The daily high exceeds 37.8 ºC for an average of 110 days every year, which normally occurs between early June and early September (Wang et al., 2016). The highest temperature can reach over 43.3 ºC (110 ºF) for an annual average of 18 days (Wang et al., 2016). The mean annual precipitation in the past 30 years is merely 204 mm (8.03 inch) with most rainfall taking place during the summer monsoon season (U.S. Climate Data, 2020). This means that residential vegetation is largely managed through a combination of automated irrigation systems (e.g., drip, sprinkler), flood irrigation (in older neighborhoods), and drought tolerant vegetation.

To study the economic and environmental tradeoffs, we selected a sample of 302 local single-family residential communities that are managed by HOAs (Figure 1). Selecting only neighborhoods managed by HOAs provides continuity in the structure and governance of landscaping. The 302 communities were derived from a random sample of single-family residential subdivisions in Maricopa County using Maricopa County Assessor's Subdivision and Parcel Data. Detailed sample selection methods can be found in Minn et al. (2015), Ye et al. (2018) and Turner & Stiller (2020).

2.2 Data

Figure 2 shows the flowchart of research design. Four data sets were used to evaluate the trade-offs among LST, OWU and PSV with regards to residential green space composition. The data sets include land cover classification, remotely sensed surface temperature imagery, model-predicted actual evapotranspiration (ET_a), and property sales records from 2010. The reason why

2010 data sets were used is because all the data and products used were available from this year. Although it sounds out of date, the purpose of this study is to generalize empirical trade-off relationships and we assume these relationships would hold over time and space for small local residential communities.

2.2.1 Land surface temperature

We calculated a summer daytime mean LST for each residential community using a combination of Landsat 5 Thematic Mapper and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data for June through September in 2010. The reason why both Landsat and ASTER images were used is because of the poor temporal resolution of single satellite data. The LST data set from Landsat 5 was obtained from Level-2 provisional surface temperature product that has a 30-m spatial resolution, which is resampled from thermal bands of 120-m spatial resolution, and has a relative accuracy of 0.19 K (Cook et al., 2014). We also acquired ASTER surface kinetic temperature product (AST08) that has 90-meter spatial resolution and a relative accuracy of 0.3 K (JPL Propulsion Laboratory, 2001). Both Landsat and ASTER LST products are calibrated, processed, and distributed by NASA and USGS. We calculated summertime mean LST value for each residential community using 23 cloud-free images, within which 7 were from ASTER and 16 were from Landsat 5.

2.2.2 Outdoor water use

The municipal water delivery system in the PMA does not have separate water meters for indoor and outdoor water use. We therefore estimated OWU using ET_a as a proxy (Singh et al., 2014). ET_a was modeled using a surface energy balance model named METRIC (Mapping

Evapotranspiration at high spatial Resolution with Internalized Calibration) (Allen et al., 2007a). Surface energy balance model is an essential approach for heat flux and evaporation estimation in applied meteorology and hydrology. More specifically, the METRIC model computes the latent heat flux as the residue of the surface energy balance, which can be written as:

$$LE = R_n - G - H, \tag{1}$$

where R_n is the net incoming radiation, G is the ground heat flux, H is the sensible heat flux, and LE is the latent heat flux. METRIC has been successfully applied to Landsat and MODIS images to predict ET_a at various spatial scales (e.g. Trezza, 2002; Hendrickx and Hong, 2005; Allen et al., 2007b; Zheng et al., 2015). Research also demonstrated ET_a prediction accuracy of 15%, 10% and 5% for daily, monthly, and seasonal timescales (Plaza et al., 2009; Shao and Lunetta, 2012). Model predictions can effectively represent ET_a for both urban and non-urban areas with or without irrigation (Allen et al., 2007b). More detailed model calculation and implementation procedures can be found in Allen et al. (2007a).

Model predicted ET_a maps were created using 22 time-series cloud-free Landsat 5 images and meteorological data collected from the weather stations in the Arizona Meteorological Network (AZMET, 2020) that covered the entire year of 2010. Gaps between each two adjacent image acquisition dates were filled using a polynomial curve-fitting method at every single image pixel location, which finally resulted in 365 daily ET_a maps of 30-meter resolution. A summertime total ET_a map was created by aggregating all the daily images in June, July, August, and September. We calculated a mean ET_a value for each selected residential community. Model predicted ET_a values were validated using actual water usage data acquired from 49 community parks in the PMA as described in Kaplan et al. (2014). Detailed validation procedure and results can be found in Wang (2018).

2.2.3 Property sales value

We obtained property sales records between 2009 to 2011 at parcel level from the Maricopa County Assessor's Office (2020). Multiple years' records were used because the number of sales records from one single year was relatively small and some communities show no record in 2010. In addition, using three-year data can reduce the large variation caused by the economic recession in 2008-2009. We calculated a mean PSV (U.S. Dollars in thousands, $k) using all the sales records within each selected residential community.

2.2.4 Land cover classification

Land cover classification for the PMA was performed by the Central Arizona – Phoenix Long-Term Ecological Research (CAP-LTER) at Arizona State University using 2010 National Agriculture Imagery Program (NAIP) imagery and an object-based image classification technique. Detailed classification procedure and metadata can be found at the CAP-LTER website (CAP-LTER, 2015) and in Li et al. (2014). This land cover map has 1-meter spatial resolution and 12 land cover classes with an overall accuracy of nearly 92%. We selected four green space classes that include grass, shrubs, trees, and open soils, and then calculated percent area of each class within each selected residential community.

2.3 Analysis

We first performed a linear regression analysis to explore the empirical relationships between landscaping factors and LST, OWU, and PSV. An optimization analysis was subsequently used to examine the tradeoffs between these variables.

2.3.1 Regression analysis

We used simple linear regression to examine the interrelationship among three dependent variables: LST, OWU and PSV. We then used multivariate linear regression analysis to quantify the empirical relationship between three dependent variables and percent land cover (grass%, shrub%, tree% and soil%) as independent variables. The regression equation is formulated as:

$$y_j = \beta_{0j} + \sum \beta_{ij} x_i + \varepsilon_j \qquad (2)$$

where:

i = index of four independent variables (grass%, shrub%, trees% and soil%);

j = index of three dependent variables (LST, OWU and PSV);

x_i = area percentage of land cover type i;

β_{0j} = intercept term of the regression model for dependent variable j;

β_{ij} = coefficient estimate for land cover type i in relation to dependent variable j;

ε_j = error term of the regression model for dependent variable j.

2.3.2 Optimization

We formulated the optimization question as an integer programming problem with an objective function to minimize the summation of model predicted LST and OWU. Consider the following notations:

I = set of all land cover types (grass, shrub, tree and soil);

J = set of established empirical relationships for LST, OWU and PSV;

Φ = set of vegetation land cover types (grass, shrub and tree);

Ψ = set of established empirical relationships for LST and OWU;

m_{x_i}= observed minimum of x_i;

u_{x_i}= observed mean of x_i;

σ_{x_i}= observed standard deviation of x_i;

$m_{\sum_{i\in\Phi} x_i}$= observed minimum of percent all vegetation cover;

$u_{\sum_{i\in\Phi} x_i}$= observed mean of percent all vegetation cover;

$\sigma_{\sum_{i\in\Phi} x_i}$= observed standard deviation of percent all vegetation cover;

$m_{\sum_{i\in I} x_i}$= observed minimum of percent all land cover;

$u_{\sum_{i\in I} x_i}$= observed mean of percent all land cover;

$\sigma_{\sum_{i\in I} x_i}$= observed standard deviation of percent all land cover;

μ_{y_j}= observed mean of y_j;

m_{y_j}= observed minimum of y_j;

The objective function is formulated as:

$$Minimize\ \sum_{j\in\Psi} y_j, \tag{3}$$

which is subject to:

$$y_j \leq \mu_{y_j}\ \forall\, j \in \Psi, \tag{4}$$

$$y_j \geq m_{y_j}\ \forall\, j \in J, \tag{5}$$

$$x_i \leq\ u_{x_i} + 2\sigma_{x_i}\ \forall\, i \in I, \tag{6}$$

$$x_i \geq\ m_{x_i}\ \forall\, i \in I, \tag{7}$$

$$\sum_{i\in\Phi} x_i \leq u_{\sum_{i\in\Phi} x_i} + 2\sigma_{\sum_{i\in\Phi} x_i}, \tag{8}$$

$$\sum_{i\in\Phi} x_i \geq m_{\sum_{i\in\Phi} x_i}, \tag{9}$$

$$\sum_{i\in \mathrm{I}} x_i \leq u_{\sum_{i\in I} x_i} + 2\sigma_{\sum_{i\in I} x_i}, \tag{10}$$

$$\sum_{i\in \mathrm{I}} x_i \geq m_{\sum_{i\in I} x_i}, \tag{11}$$

$$x_i\ integer\ \forall\, i\ \in I. \tag{12}$$

The objective function (3) is to minimize the summation of empirical estimations of LST and OWU that are derived from regression equation (2). Constraint (4) is defined to force model predicted LST and OWU to be less than the observed mean, and constraint (5) is to restrict predicted LST, OWU and PSV to be greater than the observed minimum. Constraints (6) and (7) restrict the percent area of each land cover to be between the observation minimum and +2 standard deviations from the observed mean. Similar to (6) and (7), constraints (8)-(9) and (10)-(11) restrict the area percentage of vegetation cover and all land cover between the observation minimum and +2 standard deviations of the observed mean, respectively. Integer restrictions on area percentage of land cover types are stipulated in Constraint (12).

The optimization procedure was implemented using Gurobi 9.0 Python API (Gurobi Optimization, 2020) in the Jupyter Notebook environment. We selected top 100 sub-optimal solutions to the objective function (3) that generated the smallest possible summation of LST and OWU, and then searched for the highest predicted PSV values within these 100 solutions. The top 5 best scenarios were finally selected as the optimal solutions.

3. Results

3.1 Summary statistics

The summary statistics of land cover types, LST, OWU, and PSV are shown in Table 1. The total OWU that was estimated using ET_a ranges from 105 mm to nearly 800 mm with a mean value of 453 mm for the summer months of 2010. LST ranges from 41.5 °C to 55.6 °C with a mean LST of 50.3 °C. PSV ranges from \$6.1k to \$4,700k with a mean PSV of \$340.6k and a large standard deviation of \$431.3k. For all the 302 residential neighborhoods, open soil has a mean percent area of 38.8%, which is the largest among four land cover types. This could include desert style or unfinished landscaping. This is followed by trees ($\mu_{T\%}$ = 12.1%), grass ($\mu_{G\%}$ = 8.1%), and finally shrubs ($\mu_{S\%}$ 3.2%). This land cover profile in residential communities in the PMA is generally consistent with 'xeriscaped' and other low vegetative cover yard structure types prevalent in the region. This is fairly typical too of properties in HOA neighborhoods, where vegetation composition can be regulated. Even in residential communities with relatively higher vegetative land cover, the mean percent vegetated area is only 21.1% with a maximum cover of 52.7%.

3.2 Regression results

Figure 3 shows the relationship among three dependent variables (LST, OWU and PSV) using simple linear regression. A statistically significant negative relationship was found between LST and OWU and between LST and PSV, while a statistically significant positive relationship existed between PSV and OWU. This implies that higher surface temperatures are generally found in residential communities of lower water use and lower home values. On the other hand, higher water use is often associated with lower surface temperatures and higher home values. We believe the underlying cause of these relationships is the variation of vegetation coverage.

Multiple regression results of LST, OWU, and PSV with percent vegetation cover are presented in Table 2. Model A shows that percent vegetation cover variables can be used to explain nearly 60% (adjusted R^2 = 0.598) of the total variation in LST, and the model is statistically significant at the 0.01 level. Except percent soils, all the other coefficient estimates are statistically significant and have negative contributions to LST, which means increasing percent vegetation cover can effectively lower LST in a residential community. According to the value of standardized coefficients, the cooling efficiency is ranked as: Trees > Grass > Shrubs. Theoretically speaking, a 10% increase in percent area of grass, shrubs and trees can result in an average decrease in LST of 1.4 °C, 1.2 °C and 2.4 °C, respectively. In other words, replacing grass, shrubs and open soils with trees can potentially minimize the heating effect in local residential communities in the PMA.

Model B in Table 2 shows regression results of OWU as the dependent variable. This model is also statistically significant (p-value < 0.01) and meaning that vegetation cover can explain nearly 50% of the total variation in OWU (adjusted R^2 = 0.495). Percent grass and trees have significant, positive relationships with OWU, and the coefficient estimate of percent grass is much larger than trees, which means increasing percent grass area can result in more OWU than increasing the same percent area of trees. Percent soils have a negative relationship with OWU, which means increasing the percentage of open soils can potentially reduce OWU. Percent shrub is insignificant in this model.

Model C in Table 2 shows the regression results of PSV. Although this model has a relatively lower goodness-of-fit (adjusted R^2 = 0.228), it is statistically significant at the 0.01 level. We anticipate a lower R^2 because studies using hedonic models of home price are complex and show that individual factors such as house size and lot size as well as regional factors such as parks, transportation, and schools influence home prices (Glaesener and Caruso, 2015; Seo et al., 2019). For our model, the coefficient estimates are positive and statistically significant at the 0.05 level (p-value < 0.05). The relative contribution of vegetation land cover types to PSV is ranked as: Grass > Shrubs > Trees > Soils. This result implies that increasing vegetation cover, especially grass and shrubs, can effectively maintain a relatively higher PSV.

In summary, increasing percent tree cover alone can efficiently lower LST and OWU, but its contribution to PSV is relatively low. On the other hand, increasing percent grass cover alone can lower LST and help maintain a relatively higher PSV, but it would also largely increase OWU, which is not an ideal practice for water conservation. Although shrub has a moderate contribution to PSV, its cooling efficiency is the lowest and it does not significantly lower OWU. It becomes evident that different spatial composition of vegetation cover has varying effects on urban residential microclimate. Understanding these effects can help address the trade-off issue among LST, OWU and PSV.

3.3 Optimization results

We first solved the integer programming problem and obtained the top 100 sub-optimal solutions for the lowest possible summation of LST and OWU values and their corresponding land cover compositions, and then searched for the highest predicted PSV values within these solutions. These records are therefore considered as our final optimization solutions.

We present top 5 optimization scenarios in Table 3. These five scenarios suggest that shrubs should be given the largest weight within all the vegetation types to maximize its environmental and economic benefits. On the other hand, minimizing the use of grass but maximizing open soil coverage can also contribute to lower LST and OWU. PSV can be higher if a larger percent grass cover is given, but OWU would also be higher as well. As suggested, a residential landscape that is composed of 1-2% grass, 11-13% shrubs, 7-9% trees, and 62-64% soils can result in the lowest possible LST and OWU and help maintain a relatively higher PSV at the same time. Within these scenarios, predicted LST varies from 49.8 ºC to 50.2 ºC, which is less than the observed mean LST (Table 1, μ_{LST} = 50.26 ºC). Predicted OWU ranges from 327.5

mm to 334.4 mm, which is around the mean minus one standard deviation (μ - σ = 329.7 mm) of observed OWU. Predicted PSV in these scenarios varies from $728.6k to $761.6k, which is higher than observed mean (μ_{PSV} = $340.6k) but lower than the mean plus one standard deviation (μ + σ = $771.9k).

4. Discussion

4.1 Effect of vegetation cover on LST, OWU and PSV

Our analysis shows that trees provide the greatest cooling efficiency, followed by the combination of grass and shrubs. This implies that planting more trees or replacing other land cover with trees in a desert residential neighborhood has the potential lower LST to its maximum. This result is consistent with prior studies of the effect of the urban heat island effect in Phoenix and other areas that show this relationship between vegetation and land surface temperature (see Myint et al., 2013 and Middell et al., 2015). Additionally, trees provide shade and thermal comfort co-benefits (Zhao et al., 2017; Zhao et al., 2018b). These studies support efforts by the City of Phoenix, which initiated a Tree and Shade Master Plan in 2010 to ameliorate extreme heat during the summer months by increasing tree canopy from 10% in 2010 to 25% by 2030 (City of Phoenix, 2010). Our study is the first to consider shrubs, which is the most populated native vegetation in a desert environment (Martin, 2001). Shrubs had the lowest cooling efficiency among all the vegetative types, meaning that shrubs are the least efficient way to achieve cooling as measured by LST in our study. They also do not provide the shade co-benefit of trees.

The rankings for water use efficiency are different than for cooling. Our result suggests that grass is the least water efficient vegetation type, while shrub has no significant contribution to OWU (Table 2). This finding is consistent with other studies that find that grass requires a large water inputs to survive in a hot, semi-arid desert climate (Vickers 2006) and that native shrubs are well adapted to desert climates (Odening et al., 1974; Bamberg et al., 1975; Martin et al., 2001; Stabler and Martin, 2002). Trees are species specific: most desert-adapted trees do not rely on irrigation, while fruit trees and deciduous trees that are also widely populated in local residential communities in the PMA heavily depend on irrigation to survive in a desert environment. Our result suggests that overall trees have higher water use efficiency than grass (Table 2), which can be considered as a landscaping alternative to lawn and turf.

Our results are consistent with other studies showing that vegetation increases property values in residential neighborhoods (Kestens et al., 2004, Bark et al., 2011, Escobedo et al., 2015) Generally, percent vegetative cover in desert neighborhoods also had a significant positive relationship with PSV with grass cover having the greatest contribution, followed by shrubs and trees (Table 2). However, the goodness-of-fit of the regression model is relatively low (adj. R^2 = 0.228) because we did not include other factors shown to influence home values such as property size, home size, school districts, etc. While adding such variables can potentially increase R^2 value, it’s not relevant for this study. Rather, our goal was to examine the combined effect of different types of vegetation cover on PSV. Our study, however, shows trees have much lower contribution to PSV than grass and shrubs. This result likely deviates from previous studies conducted in Québec City and Florida because PMA has a much lower percent tree cover (only 12%) and annual precipitation than temperate and humid regions (Escobedo et al., 2015; Kestens et al., 2004). We therefore suggest that it is necessary to take climate background and dominant native vegetation into consideration when examining the effect of vegetation cover on PSV because experiences and findings from some cities may not apply to the others. Moreover, trees had the least effect on property value among three vegetation types, which could be considered a benefit in some regions given that low income communities currently have the greatest need for shade trades, but are also vulnerable to displacement if housing costs increased (Landry and Chakraborty, 2009). Overall, regional social and ecological context are important in assessing the relative benefits of trees versus grass and shrubs.

4.2 Implications of optimization result and policy recommendation

Five optimization scenarios in Table 3 suggest that minimizing the use of grass in residential landscaping in a desert city can contribute to a lower LST and OWU, while PSV maintains relatively high. In face of severe drought in the Southwestern U.S., California Department of Water Resources initiated the Institutional Turf Replacement Program (ITRP) to replace more than 165,000 square feet of turf with California native and water-efficient landscaping to provide long-term water savings, and each eligible household can receive a rebate of approximately $2 per square foot of removed and replaced turf (CDWR, 2009). Tull et al. (2016) used 545 unique single-family residential turf rebates and found that the mean water savings were estimated at about 1 m^3 per square meter of turf removal per year for each household. Another study by Matlock et al. (2019) studied 227 participating customers in southern California and found the average reduced water usage was approximately 392 m^3 per year after turf removal. Both studies confirmed the effectiveness of ITRP in California, and our study further provides the theoretical basis of a similar program that can be potentially implemented in the PMA. Completely removing large grass cover or replacing grass with desert-adapted shrubs or trees can become a sustainable development practice for residential communities in desert cities to mitigate heat and conserve water.

Another recommendation is to widely adopt xeric landscape style that mostly include individually watered and low water-use exotic and native plants as a sustainable landscaping strategy as suggested by the Xeriscape™ movement that began in Denver, Colorado in 1981 (Martin, 2001). Xeriscape is a water-efficient landscaping method that has become increasingly popular in the arid southwestern U.S. (Sovocool and Morgan, 2006). Research has shown that in southern Nevada, Xeriscape can save an average of 55.8 gal/sq. ft (or 2.27 m^3/m^2) per year resulting from replacing turf grass with xeric landscape (Sovocool and Morgan, 2006). Households realized a 30% annual water use reduction after converting to xeric landscape that equals approximately 363 m^3 annually (Sovocool and Morgan, 2006). Xeriscape can also save labor and money for maintenance because of water-efficient and desert-adapted plants and efficient irrigation. On the other hand, Martin (2008) compared four landscape design archetypes and proposed an oasis landscape design that consists of a mixture of small areas of well-irrigated turf grass interspersed with drip-irrigated landscape trees and shrubs and decomposed granite mulch has an overall better performance in water conservation than the traditional xeric style landscape in Phoenix, Arizona.

4.3 Limitations and future research

This study only used summer daytime remotely sensed data for the analysis because the PMA experiences extreme heat in the summer months that has brought various concerns to its residents and sustainability. To better quantify the effect of percent vegetation cover on LST and OWU, one should also consider nighttime and other seasons. Due to the limitation of data, our study only used three inclusive vegetation types of grass, shrubs, and trees, which cannot reflect the real landscaping situation. Different vegetation species have various drought resistant capabilities. It would be ideal if major local vegetation species were identified and used in the analyses instead of using these three inclusive vegetation types. In addition, we did not have more detailed data at parcel or household level, and the analysis was performed using the entire residential community as a study unit. Urban sustainability is broadly influenced by policy makers and urban planners at larger spatial scales, but household behaviors also have a significant influence on landscape sustainability at smaller spatial scales (Cook et al., 2011).

Further research can be focused on two topics. First is to study the effect of different types of desert residential landscaping, such as mesic, xeric, and oasis, on LST, OWU and PSV at parcel level. This analysis requires extensive field surveys and very high spatial resolution remotely sensed data. The second direction can be the research on the combined effect of vegetation cover on LST, OWU and PSV for cities in other climate regions because the regional climate background also has a significant influence on the relationship.

5. Conclusions

Green infrastructure is a well-known and efficient urban heat mitigation strategy that can effectively lower ambient and surface temperatures, provide thermal comfort, and have various socio-economic and health benefits. Despite its ecosystem service values and benefits, increasing vegetated area in a desert city can also lead to a significant increase of outdoor water use, which is not ideal for long-term urban sustainable development. Moreover, landscaping is linked to property values, a central socio-economic concern in residential neighborhoods. It therefore becomes crucial for residents to balance the tradeoffs between green infrastructure in order to maximize the heat mitigation effect, to minimize water usage, while also considering property value at the lowest cost of water use.

This study has made four significant contributions to the sustainability of desert cities. First, we find that even though trees can efficiently reduce LST, its contribution to PSV is the lowest in a semi-arid desert environment. One implication of this finding is that trees might be a water effective means to mitigate urban heat and address income-based shade disparities in the city, while minimizing property value increases that could drive unintended consequences like gentrification. Second, minimizing the use of grass in a semi-arid desert city is crucial because it is the least water use efficient vegetation type, although it contributes to a higher PSV. Third, desert-adapted shrubs and trees can be widely promoted because they not only have higher water use efficiency, can significantly lower LST, but also have a relatively higher contribution to PSV. Paired, these findings suggest a slight trade-off between the most environmentally efficient landscape type (e.g., xeriscaping) and property value maximization (e.g., grass) in some existing residential neighborhoods. Nevertheless, there are multiple yard landscaping market types in Phoenix. Therefore, more work is needed to understand the extent to which the observed positive relationship between grass and property value is moderated by homeowner preferences across different style neighborhoods. Fourth, our results and findings provide strong evidence and a theoretical basis for the environmental benefits of turf removal programs and xeric or oasis style landscaping design, which can be used as a guideline by desert cities for a better design of residential landscaping for urban sustainable development in the future.

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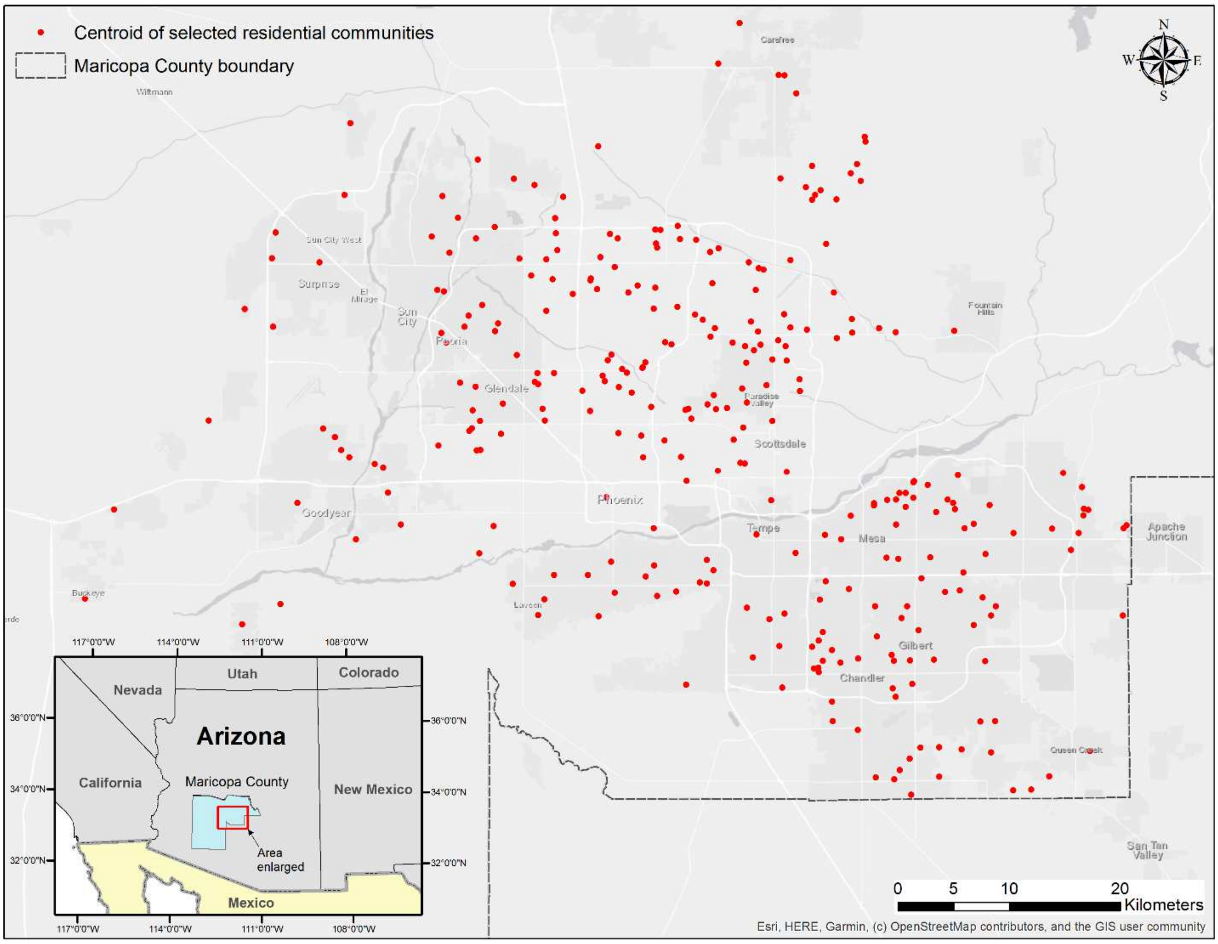


Figure 1. Map of study area and locations of selected residential communities.

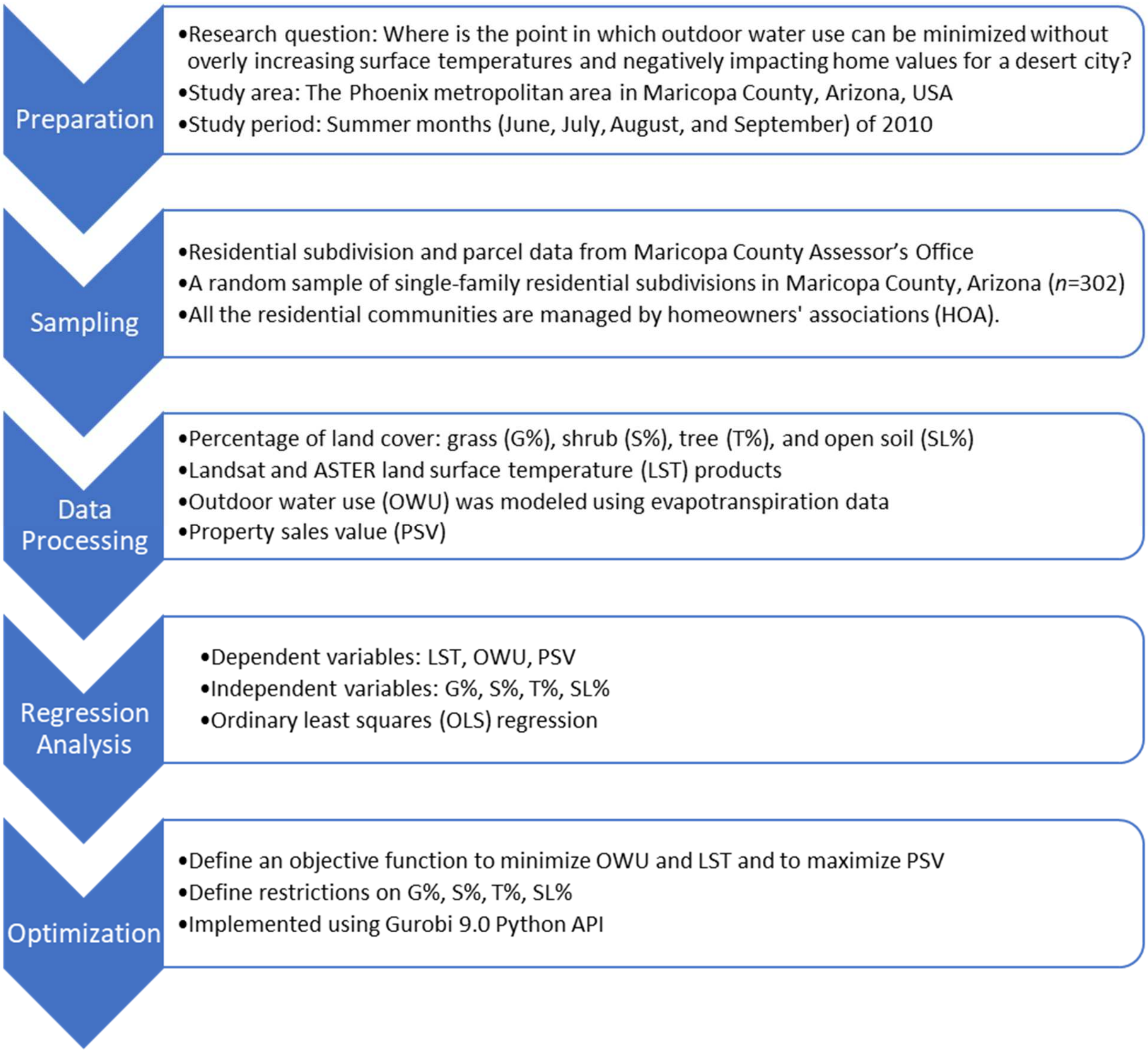


Figure 2. Flowchart of research design.

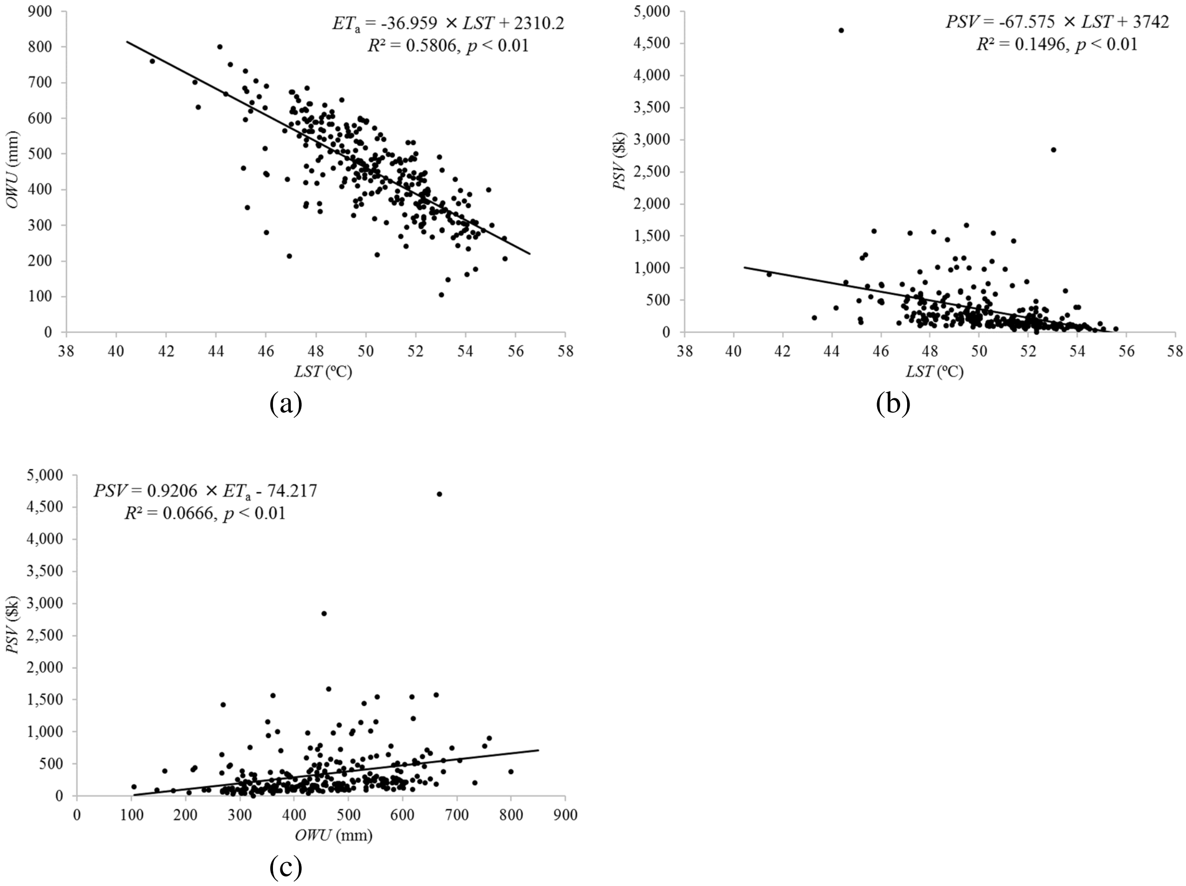


Figure 3. Simple linear regression analysis among three dependent variables: (a) LST vs. OWU, (b) LST vs. PSV, and (c) OWU vs. PSV.

Table 1. Summary statistics of all the independent and dependent variables. These values were calculated based on all the selected single-family residential communities (*n*=302).

Variable	Independent Variables				Dependent Variables		
	Grass%	Shrub%	Tree%	Soil%	LST[a] (°C)	OWU[b] (mm)	PSV[c] ($k)
Min.	0.0	0.0	0.0	7.3	41.5	104.9	32.0
Max.	34.6	17.8	42.7	97.0	55.6	800.0	4,700.0
Mean (μ)	8.0	3.2	12.1	38.8	50.3	452.8	341.4
Std. Dev. (σ)	4.8	4.5	8.1	12.8	2.5	123.0	429.2
$\mu + \sigma$	12.8	7.7	20.2	51.6	52.8	575.8	770.6
$\mu + 2\sigma$	17.6	12.1	28.3	64.4	55.3	698.8	1,199.8
$\mu - \sigma$	3.15	-	4.06	26.02	47.7	329.7	-
$\mu - 2\sigma$	-	-	-	-	45.2	206.7	-

[a] Land surface temperature

[b] Outdoor water use

[c] Property sales value

Table 2. Multiple regression results of *LST*, *OWU* and *PSV* with percent vegetation cover

Model (Dependent variable)	**A** (LST[1])				**B** (OWU[2])				**C** (PSV[3])			
R^2	0.616				0.517				0.264			
Adj. R^2	0.598				0.495				0.228			
p	< 0.01				< 0.01				< 0.01			
RMSE[a]	1.626				77.113				429.540			
Independent variable	B[b]	SE[c]	p	β[d]	B	SE	p	β	B	SE	p	β
Grass%	-0.135*	0.042	0.002	-0.242	10.172*	1.997	0.000	0.432	52.638*	13.595	0.000	0.442
Shrub%	-0.118*	0.046	0.012	-0.206	-1.588	2.175	0.467	-0.065	27.657*	12.881	0.035	0.247
Tree%	-0.243*	0.029	0.000	-0.689	3.680*	1.390	0.010	0.247	19.698*	7.926	0.015	0.300
Soil%	-0.009	0.020	0.646	-0.042	-2.114*	0.942	0.027	-0.229	12.297*	5.491	0.028	0.293
Cons.	54.183*	1.121	0.000	-	410.5*	53.139	0.000	-	-615.858	317.402	0.056	-

[1] Land surface temperature

[2] Outdoor water use

[3] Property sales value

[a] Root mean square error

[b] Unstandardized coefficients

[c] Standard error

[d] Standardized coefficients

* Statistically significant at the 0.05 level

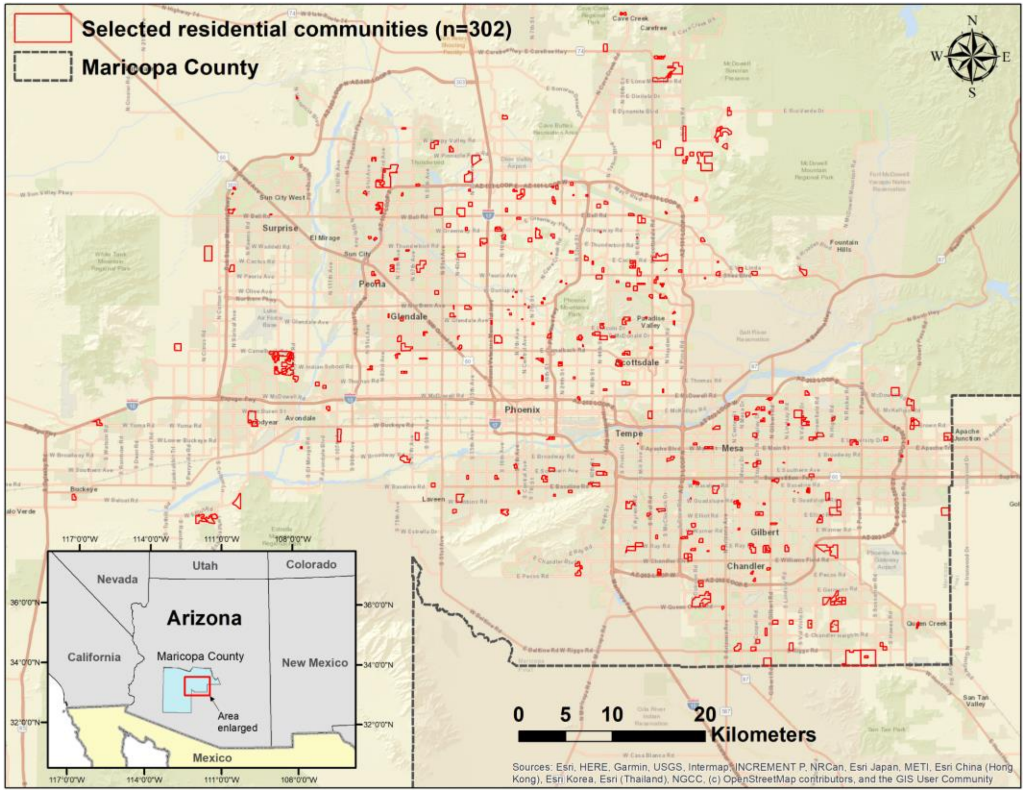
Table 3. Optimization results with top 5 scenarios

Scenario	Grass	Shrub	Tree	Soil	Predicted LST[a] (ºC)	Predicted OWU[b] (mm)	Predicted PSV[c] ($k)
a	2%	13%	7%	63%	50.1	331.3	761.6
b	2%	13%	7%	62%	50.1	333.2	749.3
c	2%	11%	8%	64%	50.2	334.4	738.2
d	1%	13%	9%	62%	49.8	334.2	736.0
e	1%	13%	8%	63%	50.0	327.5	728.6

[a] Land surface temperature

[b] Outdoor water use

[c] Property sales value



Preparation

- Research question: Where is the point in which outdoor water use can be minimized without overly increasing surface temperatures and negatively impacting home values for a desert city?
- Study area: The Phoenix metropolitan area in Maricopa County, Arizona, USA
- Study period: Summer months (June, July, August, and September) of 2010

Sampling

- Residential subdivision and parcel data from Maricopa County Assessor's Office
- A random sample of single-family residential subdivisions in Maricopa County, Arizona (*n*=302)
- All the residential communities are managed by homeowners' associations (HOA).

Data Processing

- Percentage of land cover: grass (G%), shrub (S%), tree (T%), and open soil (SL%)
- Landsat and ASTER land surface temperature (LST) products
- Outdoor water use (OWU) was modeled using evapotranspiration data
- Property sales value (PSV)

Regression Analysis

- Dependent variables: LST, OWU, PSV
- Independent variables: G%, S%, T%, SL%
- Ordinary least squares (OLS) regression

Optimization

- Define an objective function to minimize OWU and LST and to maximize PSV
- Define restrictions on G%, S%, T%, SL%
- Implemented using Gurobi 9.0 Python API