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

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Abstract:	<p>Cities in arid and semi-arid regions have been exploring urban sustainability policies, such as lowering the vegetation coverage to reduce residential outdoor water use. Meanwhile, urban residents express concerns that such policies could potentially impact home prices regardless of the reduced water costs because studies have shown that there is a positive correlation between vegetation coverage and home values. On the other hand, lower vegetation coverage in arid and semi-arid desert regions could increase surface temperatures, and consequently increases energy costs. The question is therefore where the point in which residential outdoor water use can be minimized without overly increasing surface temperatures and negatively impacting home values. This study examines the impacts of spatial composition of different vegetation types on land surface temperature (LST), outdoor water use (OWU), and property sales value (PSV) in 302 local residential communities in the Phoenix metropolitan area, Arizona using remotely sensed data and regression analysis. In addition, the spatial composition of vegetation cover was optimized to achieve a relatively lower LST and OWU and maintain a relatively higher PSV at the same time. We found that drought-tolerant landscaping that is composed of mostly shrubs and trees adapted to the desert environment is the most water efficient way to reduce LST, but grass contributes to a higher PSV. Research findings suggest that different residential landscaping strategies may be better suited for different neighborhoods and goal sets can be used by urban planners and city managers to better design urban residential landscaping for more efficient water conservation and urban heat mitigation for desert cities.</p>
Response to Reviewers:	Please see the attached file "2_response to reviewers.docx" for our responses to reviewers.

Abstract

Cities in arid and semi-arid regions have been exploring urban sustainability policies, such as lowering the vegetation coverage to reduce residential outdoor water use. Meanwhile, urban residents express concerns that such policies could potentially impact home prices regardless of the reduced water costs because studies have shown that there is a positive correlation between vegetation coverage and home values. On the other hand, lower vegetation coverage in arid and semi-arid desert regions could increase surface temperatures, and consequently increases energy costs. The question is therefore where the point in which residential outdoor water use can be minimized without overly increasing surface temperatures and negatively impacting home values. This study examines the impacts of spatial composition of different vegetation types on land surface temperature (LST), outdoor water use (OWU), and property sales value (PSV) in 302 local residential communities in the Phoenix metropolitan area, Arizona using remotely sensed data and regression analysis. In addition, the spatial composition of vegetation cover was optimized to achieve a relatively lower LST and OWU and maintain a relatively higher PSV at the same time. We found that drought-tolerant landscaping that is composed of mostly shrubs and trees adapted to the desert environment is the most water efficient way to reduce LST, but grass contributes to a higher PSV. Research findings suggest that different residential landscaping strategies may be better suited for different neighborhoods and goal sets can be used by urban planners and city managers to better design urban residential landscaping for more efficient water conservation and urban heat mitigation for desert cities.

Keywords: optimization; green space; land surface temperature; evapotranspiration; outdoor water use; property sales value

1 Optimization of Residential Green Space for Environmental Sustainability and Property

2 Appreciation in Metropolitan Phoenix, Arizona

3 4 5 1. Introduction

6 Urban regions in the United States are dominated by residential land, which creates challenges and
7 opportunities for sustainable land management due to the preponderance of outdoor space in yards.

8 ~~Recent estimates reveal~~Studies estimated that approximately 65% of all urban land is devoted to
9 single-family residential neighborhoods and it is the most prevalent zoning in areas slated for
10 future development (Burchell & Shad, 1998; Burchell & Mukherji, 2003; Hirt, 2014). Residential
11 land use is often associated with proliferating turf grass in the continental U.S., which in many
12 regions require extensive irrigation to maintain (Milesi et al., 2005; Cook and Faeth, 2006). This
13 is particularly true in the arid U.S. Southwest, where precipitation can be 18 cm or less per year
14 (Sheppard et al., 2002). Nevertheless, irrigated landscaping provides both environmental benefits
15 such as lower temperatures (Wang et al., 2016; Wang, 2018) and economic benefits such as higher
16 home values (Kestens et al., 2004, Mei et al., 2018). Research is therefore needed to better
17 understand both the relationships and tradeoffs between vegetation cover, land surface
18 temperature, water use, and home values.

19 Generally, green infrastructure contributes to a range of ecosystem services in cities (e.g.,
20 habitat provisioning, stormwater regulation, carbon sequestration), though the mix and extent of
21 services depends on vegetative type and management, and homogenous turf landscapes likely
22 provide nominal ecological benefits (Larson et al., 2016; Groffman et al., 2017). Green
23 infrastructure can also provide socioeconomic and health benefits. For illustration, large public

24 green spaces can influence social capital by providing an environmental-friendly gathering place
25 for local residents to develop and maintain neighborhood social ties (Kweon et al., 1998; Kuo et
26 al., 1998; Maas et al., 2009). The presence of green vegetation can also significantly contribute to
27 residents' sense of social safety and adjustment (Kuo et al., 1998). In addition, neighborhood parks
28 and views of natural landscapes ~~show a positive relationship~~have positive contributions to ~~with~~
29 home values (Lo and Faber, 1997; Escobedo et al. 2015). From a public health perspective, urban
30 green spaces can not only help maintain physical health, but also improves mental functioning,
31 mental health and wellbeing (Sugiyama et al., 2008).

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

46 Multiple studies have examined relationships among environmental and economic
47 variables, but never in a single study and without the focus on residential neighborhoods. For
48 instance, several studies examined the relationship between the composition and configuration of
49 urban land use land cover and land surface temperature (LST), finding that the relationship varies
50 depending on land use and region (Connors et al., 2013; Rotem-Mindali et al., 2015, Schwarz and
51 Manceur, 2015; Li et al., 2016; Wang et al., 2019). However, most studies analyzed the cooling
52 effect of vegetation at global or regional scales regardless of various vegetation types, with a few
53 exceptions that examined trees only (Myint et al., 2013, Middel et al., 2015). Similarly, studies
54 have examined relationships between vegetative cover, LST, and outdoor water use (OWU)
55 finding that small decreases in temperature are associated with large increases in water use
56 (Guhathakurta and Gober, 2007; [Kaplan et al., 2014](#); [Wang, 2018](#)). These studies do not
57 disambiguate vegetative cover type, but have shown that native shrubs are well adapted to the
58 desert climate that can thrive without much rainfall or irrigation (Martin, 2001; Stabler and Martin,
59 2002). Additionally, vegetation with large canopy and structure, such as mature trees, can also
60 provide shade to reduce temperature for better thermal comfort (Armson et al., 2012; Armson et
61 al., 2013; Middel et al., 2015; Zhao et al., 2018a). Finally, another subset of studies examined
62 relationships between urban vegetation and property sales value (PSV), generally finding a
63 positive relationship, and suggest that trees may have the most positive effect (Kestens et al., 2004,
64 Mei et al., 2018). Given variability in effect of different types of vegetative cover (i.e., trees,
65 shrubs, grass) on urban cooling, water use, and property values, understanding the outcomes
66 associated with different vegetative mixes in arid desert urban residential neighborhoods is
67 essential for minimizing trade-offs and maximizing co-benefits.

68 To better understand the related dynamics between environmental and economic tradeoffs,
69 this study examines single-family residential neighborhoods with homeowner associations
70 (HOAs) in the Phoenix metropolitan area (PMA), Arizona, USA. HOAs are entities that dictate
71 minimum landscaping requirements and claim to maintain property values over time (McKenzie,
72 1994; Wentz et al., 2016). The first objective is to examine the impacts of spatial composition of
73 different vegetation cover types on LST, OWU and PSV in major residential communities in the
74 PMA. The second objective is to optimize the spatial composition of residential green spaces in
75 order to achieve a relatively lower LST and OWU and to maintain PSV at the same time. The third
76 objective is to propose residential landscaping strategies for urban sustainability of desert cities in
77 terms of more efficient water conservation and urban heat mitigation based on research findings the
78 optimization results.

79

80

81 **2. Materials and Methods**

82 2.1 Study Area

83 The PMA is located in Maricopa County, Arizona, USA. The total population is about 4.67 million
84 residents with nearly 1.66 million households, as estimated by the 2018 American Community
85 Survey (ACS) (U.S. Census Bureau, 2019). As of 2019, the housing stock consists predominantly
86 (~76.2%) of single-family homes with an increasing number of multi-family structures and
87 mobile/manufactured homes (MAG, 2019). The 2018 mean household income of PMA was
88 \$87,435, which was lower than the national mean of \$87,864 (U.S. Census Bureau, 2019). PMA
89 residents, therefore, need to be conscious of the costs associated with cooling homes, caring for
90 landscaping, and resale values.

91 The PMA is part of the northeastern Sonoran Desert featuring a subtropical semi-arid hot
92 desert climate (Köppen climate classification: *BWh*) (Figure 1). It is characterized by long, hot
93 summers, but short, mild winters. The daily high exceeds 37.8 °C for an average of 110 days every
94 year, which normally occurs between early June and early September (Wang et al., 2016). The
95 highest temperature can reach over 43.3 °C (110 °F) for an annual average of 18 days (Wang et al.,
96 2016). The mean annual precipitation in the past 30 years is merely 204 mm (8.03 inch) with most
97 rainfall taking place during the summer monsoon season (U.S. Climate Data, 2020). This means
98 that residential vegetation is largely managed through a combination of automated irrigation
99 systems (e.g., drip, sprinkler), flood irrigation (in older neighborhoods), and drought tolerant
100 vegetation.

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

108

109 2.2 Data

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

114 2010 data sets were used is because all the data and products used were available from this year.
115 Although it sounds out of date, the purpose of this study is to generalize empirical trade-off
116 relationships and we assume these relationships would hold over time and space for small local
117 residential communities. ~~The reminder of this section describes the acquisition of these data sets
118 and the derivatives of data that are used for the subsequent analyses.~~

119

120 *2.2.1 Land surface temperature*

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

133

134 *2.2.2 Outdoor water use*

135 The municipal water delivery system in the PMA does not have separate water meters for indoor
136 and outdoor water use. We therefore estimated OWU using ET_a as a proxy (Singh et al., 2014).

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

$$142$$
$$143 \quad LE = R_n - G - H, \quad (1)$$
$$144$$

145 where R_n is the net incoming radiation, G is the ground heat flux, H is the sensible heat flux, and
146 LE is the latent heat flux. METRIC has been successfully applied to Landsat and MODIS images
147 to predict ET_a at various spatial scales (e.g. Trezza, 2002; Hendrickx and Hong, 2005; Allen et al.,
148 2007b; Zheng et al., 2015). Research also demonstrated ET_a prediction accuracy of 15%, 10% and
149 5% for daily, monthly, and seasonal timescales (Plaza et al., 2009; Shao and Lunetta, 2012). Model
150 predictions can effectively represent ET_a for both urban and non-urban areas with or without
151 irrigation (Allen et al., 2007b). More detailed model calculation and implementation procedures
152 can be found in Allen et al. (2007a).

153 Model predicted ET_a maps were created using 22 time-series cloud-free Landsat 5 images
154 and meteorological data collected from the weather stations in the Arizona Meteorological
155 Network (AZMET, 2020) that covered the entire year of 2010. Gaps between each two adjacent
156 image acquisition dates were filled using a polynomial curve-fitting method at every single image
157 pixel location, which finally resulted in 365 daily ET_a maps of 30-meter resolution. A summertime
158 total ET_a map was created by aggregating all the daily images in June, July, August and September.
159 We calculated a mean ET_a value for each selected residential community. Model predicted ET_a

160 values were validated using actual water usage data acquired from 49 community parks in the
161 PMA as described in Kaplan et al. (2014). Detailed validation procedure and results can be found
162 in Wang (2018).

163

164 *2.2.3 Property sales value*

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

171

172 *2.2.4 Land cover classification*

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

181

182 *2.3 Analysis*

183 ~~We aimed to explore both the landscaping factors that influence LST, OWU and PSV and the~~
184 ~~tradeoffs between them. To that end, we performed both a linear regression and an optimization~~
185 ~~analysis. These methods are described here.~~We first performed a linear regression analysis to
186 explore the empirical relationships between landscaping factors and LST, OWU, and PSV. An
187 optimization analysis was subsequently used to examine the tradeoffs between these variables.

188

189 *2.3.1 Regression analysis*

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

194

$$195 \quad y_j = \beta_{0j} + \sum \beta_{ij}x_i + \varepsilon_j \quad (2)$$

196

197 where:

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

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

200 x_i = area percentage of land cover type i ;

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

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

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

204

205 *2.3.2 Optimization*

206 ~~The objective of this study is to find a set of area percentage values of grass, shrub, tree and soil~~
207 ~~that can yield the lowest possible LST and OWU, and meanwhile maintain a relatively high PSV.~~
208 We ~~first defined~~ formulated the optimization question as an integer programming problem with an
209 objective function to minimize the summation of model predicted LST and OWU, ~~and then~~
210 formulated the optimization question as an integer programming problem. Consider the following
211 notations:

212

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

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

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

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

217 m_{x_i} = observed minimum of x_i ;

218 u_{x_i} = observed mean of x_i ;

219 σ_{x_i} = observed standard deviation of x_i ;

220 $m_{\sum_{i \in \Phi} x_i}$ = observed minimum of percent all vegetation cover;

221 $u_{\sum_{i \in \Phi} x_i}$ = observed mean of percent all vegetation cover;

222 $\sigma_{\sum_{i \in \Phi} x_i}$ = observed standard deviation of percent all vegetation cover;

223 $m_{\sum_{i \in I} x_i}$ = observed minimum of percent all land cover;

224 $u_{\sum_{i \in I} x_i}$ = observed mean of percent all land cover;

225 $\sigma_{\sum_{i \in I} x_i}$ = observed standard deviation of percent all land cover;

226 μ_{y_j} = observed mean of y_j ;

227 m_{y_j} = observed minimum of y_j ;

228

229 The objective function is ~~therefore~~ formulated as:

230

231
$$\text{Minimize } \sum_{j \in \Psi} y_j, \tag{3}$$

232

233 which is subject to ~~the following restrictions~~:

234

235
$$y_j \leq \mu_{y_j} \quad \forall j \in \Psi, \tag{4}$$

236

237
$$y_j \geq m_{y_j} \quad \forall j \in J, \tag{5}$$

238

239
$$x_i \leq u_{x_i} + 2\sigma_{x_i} \quad \forall i \in I, \tag{6}$$

240

241
$$x_i \geq m_{x_i} \quad \forall i \in I, \tag{7}$$

242

243
$$\sum_{i \in \Phi} x_i \leq u_{\sum_{i \in \Phi} x_i} + 2\sigma_{\sum_{i \in \Phi} x_i}, \tag{8}$$

244

245
$$\sum_{i \in \Phi} x_i \geq m_{\sum_{i \in \Phi} x_i}, \tag{9}$$

246

247
$$\sum_{i \in I} x_i \leq u_{\sum_{i \in I} x_i} + 2\sigma_{\sum_{i \in I} x_i}, \tag{10}$$

248

249
$$\sum_{i \in I} x_i \geq m_{\sum_{i \in I} x_i}, \tag{11}$$

250

251
$$x_i \text{ integer } \forall i \in I. \tag{12}$$

252

253 The objective function (3) is to minimize the summation of empirical estimations of LST and
254 OWU that are derived from regression equation (2). Constraint (4) is defined to force model
255 predicted LST and OWU to be less than the observed mean, and constraint (5) is to restrict
256 predicted LST, OWU and PSV to be greater than the observed minimum. Constraints (6) and (7)
257 restrict the percent area of each land cover to be between the observation minimum and +2 standard
258 deviations from the observed mean. Similar to (6) and (7), constraints (8)-(9) and (10)-(11) restrict
259 the area percentage of vegetation cover and all land cover between the observation minimum and
260 +2 standard deviations of the observed mean, respectively. Integer restrictions on independent
261 variables area percentage of land cover types are stipulated in Constraint (12).

262 The optimization procedure was implemented using Gurobi 9.0 Python API (Gurobi
263 Optimization, 2020) in the Jupyter Notebook environment. We selected top 100 sub-optimal
264 solutions to the objective function (3) that generated the smallest possible summation of LST and
265 OWU, and then searched for the highest predicted PSV values within these 100 solutions. The top
266 5 best scenarios were finally selected as the optimal solutions.

267

268

269 **3. Results**

270 3.1 Summary statistics

271 The summary statistics of residential-green-space land cover types, LST, OWU₁ and PSV are
272 shown in Table 1. The total OWU that was estimated using actual evapotranspiration (ET_a) ranges

273 from 105 mm to nearly 800 mm with a mean value of 453 mm [for the summer months of 2010](#).
274 LST ranges from 41.5 °C to 55.6 °C with a mean LST of 50.3 °C. PSV ranges from \$6.1k to
275 \$4,700k with a mean PSV of \$340.6k and a large standard deviation of \$431.3k. For ~~these all the~~
276 [302 residential](#) neighborhoods, open soil has a mean percent area of 38.8%, which is the largest
277 among four land cover types. This could include desert style or unfinished landscaping. This is
278 followed by trees ($\mu_T\% = 12.1\%$), grass ($\mu_G\% = 8.1\%$), and finally shrubs ($\mu_S\% = 3.2\%$). This land
279 cover profile in residential communities in the PMA is generally consistent with ‘xeriscaped’ and
280 other low vegetative cover yard structure types prevalent in the region. This is fairly typical too of
281 properties in HOA neighborhoods, where vegetation composition can be regulated. Even in
282 residential communities with relatively higher vegetative land cover, the mean percent vegetated
283 area is only 21.1% with a maximum cover of 52.7%.

284

285 3.2 Regression results

286 Figure [2-3](#) shows the relationship among three dependent variables (LST, OWU and PSV) using
287 simple linear regression. ~~LST and OWU have a strong, negative relationship, which means~~
288 ~~vegetation can significantly cool down LST but increase OWU as well. PSV is negatively~~
289 ~~correlated with LST but has a positive relationship with OWU, which means higher PSV values~~
290 ~~are generally found in more vegetated residential communities with lower LST but higher OWU. A~~
291 ~~statistically significant negative relationship was found between LST and OWU and between LST~~
292 ~~and PSV, while a statistically significant positive relationship existed between PSV and OWU.~~
293 ~~This implies that higher surface temperatures are generally found in residential communities of~~
294 ~~lower water use and lower home values. On the other hand, higher water use is often associated~~

295 [with lower surface temperatures and higher home values. We believe the underlying cause of these](#)
296 [relationships is the variation of vegetation coverage.](#)

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

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

316 Model C in Table 2 shows the regression results of PSV. Although this model has a
317 relatively lower goodness-of-fit (adjusted $R^2 = 0.228$), it is statistically significant at the 0.01 level.

318 We anticipate a lower R^2 because studies using hedonic models of home price are complex and
319 show that individual factors such as house size and lot size as well as regional factors such as
320 parks, transportation, and schools influence home prices (Glaesener and Caruso, 2015; Seo et al.,
321 2019). For our model, the coefficient estimates are positive and statistically significant at the 0.05
322 level (p -value < 0.05). The relative contribution of vegetation land cover types to PSV is ranked
323 as: Grass > Shrubs > Trees > Soils. This result implies that increasing vegetation cover, especially
324 grass and shrubs, can effectively maintain a relatively higher PSV.

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

333

334 3.3 Optimization results

335 We first solved the integer programming problem and obtained the top 100 sub-optimal solutions
336 for the lowest possible summation of LST and OWU values and their corresponding land cover
337 compositions, and then searched for the highest predicted PSV values within these solutions. These
338 records are therefore considered as our final optimization solutions ~~because they not only have the~~
339 ~~lowest possible LST and OWU values, but also provide the highest possible PSV.~~

340 We present top 5 optimization scenarios in Table 3. These five scenarios suggest that
341 shrubs should be given the largest weight within all the vegetation types to maximize its
342 environmental and economic benefits. On the other hand, minimizing the use of grass but
343 maximizing open soil coverage can also contribute to lower LST and OWU. PSV can be higher if
344 a larger percent grass cover is given, but OWU would also be higher as well. As suggested, a
345 residential landscape that is composed of 1-2% grass, 11-13% shrubs, 7-9% trees, and 62-64%
346 soils can result in the lowest possible LST and OWU and help maintain a relatively higher PSV at
347 the same time. Within these scenarios, predicted LST varies from 49.8 °C to 50.2 °C, which is less
348 than the observed mean LST (Table 1, $\mu_{LST} = 50.26$ °C). Predicted OWU ranges from 327.5 mm
349 to 334.4 mm, which is around the mean minus one standard deviation ($\mu - \sigma = 329.7$ mm) of
350 observed OWU. Predicted PSV in these scenarios varies from \$728.6k to \$761.6k, which is higher
351 than observed mean ($\mu_{PSV} = \$340.6k$) but lower than the mean plus one standard deviation ($\mu + \sigma$
352 = \$771.9k).

353

354

355 **4. Discussion**

356 4.1 Effect of vegetation cover on LST, OWU and PSV

357 Our analysis shows that trees provide the greatest cooling efficiency, followed by the combination
358 of grass and shrubs. This implies that planting more trees or replacing other land cover with trees
359 in a desert residential neighborhood has the potential lower LST to its maximum. This result is
360 consistent with prior studies of the effect of the urban heat island effect in Phoenix and other areas
361 that show this relationship between vegetation and land surface temperature (see Myint et al., 2013
362 and Middell et al., 2015). Additionally, trees provide shade and thermal comfort co-benefits (Zhao

363 et al., 2017; Zhao et al., 2018b). These studies support efforts by the City of Phoenix, which
364 initiated a Tree and Shade Master Plan in 2010 to ameliorate extreme heat during the summer
365 months by increasing tree canopy from 10% in 2010 to 25% by 2030 (City of Phoenix, 2010). Our
366 study is the first to consider shrubs, which is the most populated native vegetation in a desert
367 environment (Martin, 2001). Shrubs had the lowest cooling efficiency among all the vegetative
368 types, meaning that shrubs are the least efficient way to achieve cooling as measured by LST in
369 our study. They also do not provide the shade co-benefit of trees.

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

380 Our results are consistent with other studies showing that vegetation increases property
381 values in residential neighborhoods (Kestens et al., 2004, Bark et al., 2011, Escobedo et al., 2015)
382 Generally, percent vegetative cover in desert neighborhoods also had a significant positive
383 relationship with PSV with grass cover having the greatest contribution, followed by shrubs and
384 trees (Table 2). However, the goodness-of-fit of the regression model is relatively low (adj. $R^2 =$
385 0.228) because we did not include other factors shown to influence home values such as property

386 size, home size, school districts, etc. While adding such variables can potentially increase R^2 value,
387 it's not relevant for this study. Rather, our goal was to examine the combined effect of different
388 types of vegetation cover on PSV. Our study, however, shows trees have much lower contribution
389 to PSV than grass and shrubs. This result likely deviates from previous studies conducted in
390 Québec City and Florida because PMA has a much lower percent tree cover (only 12%) and annual
391 precipitation than temperate and humid regions (Escobedo et al., 2015; Kestens et al., 2004). We
392 therefore suggest that it is necessary to take climate background and dominant native vegetation
393 into consideration when examining the effect of vegetation cover on PSV because experiences and
394 findings from some cities may not apply to the others. Moreover, trees had the least effect on
395 property value among three vegetation types, which could be considered a benefit in some regions
396 given that low income communities currently have the greatest need for shade trades, but are also
397 vulnerable to displacement if housing costs increased (Landry and Chakraborty, 2009). Overall,
398 regional social and ecological context are important in assessing the relative benefits of trees versus
399 grass and shrubs.

400

401 4.2 Implications of optimization result and policy recommendation

402 Five optimization scenarios in Table 3 suggest that minimizing the use of grass in residential
403 landscaping in a desert city can contribute to a lower LST and OWU, while PSV maintains
404 relatively high. In face of severe drought in the Southwestern U.S., California Department of Water
405 Resources initiated the Institutional Turf Replacement Program (ITRP) to replace more than
406 165,000 square feet of turf with California native and water-efficient landscaping to provide long-
407 term water savings, and each eligible household can receive a rebate of approximately \$2 per
408 square foot of removed and replaced turf (CDWR, 2009). Tull et al. (2016) used 545 unique single-

409 family residential turf rebates and found that the mean water savings were estimated at about 1 m³
410 per square meter of turf removal per year for each household. Another study by Matlock et al.
411 (2019) studied 227 participating customers in southern California and found the average reduced
412 water usage was approximately 392 m³ per year after turf removal. Both studies confirmed the
413 effectiveness of ITRP in California, and our study further provides the theoretical basis of a similar
414 program that can be potentially implemented in the PMA. Completely removing large grass cover
415 or replacing grass with desert-adapted shrubs or trees can become a sustainable development
416 practice for residential communities in desert cities to mitigate heat and conserve water.

417 Another recommendation is to widely adopt xeric landscape style that mostly include
418 individually watered and low water-use exotic and native plants as a sustainable landscaping
419 strategy as suggested by the Xeriscape™ movement that began in Denver, Colorado in 1981
420 (Martin, 2001). Xeriscape is a water-efficient landscaping method that has become increasingly
421 popular in the arid southwestern U.S. (Sovocool and Morgan, 2006). Research has shown that in
422 southern Nevada, Xeriscape can save an average of 55.8 gal/sq. ft (or 2.27 m³/m²) per year
423 resulting from replacing turf grass with xeric landscape (Sovocool and Morgan, 2006). Households
424 realized a 30% annual water use reduction after converting to xeric landscape that equals
425 approximately 363 m³ annually (Sovocool and Morgan, 2006). Xeriscape can also save labor and
426 money for maintenance because of water-efficient and desert-adapted plants and efficient
427 irrigation. On the other hand, Martin (2008) compared four landscape design archetypes and
428 proposed an oasis landscape design that consists of a mixture of small areas of well-irrigated turf
429 grass interspersed with drip-irrigated landscape trees and shrubs and decomposed granite mulch
430 has an overall better performance in water conservation than the traditional xeric style landscape
431 in Phoenix, Arizona.

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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. ~~In order to~~ better quantify the ~~actual~~ effect of percent vegetation cover on LST and OWU, one should also consider nighttime and situations in other seasons ~~and nighttime~~. Due to the limitation of data ~~limitation~~, 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.

455 **5. Conclusions**

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

465 This study has made four significant contributions to the sustainability of desert cities.
466 First, we find that even though trees can efficiently reduce LST, its contribution to PSV is the
467 lowest in a semi-arid desert environment. One implication of this finding is that trees might be a
468 water effective means to mitigate urban heat and address income-based shade disparities in the
469 city, while minimizing property value increases that could drive unintended consequences like
470 gentrification. Second, minimizing the use of grass in a semi-arid desert city is crucial because it
471 is the least water use efficient vegetation type, although it contributes to a higher PSV. Third,
472 desert-adapted shrubs and trees can be widely promoted because they not only have higher water
473 use efficiency, can significantly lower LST, but also have a relatively higher contribution to PSV.
474 Paired, these findings suggest a slight trade-off between the most environmentally efficient
475 landscape type (e.g., xeriscaping) and property value maximization (e.g., grass) in some existing
476 residential neighborhoods. Nevertheless, there are multiple yard landscaping market types in
477 Phoenix. Therefore, more work is needed to understand the extent to which the observed positive

478 relationship between grass and property value is moderated by homeowner preferences across
479 different style neighborhoods. Fourth, our results and findings provide strong evidence and a
480 theoretical basis for the environmental benefits of turf removal programs and xeric or oasis style
481 landscaping design, which can be used as a guideline by desert cities for a better design of
482 residential landscaping for urban sustainable development in the future.

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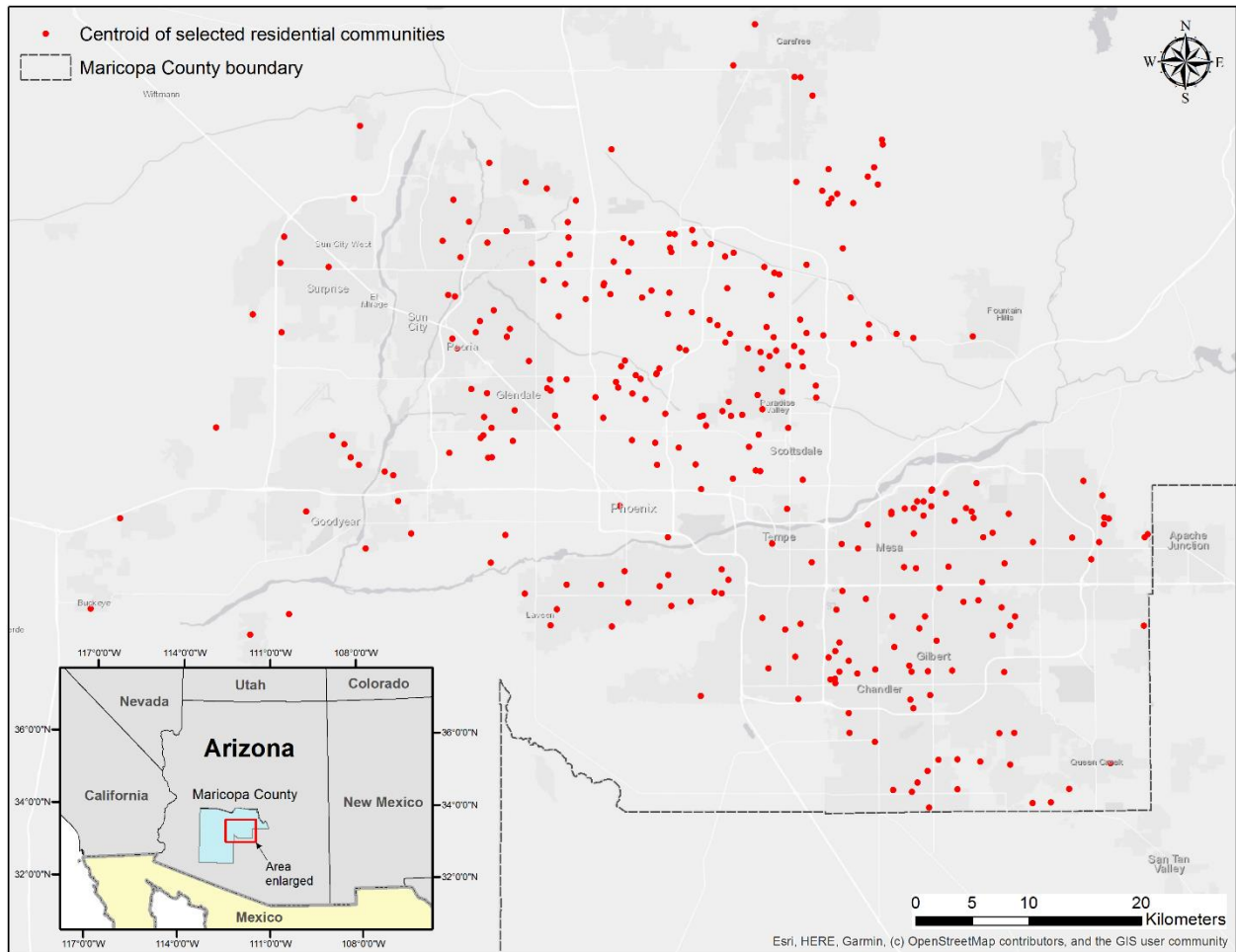
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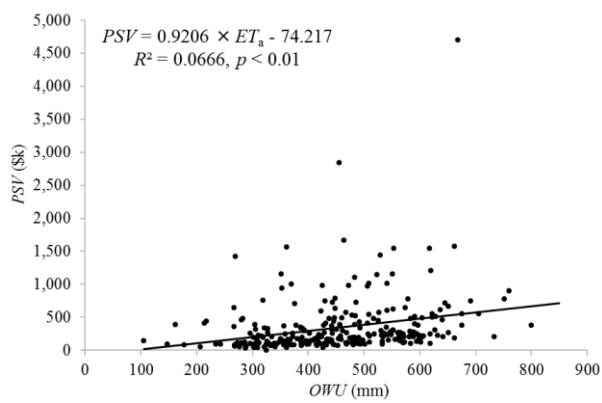
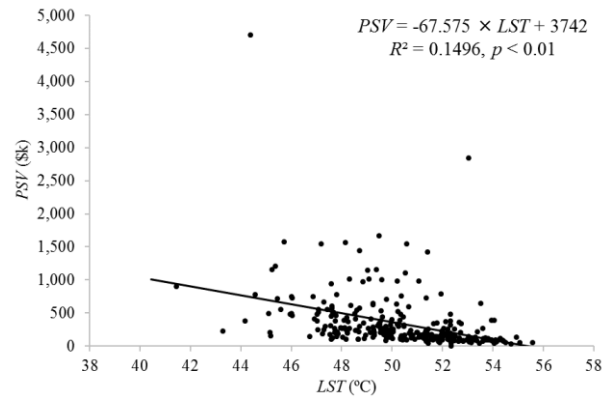
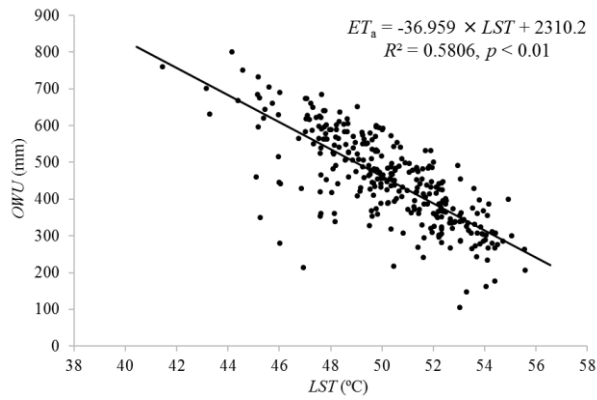
Figure 1. Map of study area and locations of selected residential communities.



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688 [Figure 2. Flowchart of research design.](#)

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 691 Figure 23. Simple linear regression analysis among three dependent variables: (a) LST vs. OWU,
 692 (b) LST vs. PSV, and (c) OWU vs. PSV.

693

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

696

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	-

697

698 [^a Land surface temperature](#)

699 [^b Outdoor water use](#)

700 [^c Property sales value](#)

701

702

703

704

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

706

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

707

708 [¹ Land surface temperature](#)

709 [² Outdoor water use](#)

710 [³ Property sales value](#)

711 ^a Root mean square error

712 ^b Unstandardized coefficients

713 ^c Standard error

714 ^d Standardized coefficients

715 * Statistically significant at the 0.05 level

716

717 Table 3. Optimization results with top 5 scenarios

718

Scenario	Grass	Shrub	Tree	Soil	Predicted LST ^a (°C)	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

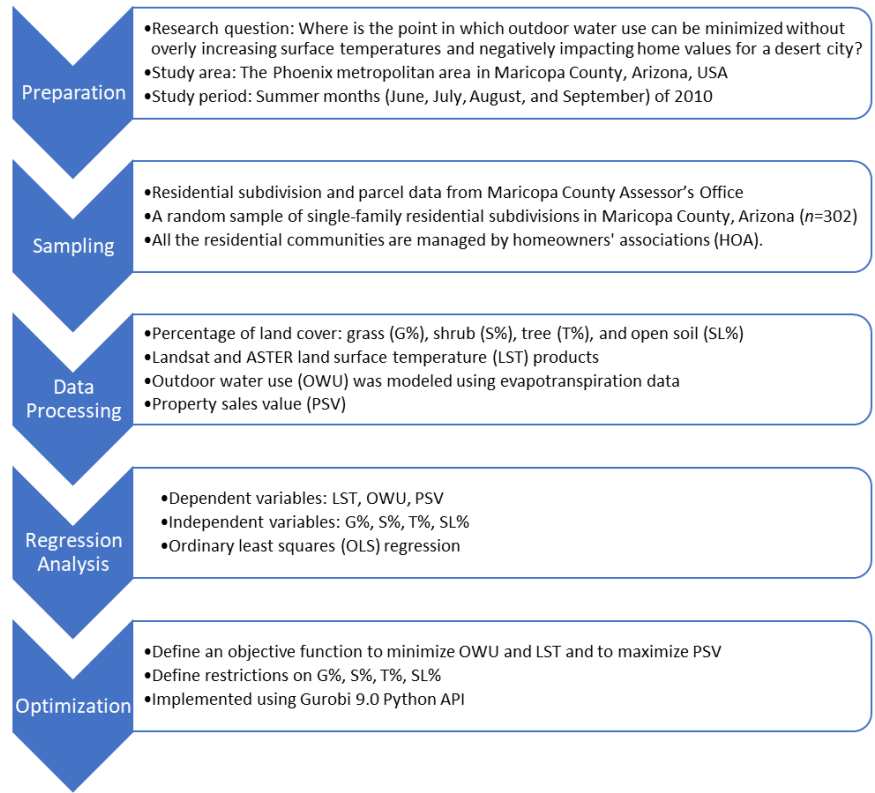
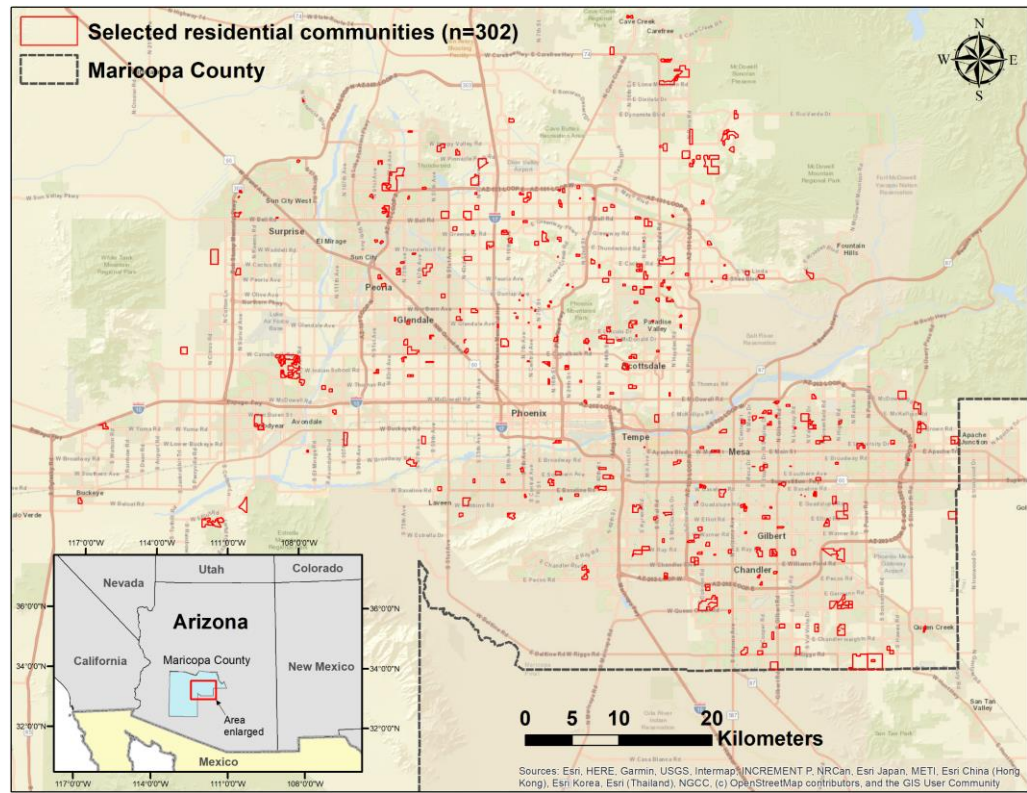
719 ^a [Land surface temperature](#)

720 ^b [Outdoor water use](#)

721 ^c [Property sales value](#)

722

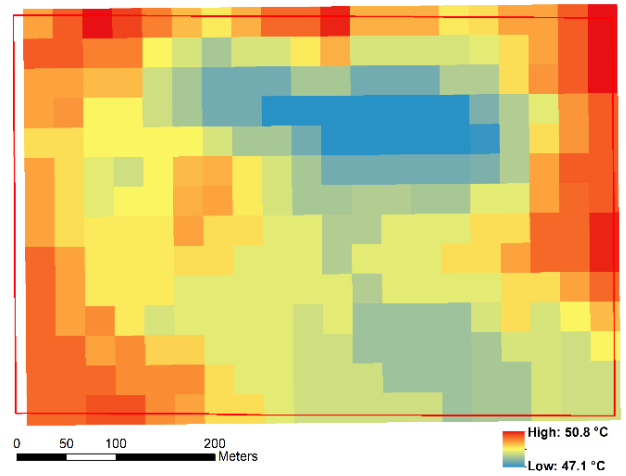
Graphical Abstract



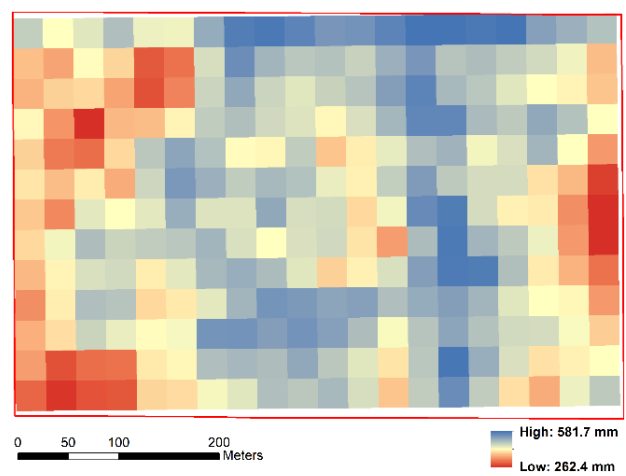
A Sample Residential Community with Land Cover Types and Land Parcels



Land Surface Temperature



Outdoor Water Use (evapotranspiration)



Highlights

- Residential ~~green spaces~~landscape composition was optimized for environmental sustainability
- ~~A relatively higher home value can be maintained by the optimization strategy~~The Phoenix metropolitan area in Arizona was used as a case study
- Drought-tolerant ~~landscaping~~desert landscape is the most water efficient ~~way to reduce temperature~~
- Grass coverage contributes to higher home values but is the least water efficient
- Trees ~~are the most efficiently to reduce~~lower surface temperature ~~and but have less water demand~~contribute the least to home values

Highlights

- Residential landscape composition was optimized for environmental sustainability
- The Phoenix metropolitan area in Arizona was used as a case study
- Drought-tolerant desert landscape is the most water efficient
- Grass coverage contributes to higher home values but is the least water efficient
- Trees efficiently lower surface temperature but contribute the least to home values

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

3
4
5 **1. Introduction**

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

19 Generally, green infrastructure contributes to a range of ecosystem services in cities (e.g.,
20 habitat provisioning, stormwater regulation, carbon sequestration), though the mix and extent of
21 services depends on vegetative type and management, and homogenous turf landscapes likely
22 provide nominal ecological benefits (Larson et al., 2016; Groffman et al., 2017). Green
23 infrastructure can also provide socioeconomic and health benefits. For illustration, large public

24 green spaces can influence social capital by providing an environmental-friendly gathering place
25 for residents to develop and maintain neighborhood social ties (Kweon et al., 1998; Kuo et al.,
26 1998; Maas et al., 2009). The presence of green vegetation can also significantly contribute to
27 residents' sense of social safety and adjustment (Kuo et al., 1998). In addition, neighborhood parks
28 and views of natural landscapes have positive contributions to home values (Lo and Faber, 1997;
29 Escobedo et al. 2015). From a public health perspective, urban green spaces can not only help
30 maintain physical health, but also improves mental functioning, mental health and wellbeing
31 (Sugiyama et al., 2008).

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

45 Multiple studies have examined relationships among environmental and economic
46 variables, but never in a single study and without the focus on residential neighborhoods. For

47 instance, several studies examined the relationship between the composition and configuration of
48 urban land use land cover and land surface temperature (LST), finding that the relationship varies
49 depending on land use and region (Connors et al., 2013; Rotem-Mindali et al., 2015, Schwarz and
50 Manceur, 2015; Li et al., 2016; Wang et al., 2019). However, most studies analyzed the cooling
51 effect of vegetation at global or regional scales regardless of various vegetation types, with a few
52 exceptions that examined trees only (Myint et al., 2013, Middel et al., 2015). Similarly, studies
53 have examined relationships between vegetative cover, LST, and outdoor water use (OWU)
54 finding that small decreases in temperature are associated with large increases in water use
55 (Guhathakurta and Gober, 2007; Kaplan et al., 2014; Wang, 2018). These studies do not
56 disambiguate vegetative cover type but have shown that native shrubs are well adapted to the desert
57 climate that can thrive without much rainfall or irrigation (Martin, 2001; Stabler and Martin, 2002).
58 Additionally, vegetation with large canopy and structure, such as mature trees, can also provide
59 shade to reduce temperature for better thermal comfort (Armson et al., 2012; Armson et al., 2013;
60 Middel et al., 2015; Zhao et al., 2018a). Finally, another subset of studies examined relationships
61 between urban vegetation and property sales value (PSV), generally finding a positive relationship,
62 and suggest that trees may have the most positive effect (Kestens et al., 2004, Mei et al., 2018).
63 Given variability in effect of different types of vegetative cover (i.e., trees, shrubs, grass) on urban
64 cooling, water use, and property values, understanding the outcomes associated with different
65 vegetative mixes in arid desert urban residential neighborhoods is essential for minimizing trade-
66 offs and maximizing co-benefits.

67 To better understand the related dynamics between environmental and economic tradeoffs,
68 this study examines single-family residential neighborhoods with homeowner associations
69 (HOAs) in the Phoenix metropolitan area (PMA), Arizona, USA. HOAs are entities that dictate

70 minimum landscaping requirements and claim to maintain property values over time (McKenzie,
71 1994; Wentz et al., 2016). The first objective is to examine the impacts of spatial composition of
72 different vegetation cover types on LST, OWU and PSV in major residential communities in the
73 PMA. The second objective is to optimize the spatial composition of residential green spaces in
74 order to achieve a relatively lower LST and OWU and to maintain PSV at the same time. The third
75 objective is to propose residential landscaping strategies for urban sustainability of desert cities in
76 terms of water conservation and urban heat mitigation based on the optimization results.

77

78

79 **2. Materials and Methods**

80 2.1 Study Area

81 The PMA is located in Maricopa County, Arizona, USA. The total population is about 4.67 million
82 residents with nearly 1.66 million households, as estimated by the 2018 American Community
83 Survey (ACS) (U.S. Census Bureau, 2019). As of 2019, the housing stock consists predominantly
84 (~76.2%) of single-family homes with an increasing number of multi-family structures and
85 mobile/manufactured homes (MAG, 2019). The 2018 mean household income of PMA was
86 \$87,435, which was lower than the national mean of \$87,864 (U.S. Census Bureau, 2019). PMA
87 residents, therefore, need to be conscious of the costs associated with cooling homes, caring for
88 landscaping, and resale values.

89 The PMA is part of the northeastern Sonoran Desert featuring a subtropical semi-arid hot
90 desert climate (Köppen climate classification: *BWh*) (Figure 1). It is characterized by long, hot
91 summers, but short, mild winters. The daily high exceeds 37.8 °C for an average of 110 days every
92 year, which normally occurs between early June and early September (Wang et al., 2016). The

93 highest temperature can reach over 43.3 °C (110 °F) for an annual average of 18 days (Wang et al.,
94 2016). The mean annual precipitation in the past 30 years is merely 204 mm (8.03 inch) with most
95 rainfall taking place during the summer monsoon season (U.S. Climate Data, 2020). This means
96 that residential vegetation is largely managed through a combination of automated irrigation
97 systems (e.g., drip, sprinkler), flood irrigation (in older neighborhoods), and drought tolerant
98 vegetation.

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

106

107 2.2 Data

108 Figure 2 shows the flowchart of research design. Four data sets were used to evaluate the trade-
109 offs among LST, OWU and PSV with regards to residential green space composition. The data
110 sets include land cover classification, remotely sensed surface temperature imagery, model-
111 predicted actual evapotranspiration (ET_a), and property sales records from 2010. The reason why
112 2010 data sets were used is because all the data and products used were available from this year.
113 Although it sounds out of date, the purpose of this study is to generalize empirical trade-off
114 relationships and we assume these relationships would hold over time and space for small local
115 residential communities.

116

117 *2.2.1 Land surface temperature*

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

130

131 *2.2.2 Outdoor water use*

132 The municipal water delivery system in the PMA does not have separate water meters for indoor
133 and outdoor water use. We therefore estimated OWU using ET_a as a proxy (Singh et al., 2014).
134 ET_a was modeled using a surface energy balance model named METRIC (Mapping
135 Evapotranspiration at high spatial Resolution with Internalized Calibration) (Allen et al., 2007a).
136 Surface energy balance model is an essential approach for heat flux and evaporation estimation in
137 applied meteorology and hydrology. More specifically, the METRIC model computes the latent
138 heat flux as the residue of the surface energy balance, which can be written as:

139

140

$$LE = R_n - G - H, \quad (1)$$

141

142 where R_n is the net incoming radiation, G is the ground heat flux, H is the sensible heat flux, and

143 LE is the latent heat flux. METRIC has been successfully applied to Landsat and MODIS images

144 to predict ET_a at various spatial scales (e.g. Trezza, 2002; Hendrickx and Hong, 2005; Allen et al.,

145 2007b; Zheng et al., 2015). Research also demonstrated ET_a prediction accuracy of 15%, 10% and

146 5% for daily, monthly, and seasonal timescales (Plaza et al., 2009; Shao and Lunetta, 2012). Model

147 predictions can effectively represent ET_a for both urban and non-urban areas with or without

148 irrigation (Allen et al., 2007b). More detailed model calculation and implementation procedures

149 can be found in Allen et al. (2007a).

150 Model predicted ET_a maps were created using 22 time-series cloud-free Landsat 5 images

151 and meteorological data collected from the weather stations in the Arizona Meteorological

152 Network (AZMET, 2020) that covered the entire year of 2010. Gaps between each two adjacent

153 image acquisition dates were filled using a polynomial curve-fitting method at every single image

154 pixel location, which finally resulted in 365 daily ET_a maps of 30-meter resolution. A summertime

155 total ET_a map was created by aggregating all the daily images in June, July, August, and

156 September. We calculated a mean ET_a value for each selected residential community. Model

157 predicted ET_a values were validated using actual water usage data acquired from 49 community

158 parks in the PMA as described in Kaplan et al. (2014). Detailed validation procedure and results

159 can be found in Wang (2018).

160

161 *2.2.3 Property sales value*

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

168

169 *2.2.4 Land cover classification*

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

178

179 *2.3 Analysis*

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

183

184 *2.3.1 Regression analysis*

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

189

$$190 \quad y_j = \beta_{0j} + \sum \beta_{ij}x_i + \varepsilon_j \quad (2)$$

191

192 where:

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

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

195 x_i = area percentage of land cover type i ;

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

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

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

199

200 2.3.2 Optimization

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

204

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

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

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

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

209 m_{x_i} = observed minimum of x_i ;

210 u_{x_i} = observed mean of x_i ;

211 σ_{x_i} = observed standard deviation of x_i ;

212 $m_{\sum_{i \in \Phi} x_i}$ = observed minimum of percent all vegetation cover;

213 $u_{\sum_{i \in \Phi} x_i}$ = observed mean of percent all vegetation cover;

214 $\sigma_{\sum_{i \in \Phi} x_i}$ = observed standard deviation of percent all vegetation cover;

215 $m_{\sum_{i \in I} x_i}$ = observed minimum of percent all land cover;

216 $u_{\sum_{i \in I} x_i}$ = observed mean of percent all land cover;

217 $\sigma_{\sum_{i \in I} x_i}$ = observed standard deviation of percent all land cover;

218 μ_{y_j} = observed mean of y_j ;

219 m_{y_j} = observed minimum of y_j ;

220

221 The objective function is formulated as:

222

$$223 \quad \text{Minimize } \sum_{j \in \Psi} y_j, \quad (3)$$

224

225 which is subject to:

226

$$227 \quad y_j \leq \mu_{y_j} \quad \forall j \in \Psi, \quad (4)$$

228

$$229 \quad y_j \geq m_{y_j} \quad \forall j \in J, \quad (5)$$

230

$$231 \quad x_i \leq u_{x_i} + 2\sigma_{x_i} \quad \forall i \in I, \quad (6)$$

232

$$233 \quad x_i \geq m_{x_i} \quad \forall i \in I, \quad (7)$$

234

$$235 \quad \sum_{i \in \Phi} x_i \leq u_{\sum_{i \in \Phi} x_i} + 2\sigma_{\sum_{i \in \Phi} x_i}, \quad (8)$$

236

$$237 \quad \sum_{i \in \Phi} x_i \geq m_{\sum_{i \in \Phi} x_i}, \quad (9)$$

238

$$239 \quad \sum_{i \in I} x_i \leq u_{\sum_{i \in I} x_i} + 2\sigma_{\sum_{i \in I} x_i}, \quad (10)$$

240

$$241 \quad \sum_{i \in I} x_i \geq m_{\sum_{i \in I} x_i}, \quad (11)$$

242

$$243 \quad x_i \text{ integer } \forall i \in I. \quad (12)$$

244

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

252 +2 standard deviations of the observed mean, respectively. Integer restrictions on area percentage
253 of land cover types are stipulated in Constraint (12).

254 The optimization procedure was implemented using Gurobi 9.0 Python API (Gurobi
255 Optimization, 2020) in the Jupyter Notebook environment. We selected top 100 sub-optimal
256 solutions to the objective function (3) that generated the smallest possible summation of LST and
257 OWU, and then searched for the highest predicted PSV values within these 100 solutions. The top
258 5 best scenarios were finally selected as the optimal solutions.

259

260

261 **3. Results**

262 3.1 Summary statistics

263 The summary statistics of land cover types, LST, OWU, and PSV are shown in Table 1. The total
264 OWU that was estimated using ET_a ranges from 105 mm to nearly 800 mm with a mean value of
265 453 mm for the summer months of 2010. LST ranges from 41.5 °C to 55.6 °C with a mean LST
266 of 50.3 °C. PSV ranges from \$6.1k to \$4,700k with a mean PSV of \$340.6k and a large standard
267 deviation of \$431.3k. For all the 302 residential neighborhoods, open soil has a mean percent area
268 of 38.8%, which is the largest among four land cover types. This could include desert style or
269 unfinished landscaping. This is followed by trees ($\mu_{T\%} = 12.1\%$), grass ($\mu_{G\%} = 8.1\%$), and finally
270 shrubs ($\mu_{S\%} = 3.2\%$). This land cover profile in residential communities in the PMA is generally
271 consistent with ‘xeriscaped’ and other low vegetative cover yard structure types prevalent in the
272 region. This is fairly typical too of properties in HOA neighborhoods, where vegetation
273 composition can be regulated. Even in residential communities with relatively higher vegetative
274 land cover, the mean percent vegetated area is only 21.1% with a maximum cover of 52.7%.

275

276 3.2 Regression results

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

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

295 Model B in Table 2 shows regression results of OWU as the dependent variable. This model
296 is also statistically significant (p -value < 0.01) and meaning that vegetation cover can explain
297 nearly 50% of the total variation in OWU (adjusted $R^2 = 0.495$). Percent grass and trees have

298 significant, positive relationships with OWU, and the coefficient estimate of percent grass is much
299 larger than trees, which means increasing percent grass area can result in more OWU than
300 increasing the same percent area of trees. Percent soils have a negative relationship with OWU,
301 which means increasing the percentage of open soils can potentially reduce OWU. Percent shrub
302 is insignificant in this model.

303 Model C in Table 2 shows the regression results of PSV. Although this model has a
304 relatively lower goodness-of-fit (adjusted $R^2 = 0.228$), it is statistically significant at the 0.01 level.
305 We anticipate a lower R^2 because studies using hedonic models of home price are complex and
306 show that individual factors such as house size and lot size as well as regional factors such as
307 parks, transportation, and schools influence home prices (Glaesener and Caruso, 2015; Seo et al.,
308 2019). For our model, the coefficient estimates are positive and statistically significant at the 0.05
309 level (p -value < 0.05). The relative contribution of vegetation land cover types to PSV is ranked
310 as: Grass > Shrubs > Trees > Soils. This result implies that increasing vegetation cover, especially
311 grass and shrubs, can effectively maintain a relatively higher PSV.

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

320

321 3.3 Optimization results

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

326 We present top 5 optimization scenarios in Table 3. These five scenarios suggest that
327 shrubs should be given the largest weight within all the vegetation types to maximize its
328 environmental and economic benefits. On the other hand, minimizing the use of grass but
329 maximizing open soil coverage can also contribute to lower LST and OWU. PSV can be higher if
330 a larger percent grass cover is given, but OWU would also be higher as well. As suggested, a
331 residential landscape that is composed of 1-2% grass, 11-13% shrubs, 7-9% trees, and 62-64%
332 soils can result in the lowest possible LST and OWU and help maintain a relatively higher PSV at
333 the same time. Within these scenarios, predicted LST varies from 49.8 °C to 50.2 °C, which is less
334 than the observed mean LST (Table 1, $\mu_{LST} = 50.26$ °C). Predicted OWU ranges from 327.5 mm
335 to 334.4 mm, which is around the mean minus one standard deviation ($\mu - \sigma = 329.7$ mm) of
336 observed OWU. Predicted PSV in these scenarios varies from \$728.6k to \$761.6k, which is higher
337 than observed mean ($\mu_{PSV} = \$340.6k$) but lower than the mean plus one standard deviation ($\mu + \sigma$
338 = \$771.9k).

339

340

341 4. Discussion

342 4.1 Effect of vegetation cover on LST, OWU and PSV

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

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

366 Our results are consistent with other studies showing that vegetation increases property
367 values in residential neighborhoods (Kestens et al., 2004, Bark et al., 2011, Escobedo et al., 2015)
368 Generally, percent vegetative cover in desert neighborhoods also had a significant positive
369 relationship with PSV with grass cover having the greatest contribution, followed by shrubs and
370 trees (Table 2). However, the goodness-of-fit of the regression model is relatively low (adj. $R^2 =$
371 0.228) because we did not include other factors shown to influence home values such as property
372 size, home size, school districts, etc. While adding such variables can potentially increase R^2 value,
373 it's not relevant for this study. Rather, our goal was to examine the combined effect of different
374 types of vegetation cover on PSV. Our study, however, shows trees have much lower contribution
375 to PSV than grass and shrubs. This result likely deviates from previous studies conducted in
376 Québec City and Florida because PMA has a much lower percent tree cover (only 12%) and annual
377 precipitation than temperate and humid regions (Escobedo et al., 2015; Kestens et al., 2004). We
378 therefore suggest that it is necessary to take climate background and dominant native vegetation
379 into consideration when examining the effect of vegetation cover on PSV because experiences and
380 findings from some cities may not apply to the others. Moreover, trees had the least effect on
381 property value among three vegetation types, which could be considered a benefit in some regions
382 given that low income communities currently have the greatest need for shade trees, but are also
383 vulnerable to displacement if housing costs increased (Landry and Chakraborty, 2009). Overall,
384 regional social and ecological context are important in assessing the relative benefits of trees versus
385 grass and shrubs.

386

387 4.2 Implications of optimization result and policy recommendation

388 Five optimization scenarios in Table 3 suggest that minimizing the use of grass in residential
389 landscaping in a desert city can contribute to a lower LST and OWU, while PSV maintains
390 relatively high. In face of severe drought in the Southwestern U.S., California Department of Water
391 Resources initiated the Institutional Turf Replacement Program (ITRP) to replace more than
392 165,000 square feet of turf with California native and water-efficient landscaping to provide long-
393 term water savings, and each eligible household can receive a rebate of approximately \$2 per
394 square foot of removed and replaced turf (CDWR, 2009). Tull et al. (2016) used 545 unique single-
395 family residential turf rebates and found that the mean water savings were estimated at about 1 m³
396 per square meter of turf removal per year for each household. Another study by Matlock et al.
397 (2019) studied 227 participating customers in southern California and found the average reduced
398 water usage was approximately 392 m³ per year after turf removal. Both studies confirmed the
399 effectiveness of ITRP in California, and our study further provides the theoretical basis of a similar
400 program that can be potentially implemented in the PMA. Completely removing large grass cover
401 or replacing grass with desert-adapted shrubs or trees can become a sustainable development
402 practice for residential communities in desert cities to mitigate heat and conserve water.

403 Another recommendation is to widely adopt xeric landscape style that mostly include
404 individually watered and low water-use exotic and native plants as a sustainable landscaping
405 strategy as suggested by the Xeriscape™ movement that began in Denver, Colorado in 1981
406 (Martin, 2001). Xeriscape is a water-efficient landscaping method that has become increasingly
407 popular in the arid southwestern U.S. (Sovocool and Morgan, 2006). Research has shown that in
408 southern Nevada, Xeriscape can save an average of 55.8 gal/sq. ft (or 2.27 m³/m²) per year
409 resulting from replacing turf grass with xeric landscape (Sovocool and Morgan, 2006). Households
410 realized a 30% annual water use reduction after converting to xeric landscape that equals

411 approximately 363 m³ annually (Sovocool and Morgan, 2006). Xeriscape can also save labor and
412 money for maintenance because of water-efficient and desert-adapted plants and efficient
413 irrigation. On the other hand, Martin (2008) compared four landscape design archetypes and
414 proposed an oasis landscape design that consists of a mixture of small areas of well-irrigated turf
415 grass interspersed with drip-irrigated landscape trees and shrubs and decomposed granite mulch
416 has an overall better performance in water conservation than the traditional xeric style landscape
417 in Phoenix, Arizona.

418

419 4.3 Limitations and future research

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

432 Further research can be focused on two topics. First is to study the effect of different types
433 of desert residential landscaping, such as mesic, xeric, and oasis, on LST, OWU and PSV at parcel

434 level. This analysis requires extensive field surveys and very high spatial resolution remotely
435 sensed data. The second direction can be the research on the combined effect of vegetation cover
436 on LST, OWU and PSV for cities in other climate regions because the regional climate background
437 also has a significant influence on the relationship.

438

439

440 **5. Conclusions**

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

450 This study has made four significant contributions to the sustainability of desert cities.
451 First, we find that even though trees can efficiently reduce LST, its contribution to PSV is the
452 lowest in a semi-arid desert environment. One implication of this finding is that trees might be a
453 water effective means to mitigate urban heat and address income-based shade disparities in the
454 city, while minimizing property value increases that could drive unintended consequences like
455 gentrification. Second, minimizing the use of grass in a semi-arid desert city is crucial because it
456 is the least water use efficient vegetation type, although it contributes to a higher PSV. Third,

457 desert-adapted shrubs and trees can be widely promoted because they not only have higher water
458 use efficiency, can significantly lower LST, but also have a relatively higher contribution to PSV.
459 Paired, these findings suggest a slight trade-off between the most environmentally efficient
460 landscape type (e.g., xeriscaping) and property value maximization (e.g., grass) in some existing
461 residential neighborhoods. Nevertheless, there are multiple yard landscaping market types in
462 Phoenix. Therefore, more work is needed to understand the extent to which the observed positive
463 relationship between grass and property value is moderated by homeowner preferences across
464 different style neighborhoods. Fourth, our results and findings provide strong evidence and a
465 theoretical basis for the environmental benefits of turf removal programs and xeric or oasis style
466 landscaping design, which can be used as a guideline by desert cities for a better design of
467 residential landscaping for urban sustainable development in the future.

468

469

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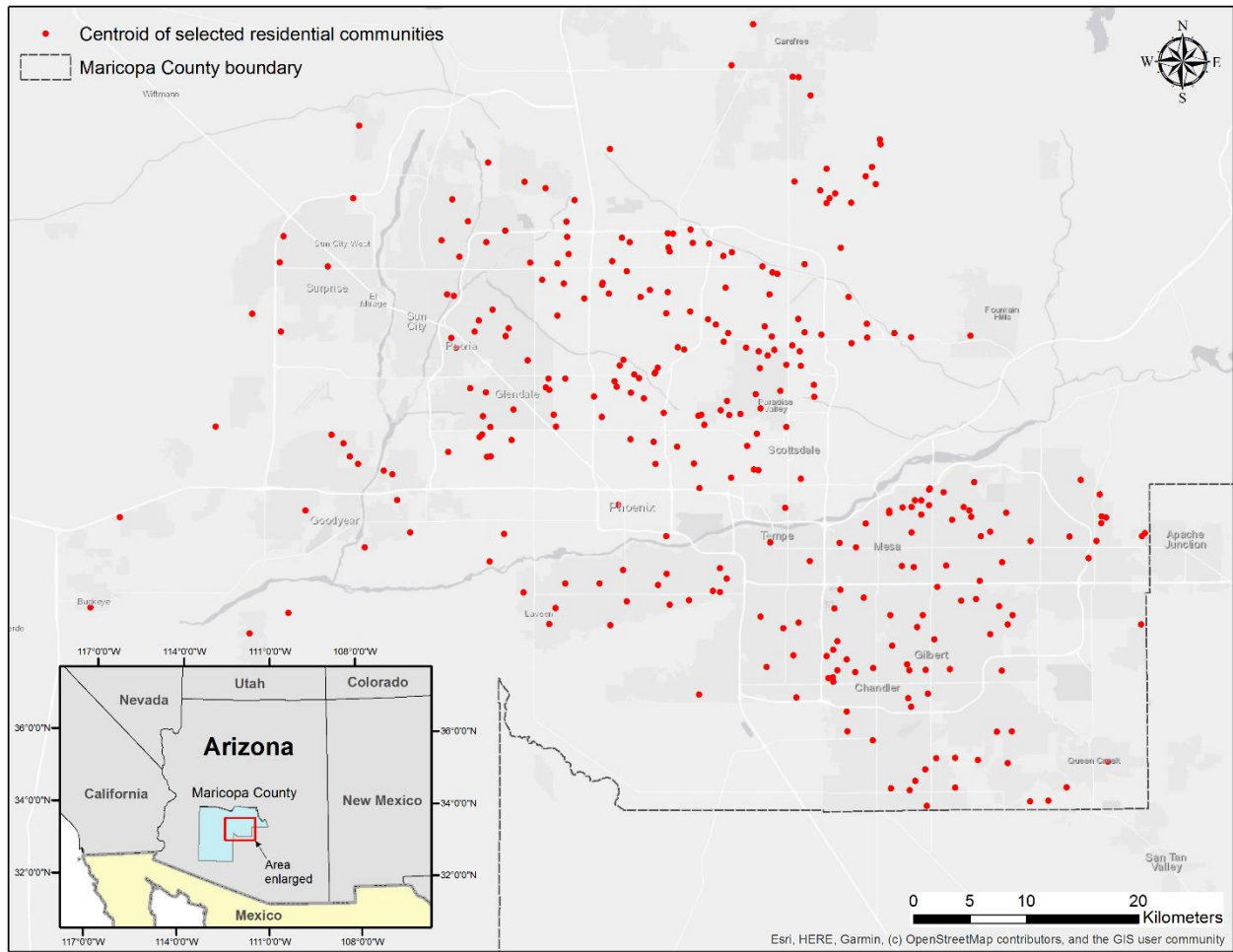
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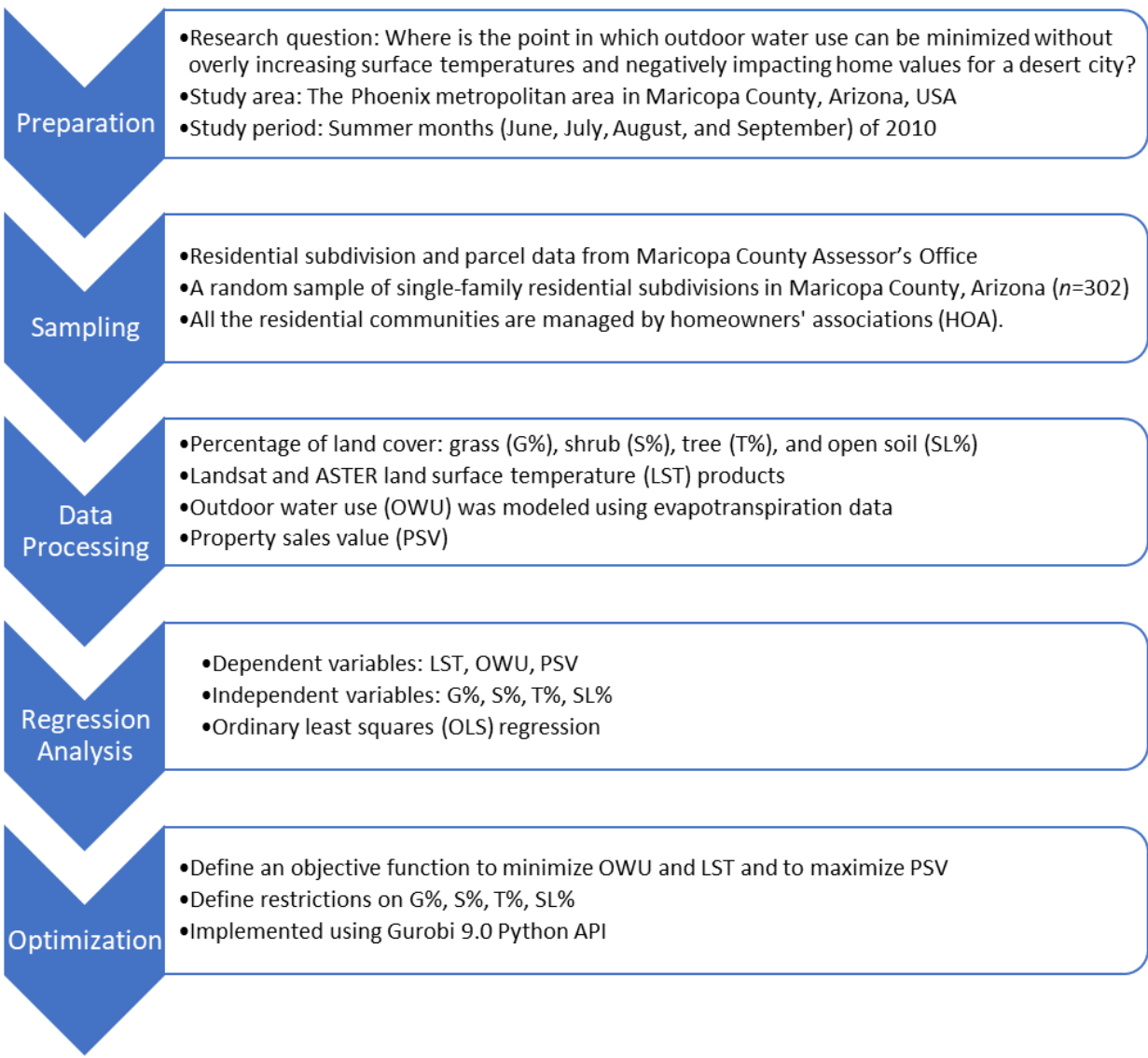


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670 Figure 1. Map of study area and locations of selected residential communities.

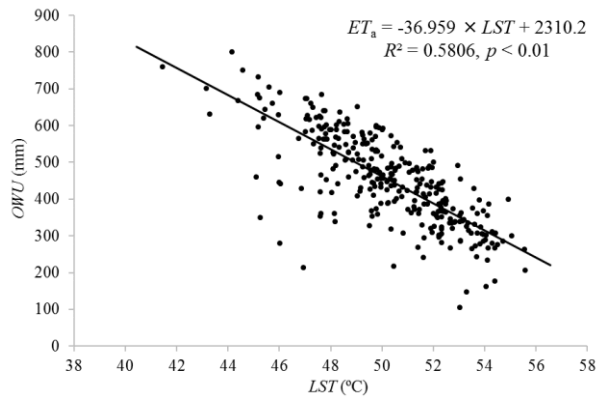
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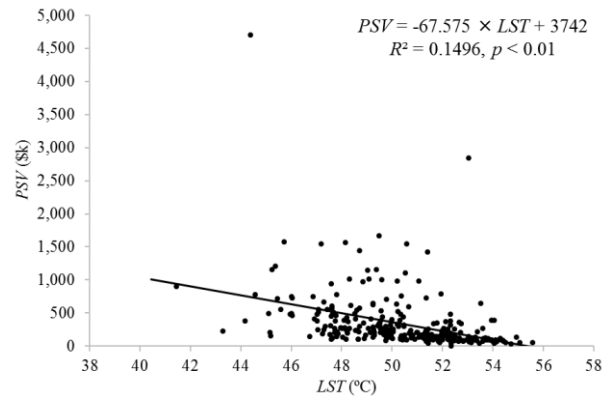
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673 Figure 2. Flowchart of research design.

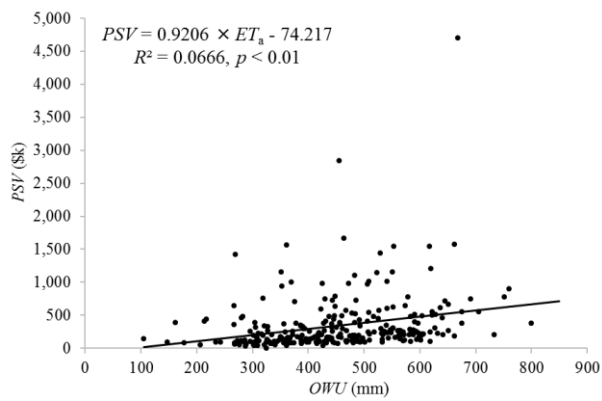
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(a)



(b)



(c)

675

676 Figure 3. Simple linear regression analysis among three dependent variables: (a) LST vs. OWU,

677 (b) LST vs. PSV, and (c) OWU vs. PSV.

678

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

681

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	-

682

683 ^a Land surface temperature

684 ^b Outdoor water use

685 ^c Property sales value

686

687

688

689

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

691

Model (Dependent variable)	A (LST¹)				B (OWU²)				C (PSV³)			
<i>R</i> ²	0.616				0.517				0.264			
Adj. <i>R</i> ²	0.598				0.495				0.228			
<i>p</i>	< 0.01				< 0.01				< 0.01			
RMSE ^a	1.626				77.113				429.540			
Independent variable	<i>B</i> ^b	<i>SE</i> ^c	<i>p</i>	β ^d	<i>B</i>	<i>SE</i>	<i>p</i>	β	<i>B</i>	<i>SE</i>	<i>p</i>	β
<i>Grass%</i>	-0.135*	0.042	0.002	-0.242	10.172*	1.997	0.000	0.432	52.638*	13.595	0.000	0.442
<i>Shrub%</i>	-0.118*	0.046	0.012	-0.206	-1.588	2.175	0.467	-0.065	27.657*	12.881	0.035	0.247
<i>Tree%</i>	-0.243*	0.029	0.000	-0.689	3.680*	1.390	0.010	0.247	19.698*	7.926	0.015	0.300
<i>Soil%</i>	-0.009	0.020	0.646	-0.042	-2.114*	0.942	0.027	-0.229	12.297*	5.491	0.028	0.293
<i>Cons.</i>	54.183*	1.121	0.000	-	410.5*	53.139	0.000	-	-615.858	317.402	0.056	-

692

693 ¹ Land surface temperature

694 ² Outdoor water use

695 ³ Property sales value

696 ^a Root mean square error

697 ^b Unstandardized coefficients

698 ^c Standard error

699 ^d Standardized coefficients

700 * Statistically significant at the 0.05 level

701

702 Table 3. Optimization results with top 5 scenarios

703

Scenario	Grass	Shrub	Tree	Soil	Predicted LST ^a (°C)	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

704 ^a Land surface temperature

705 ^b Outdoor water use

706 ^c Property sales value

707

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: