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Determinants of single family residential water use across scales in four western US cities

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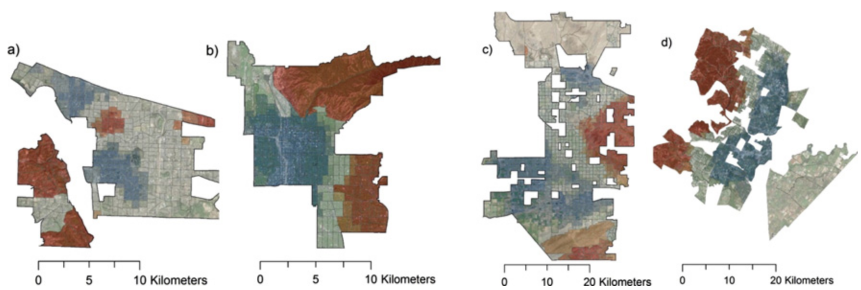
HIGHLIGHTS

- Common and different variables explain SFR water use variations by season and city.
- Tax assessed value and building age are common determinants of SFR water use.
- Impervious surface area is a significant predictor for summer SFR water use.
- Spatial variations of SFR water use are smoothed at a coarser spatial scale.
- SFR water use shows strong spatial dependence and neighboring effects.

GRAPHICAL ABSTRACT

Hotspots (red) and cold spots (blue) of summer (June–September) household water use at the Census Block Group scale based on the Getis-Ord Gi* statistic - a) Portland, Oregon; b) Salt Lake City, Utah; c) Phoenix, Arizona; and d) Austin, Texas.



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ABSTRACT

A growing body of literature examines urban water sustainability with increasing evidence that locally-based physical and social spatial interactions contribute to water use. These studies however are based on single-city analysis and often fail to consider whether these interactions occur more generally. We examine a multi-city comparison using a common set of spatially-explicit water, socioeconomic, and biophysical data. We investigate the relative importance of variables for explaining the variations of single family residential (SFR) water uses at Census Block Group (CBG) and Census Tract (CT) scales in four representative western US cities – Austin, Phoenix, Portland, and Salt Lake City, - which cover a wide range of climate and development density. We used both ordinary least squares regression and spatial error regression models to identify the influence of spatial dependence on water use patterns. Our results show that older downtown areas show lower water use than newer suburban areas in all four cities. Tax assessed value and building age are the main determinants of SFR water use across the four cities regardless of the scale. Impervious surface area becomes an important variable for summer water use in all cities, and it is important in all seasons for arid environments such as Phoenix. CT level analysis shows better model predictability than CBG analysis. In all cities, seasons, and spatial scales, spatial error regression models better explain the variations of SFR water use. Such a spatially-varying relationship of urban water consumption provides additional evidence for the need to integrate urban land use planning and municipal water planning.

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1. Introduction

The cities of the 21st century are subject to increasing pressure to develop a sustainable water supply in the global south and north due to water stresses associated with growing populations (Grafton et al., 2011), inadequate and aging water infrastructure (Clark et al., 1999; Grigg, 2005), poor regulation (Massarutto and Ermano, 2013), and climate variability (Hunt and Watkiss, 2011). While per capita water use has declined in recent years in the global north (Chang et al., 2014; Ashoori et al., 2016), the absolute growth in population could negate the effect of water conservation in many places. Furthermore, as urban areas grow, new infrastructure is needed requiring new investment as well as investment in updating, maintaining, and replacing old infrastructure. Similarly, the effectiveness and financing of water infrastructure depends on public and private regulatory agreements to deliver reliable and safe water. Finally, climate variability and change will likely reduce water supplies in many areas around the world, particularly in semi-arid and arid climates, compounding the challenges faced by water providers (IPCC, 2014).

To address these ranging concerns of water security, many urban water providers have designed and implemented water conservation programs (Mini et al., 2014). These programs typically involve incentives, such as rebates on water saving bathroom fixtures, conversion programs for high water use landscaping, and seasonally based pricing structures. These water conservation programs have been typically applied at the water provider scale, neglecting the spatial and temporal heterogeneity of single family residential (SFR) water use patterns in complex urban water systems, and thus lowering the effectiveness of such programs in terms of reducing SFR water use. For these conservation programs to be successful, we first need to know what factors affect SFR water use, where the hotspots of SFR water use are, and how the water use patterns vary over space and time.

Prior research investigating the factors influencing SFR water use show that structural (lot and property characteristics), environmental, spatial, social, and behavioral factors influence water use (Guhathakurta and Gober, 2007; Wentz and Gober, 2007; Balling and Cubaque, 2009; Chang et al., 2010a; House-Peters and Chang, 2011a, 2011b; March and Saurí, 2010; Polebitski et al., 2011; Breyer et al., 2012; Aggarwal et al., 2012; Fielding et al., 2012; Halper et al., 2012; Giner et al., 2013; Saurí, 2013). Table 1 summarizes these factors with examples of the impact on water use. A dominant theme in the literature is the impact of climate variables on household water use. Many studies positively correlate higher water consumption with warmer temperatures associated with seasonal variations (Rockaway et al., 2011; Chang et al., 2014; Prandvash and Chang, 2016) with some studies specifically identifying the concentration of the urban heat island effect as a determining factor (Guhathakurta and Gober, 2007; Gober et al., 2012). Many cities throughout the eastern, central, and northwestern portions of the United States are also facing water shortages and drought, influencing water use (Hornberger et al., 2015; Chang and Bonnette, 2016). The combination of projected rises in air temperature with decreases in precipitation will further diminish water supply for increasing municipal water demand into the future.

In addition to climate variation in different cities, local variations, such as those found at the household and tract level are likely due to other factors, such as the use of pools, the size and style of lawns, micro-climate variations, and other external factors (Guhathakurta and Gober, 2007; Balling and Cubaque, 2009). Research on single-family housing water use is shifting from aggregated generalities of water use at the city scale to specific, parcel level analysis (Ferrara; 2008, Fox et al., 2009; Arbue's et al., 2010; Gage and Cooper, 2015; Ojeda et al., 2017). Studies at the parcel level report higher water use is aligned with larger irrigation areas, higher incomes, warmer climates, larger house sizes, and a larger household size (Wilson and Boehland, 2005; Harlan et al., 2009; Gato-Trinidad et al., 2011; Romero and Dukes, 2013). These studies, however, tend to be limited to a small sample within a community, focus on water use associated with rate-changes, or focus on weekly water consumption rather than seasonal. It is challenging therefore to examine the impact of neighborhood influences that, at the aggregate scale, have shown to be influential (Ouyang et al., 2014). This limits the usefulness of the results for water policy implementations because it is difficult to influence either individual behavior or the residents of an entire city using a single water policy. The ability to analyze and understand scalar dynamics within cities at Census Track (CT) and parcel is important for making decision-relevant water policy.

While there have been a number of studies investigating various factors affecting SFR water use at different scales of analysis, few studies have compared multiple cities in a spatially explicit way using a common data set with the same study design. As such, it has been difficult to directly compare the locally varying SFR water use patterns across different cities. A small number of exceptional case studies were conducted as part of a collaborative research effort between Portland and Phoenix (Breyer et al., 2012; Gober et al., 2012; Lee et al., 2015), showing some common and contrasting predictors of urban water use in both places. However, there exist no studies comparing SFR water use in

Table 1
Generalized factors that explain increases and decreases to single family residential water use.

Factor type	Examples	Impact on water	Notes	References
Structural	⇧Lot size	+		Chang et al., 2010a, 2010b; Polebitski et al., 2011; Halper et al., 2015
	⇧Turf	+		Giner et al., 2013; Mini et al., 2014; Gage and Cooper, 2015
	⇧Swimming pools	+		Domene and SaurÍ, 2006; Wentz and Gober, 2007; Larson et al., 2009
	>Building age	±	1	Chang et al., 2010a, 2010b; Reynaud, 2013; Ouyang et al., 2014; Halper et al., 2015
Environmental	⇧Urban heat island	+		Guhathakurta and Gober, 2007; Balling and Cubaque, 2009; Gober et al., 2012
	Summer	+		Chang et al., 2014; Prandvash and Chang, 2016
	⇧Drought	±	2	Polebitski and Palmer, 2013; Breyer and Chang, 2014
Spatial	⇧Building density	−		Wilson and Boehland, 2005; House-Peters et al., 2010; Breyer et al., 2012
	Neighborhood		3	Wentz et al., 2016; Gage and Cooper, 2015
	Park or common pool	−		Halper et al., 2012
Socioeconomic	⇧Income	+		Harlan et al., 2009; March and Saurí, 2010; Fielding et al., 2012
	⇧Education	+	4	House-Peters et al., 2010; Baerenklau et al., 2014
	⇧Incentives	−		Lee, 2016
	Price structure	±	5	Grafton et al., 2011; Yoo et al., 2014
Behavioral	⇧Graywater reuse	-		Straus et al., 2016
	⇧Short shower times			Jorgensen et al., 2013; Liu et al., 2016
	⇧Turning off faucet when teeth brushing			Suero et al., 2012

Notes: 1 = depends on study; 2 = depends on water restriction regulations; 3 = neighbors having similar water use habits; 4 = correlation with income; 5 = depends on the policy.

more than two cities using spatially explicit data. We address this research gap by answering the following research questions:

(1) What are the spatial patterns of SFR water use in four western cities?
(2) What are the main determinants of SFR water use in four western US cities?
(3) How do determinants of SFR water use vary by season and spatial scale?
(4) What are the neighboring effects in SFR water use and how can we better model the variation in SFR water use?

2. Data and method

2.1. Study area

The present study focuses on four western US cities: Austin, Texas; Phoenix, Arizona; Portland, Oregon; and Salt Lake City, Utah (Fig. 1). These four cities were chosen because they represent a range of climates from relatively humid (Portland, Austin) to semi-arid (Salt Lake City) to arid (Phoenix), and climate change is likely to reduce water supply and increase demand in these regions in the mid- to late-21st century (Table 2). Additionally, these four cities exhibit a range of city size in terms of population and have a population growth rate higher than the national average in the past decade, with population projected to increase further in coming decades. In Austin, Portland, and Salt Lake City, 100% of residents are supplied by the public water utilities in each city. The provision boundaries of these utilities extend beyond the municipal boundaries to provide water to additional residents living outside of each city boundary (Austin Water, 2017a; Portland Water Bureau, 2017). While the majority of residents in Phoenix are served by municipal water, there are also pockets in Phoenix that use “flood” irrigation that is not monitored through municipal sources as the water is directly from the Salt River Valley. This occurs in some of the older neighborhoods.

All four cities have implemented active water conservation programs since the 1990s to address the need of water savings and sustainability. Phoenix started a water conservation program in the mid-1990s (Campbell et al., 1999) that has resulted in multiple efforts such as

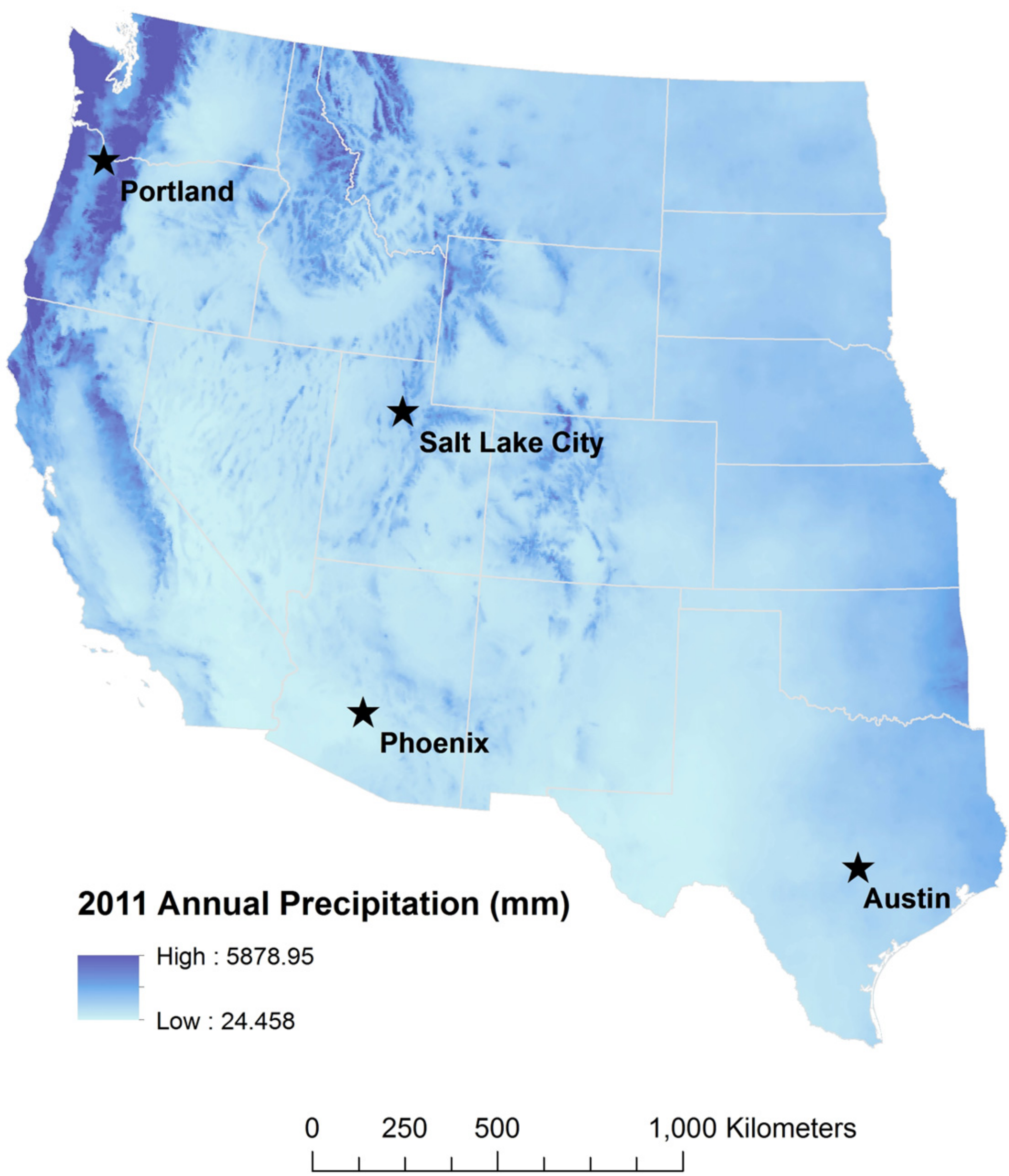

Fig. 1. Location of the four western US cities selected for the study.

Table 2
Demographic and water provider characteristics of the study cities.

	Austin	Phoenix	Portland	Salt Lake City
Area, km^2	770	1330	345	287
Population, 2010	811,456	1,447,624	583,800	186,439
Population density, person/km^2	1053.8	1088.4	1692.2	649.6
Growth rate, 2010–2015, %	15.0	8.0	8.3	3.3
Water provider	Austin Water Utility	Phoenix Water Services	Portland Water Bureau	The Salt Lake City
Population served by the water provider, 2016	977,491	1.5 million	597,400	City residents + 74,000 properties
Water source	Colorado River	Colorado River, supplemented by wells during summer	Bull Run reservoir, supplemented by wells during summer	Mountain streams, supplemented by wells during summer
Future water supply	projected to decline by 20% in the 2050s and 35% in the 2090s (Udall and Oerpeck, 2017)	projected to decline by 20% in the 2050s and 35% in the 2090s (Udall and Oerpeck, 2017)	Summer supply projected to decline by 10–15% in the 21st century	Projections are variable depending on precipitation scenarios (Bureau of Land Reclamation, 2016)

rebates for water saving appliances, ground cover conversion, tree shade programs, and free public education programs. Similarly, Portland initiated a water conservation program in response to the 1992 drought with efforts such as rebates for replacing old indoor water-using devices and outdoor irrigation controllers. Salt Lake City public utility actively promotes water conservation through public education, demonstration projects, and tiered water rates. Like Portland, Austin has also pursued conservation aggressively due to drought conditions. In 2011, the year for which we have water use data, Austin implemented water use restrictions on all residential properties. Based on address, properties could not automatically irrigate more than once per week. Simultaneously, Austin residents were encouraged to purchase and install more efficient irrigation technologies, as well as more efficient appliances. Wasting water was also punishable by fines (Austin Water, 2017b).

2.2. Water use data

The dependent variable used to answer the posed research questions was monthly household water use at the Census Block Group (CBG) and Census Tract (CT) levels for the year 2011 for all cities. These data were acquired from municipal public utility organizations: the Austin Water Utility, the City of Phoenix Water and Sewer, the Portland Water Bureau, and the Salt Lake City Department of Public Utilities. The Austin and Salt Lake City water use data sets were provided at the parcel level in monthly intervals, and were then aggregated to the CBG and CT levels. The Phoenix water use data set was provided at the CBG level in monthly intervals, and aggregated to the Tract levels. Finally, the Portland water use data set was provided at the parcel level in non-standard time intervals. Monthly intervals were calculated from the data, and then they were aggregated to the Block Group and Tract levels. For each of the chosen study areas summer (June–September) and winter average (December–February) monthly water use values were also analyzed (Figs. 2 to 4), and descriptive statistics were calculated (Table 2). The parcel data were regularly reviewed by utility staffs at each water utility to ensure the accuracy of the readings. During the data integration process, we reviewed a random sample of records to verify that the records between the public utility records and tax assessors data remain the same. For illustration, we only present the spatial pattern of water use at the CBG scale.

2.3. Water price

The four cities have slightly different water pricing systems. In Austin and Phoenix, residential water rates are charged based on meter size and a tiered water rate structure. Phoenix has a fixed rate for water use up to 4488 gal per month in non-summer (October–May) months and 7480 gal per month in summer (June to September). For the water use beyond the fixed rate volume, the usage rate is approximately $1 higher above the flat rate in summer months. In Portland, water bills are based on a base charge and a water volume charge (Portland Water Bureau, 2017). Although water is relatively abundant and the delivery cost is not high due to an upstream water source, Portland's water price is one of highest in U.S. because it contains other charges for upgrading stormwater facilities and improving environmental conditions associated with storm runoff. In Phoenix and Portland, water bills include environmental (stormwater) and sewer charges that are determined by winter months' water uses. In Austin, there is a two-tiered volume charge for wastewater (Austin Water, 2017c). Salt Lake City employs a tiered pricing structure; as water use increases, so does the price per unit. Water price in Salt Lake City is one of the lowest in U.S. because of the availability of high quality water from nearby canyons that flow downhill into the city. The public utility has low water treatment and pumping costs. City water bills do not include other environmental or wastewater charges as the utility is required to sell water at the cost of provision.

While water price is not necessarily the most influential determinant of water demand (Espey et al., 1997) and other factors influence water use more than price (Jorgensen et al., 2009), in Phoenix, price elasticity of water demand was found to be higher in low level water users than high level water users (Yoo et al., 2014). However, there are no known case studies on price elasticity in the other three study cities considered here. Considering that our focus is a single year comparison across neighborhoods in four cities and pricing structures do not vary within each city, price was not included in our analysis. Instead, price information could be used for interpreting the magnitude of water use levels across the study cities. The relative magnitude of water use among the four cities is substantially different; residents of arid Phoenix and semi-arid Salt Lake City use more than two times more water than relatively wet Portland residents annually. The discrepancy in residential water use between the cities becomes greater during the summer. Portland residents use only a quarter of the amount of residential water used by Salt Lake City residents during summer months. The increasing difference in water use during the summer could be associated with outdoor water use and pools (Wentz and Gober, 2007; Ouyang et al., 2014).

2.4. Exploratory variables

Based on a review of recent literature and the accessibility of data at the chosen scales, six climatic and property characteristic variables were chosen to explain the variation of household water use across the four

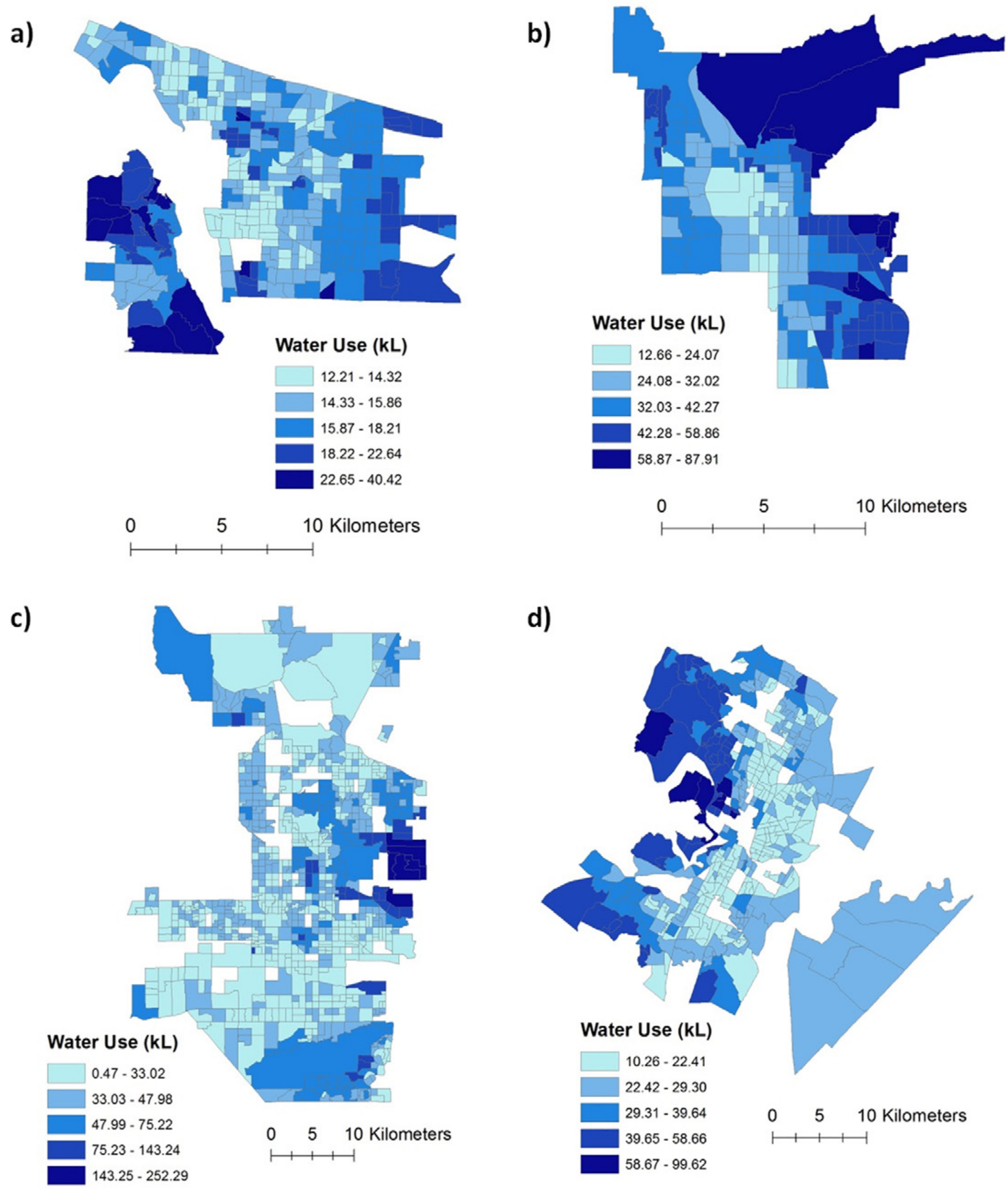

Fig. 2. Average monthly household water use at the Census Block Group level – a) Portland, Oregon; b) Salt Lake City, Utah; c) Phoenix, Arizona; and d) Austin, Texas. The missing block groups include primarily industrial or commercial, or park areas.

study areas (Table 3). Mean monthly maximum temperature (degrees Celsius) and monthly precipitation (mm) were acquired from Oregon State's PRISM Climate Group (PRISM, 2015). As with the dependent variable, these climatic variables were recalculated into annual, summer, and winter values. The four property characteristics analyzed were lot size (hectares), tax assessed property value, home age, and percent impervious surface. The first three variables were obtained from County or City tax assessor's offices (City of Austin, 2016, City of Phoenix, Metro, 2016; Salt Lake County, 2016). Impervious surface measurements were initially conducted at the parcel level, and then aggregated up to the CBG level. The impervious surface areas essentially represent non-vegetative surfaces such as building footprints, driveways, sidewalks, rocks, gravel, etc. Impervious surface areas were calculated by subtracting canopy areas from total parcel size. For Portland, canopy areas were detected using a combination of normalized difference vegetation index (NDVI) from the imagery at a 1 m resolution collected in the summer of 2014 and feature heights from LiDAR (accuracy > 90%). For Austin and Salt Lake City, we used data from the National Agricultural Inventory Program for 2011 at a 1 m resolution and LiDAR layers to classify two different land covers (vegetation/non-vegetation). The accuracy of this classification is higher than 88.9% (Stoker et al., 2017). For Phoenix, we used QuickBird multispectral data at 2.5 m spatial resolution acquired on May 29, 2007 (Myint et al., 2011). Three of the other property characteristics were acquired through tax assessor reports from each of the four study areas.

2.5. Exploratory spatial analysis

We used Moran's I (Moran, 1950), a measure of spatial autocorrelation, to investigate the degree and strength of spatial dependence in

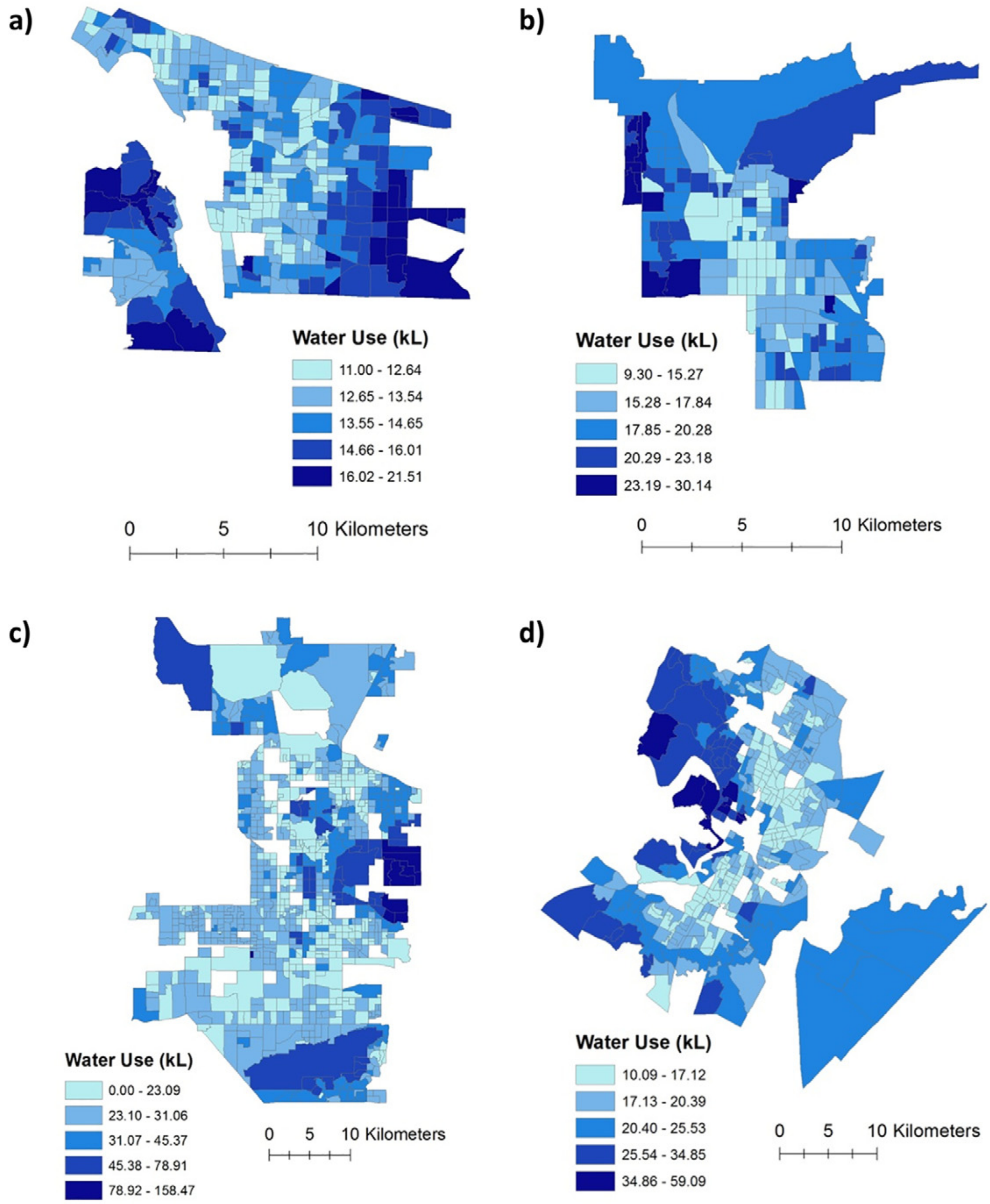

Fig. 3. Average winter (December–February) monthly household water use at the Census Block Group level – a) Portland, Oregon; b) Salt Lake City, Utah; c) Phoenix, Arizona; and d) Austin, Texas. The missing block groups include primarily industrial or commercial, or park areas.

water uses at both CBG and CT scales. Spatial autocorrelation is measured by a correlation between neighboring CBG or CT. Moran's I is defined as follows.

$$I = \frac{n}{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{1}$$

where, X_i and X_j refer to water use in spatial unit i and spatial unit j, respectively. $\overline{X}$ is the overall mean water use, and W_{ij} is the weight matrix. For the weight matrix we used the queen contiguity measure that considers an edge or a vertex as neighbors. That is, if CBG (or CT) i and j are adjacent neighbors, $W_{ij} = 1$, otherwise $W_{ij} = 0$. Like the correlation coefficient, I is positive if both X_i and X_j lie either above or below the mean, while it is negative if one is above the mean and the other is below the mean (O'Sullivan and Unwin, 2010). Considering water use patterns show neighborhood effect by distance, we used the queen continuity matrix that has been used in other water use studies (Chang et al., 2010a; House-Peters et al., 2010). The significance of Moran's I was tested using a randomized test with 999 permutations and at a significance level of $p \leq 0.01$ using the GeoDa software (Anselin et al., 2006). Local hotspots (high water use areas surrounded by high water use areas) and cold spots (low water use areas surrounded by low water use areas) of water use are identified by the Getis-Ord Gi* statistic (Ord and Getis, 1995), a method used in a previous water use study (Gage and Cooper, 2015).

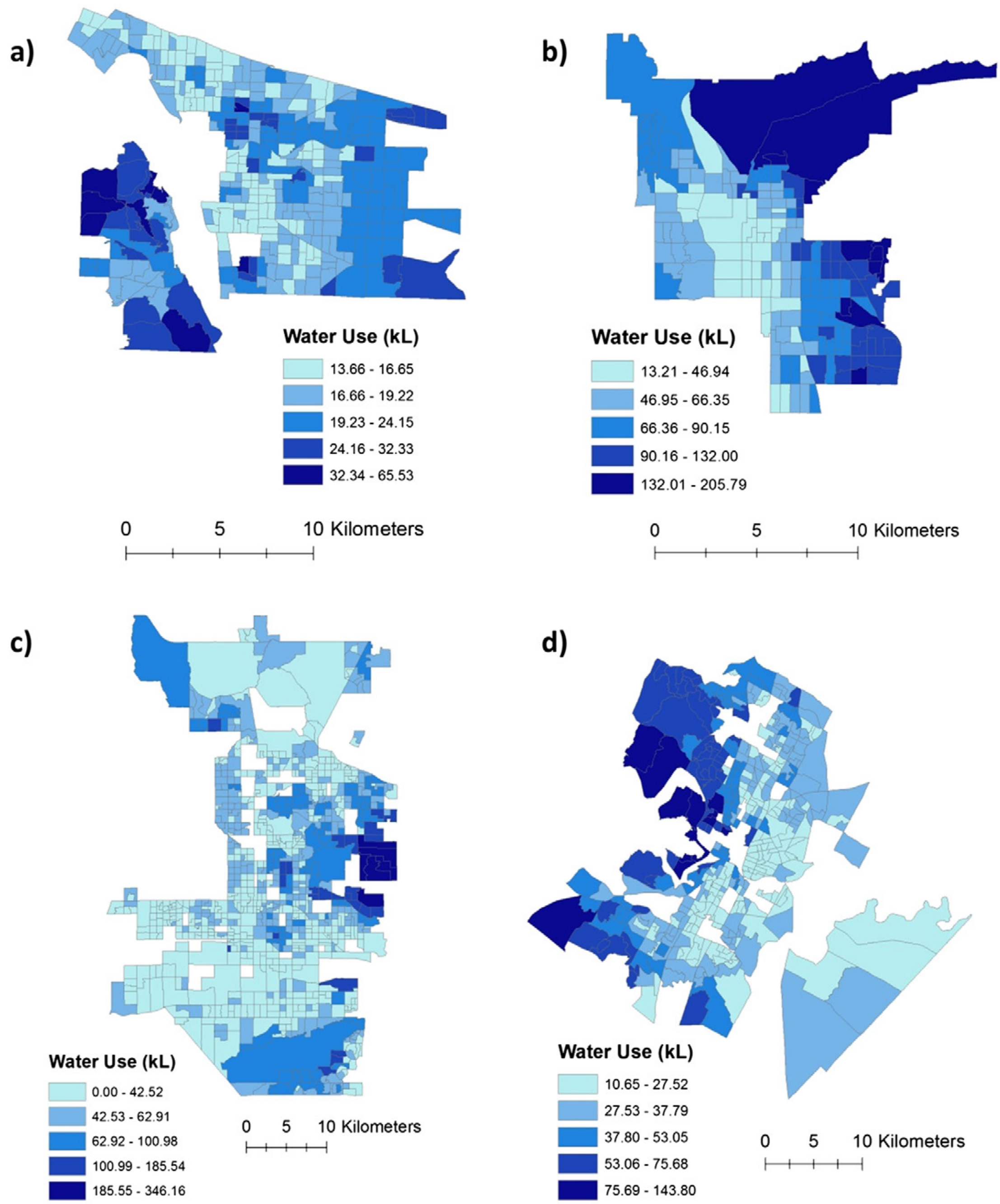

Fig. 4. Average summer (June–September) monthly household water use at the Census Block Group level – a) Portland, Oregon; b) Salt Lake City, Utah; c) Phoenix, Arizona; and d) Austin, Texas. The missing block groups include primarily industrial or commercial, or park areas.

2.6. Ordinary least squares regression (OLS)

An exploratory OLS regression analysis of annual, summer, and winter monthly household water use was conducted for each city at the CBG and CT levels using the Exploratory Regression tool in ESRI's ArcGIS 10.3. For each city, at each of the chosen scales, models were created with annual, summer, and winter water use as the dependent variables. All six of the exploratory variables described above were included in each analysis to determine the model with the best fit for each scenario (Table 2). While lot size, assessed property value, home age, and percent impervious surface were consistent across the models for each scale in each city, the climatic variables (Monthly Max Temperature and Monthly Precipitation) used annual, summer, and winter values corresponding to their dependent variable. The results of this analysis allowed us to determine the most suitable model for each scenario. We used ArcGIS's exploratory regression tool to identify the best set of independent variables that minimize Akaike information criterion (AIC) values and do not have multicollinearity.

Once these best fit models were determined, a more comprehensive OLS model was run using GeoDa software (Anselin, 2005). The models were created for each dependent variable using only those exploratory variables that were included in each of the best fit models from the exploratory analysis. This tool provides a more thorough explanation of the models generated.

Table 3
Mean and standard deviation values for the six chosen variables for explaining single family residential water use at the Census Block Group (CBG) and Census Tract (CT) scales for Austin, Phoenix, Portland, and Salt Lake City (numbers in parenthesis are standard deviation of each variable).
Data source: Salt Lake County.

City	Austin		Phoenix		Portland		Salt Lake City	
Scale	CBG	CT	CBG	CT	CBG	CT	CBG	CT
Monthly maximum temperature, °C	28.24 (0.15)	28.23 (0.15)	29.70 (0.50)	29.72 (0.51)	15.70 (0.06)	15.70 (0.06)	16.51 (0.47)	16.51 (0.53)
Monthly precipitation, mm	36.96 (1.41)	36.94 (1.48)	10.49 (1.40)	10.46 (1.46)	90.98 (2.50)	91.26 (2.59)	49.26 (3.79)	49.24 (3.99)
Lot size, ha	0.01 (0.007)	0.02 (0.021)	0.22 (0.497)	0.26 (0.671)	0.01 (0.009)	0.08 (0.070)	0.07 (0.025)	0.07 (0.025)
Tax assessed value, $10K	25.19 (17.33)	24.13 (14.98)	17.69 (25.66)	17.85 (20.43)	32.52 (14.53)	33.09 (12.70)	25.42 (10.33)	25.30 (12.95)
Building age, year	42.45 (22.91)	40.09 (21.55)	30.38 (20.06)	30.09 (19.74)	73.27 (17.92)	70.64 (16.93)	73.14 (22.40)	74.00 (21.61)
Impervious surface, %	40 (10.99)	40 (10.60)	10 (6.19)	10 (5.17)	48 (12.81)	47 (11.71)	55 (6.15)	55 (6.24)

2.7. Spatial error regression

While the OLS regression models provide insight into the drivers of household water use in these study areas, it does not account for spatial variation in the phenomenon. In order to address the spatial interactions inherent in household water use, a spatial error regression model was created for each city, at each scale, using annual, summer, and winter monthly water use as the dependent variables. Spatial error regression models were chosen over spatial lag regression models following the Lagrange Multiplier test (Anselin, 2005). Using a queen contiguity weight matrix, these models were created using the GeoDa software (Anselin et al., 2006). The exploratory variables used for each model were the same used in the corresponding ordinary least squares regression models. Because water use is at least in part a spatial phenomenon, the spatial error models should provide a more accurate representation of the drivers of household water use in the study areas. The spatial error models are as follows.

$$Y_i = X_i\beta_i + \varepsilon; \varepsilon = \lambda W\varepsilon + \xi \quad (2)$$

where, Y_i and is the dependent variable (i.e. water use) at neighbor *i* and *j*

X_i = independent variable at *i*
β_i = regression coefficient
ε = random error terms
λ = autoregressive coefficients of the spatial error model
ξ = homoskedastic and independent error term

3. Results

3.1. Average monthly SFR water use

As shown in Fig. 2, in all cities, average monthly SFR water use shows a strong spatial gradient. High water use CBGs are typically found in periphery areas, while low water use areas are mostly located in central areas of each city. CBGs are relatively small near the central area of each city and tend to increase in size as distance from the urban core increases, reflecting the relative density of urban development. In Austin and Portland, the highest water use CBGs are found in the western part of the cities, while in Phoenix and Salt Lake City, they are found in the eastern part of the cities. In all cases, there exist significant positive spatial autocorrelation ($p < 0.05$) in average monthly SFR water use, as measured by high Moran's I index values, which range from 0.62 to 0.72.

Across the four study cities, building age (−) and tax assessed value (+) are two of the common significant variables for explaining variations in average monthly SFR water use at both CBG and CT scales (Table 3). This suggests that neighborhoods with newer and more expensive houses use more water annually than those with older and less expensive houses. Percent impervious surface area is negatively associated with average monthly SFR water use in all but one city (Austin). The relative influence of impervious surface area increases as cities become drier. Phoenix had the highest absolute value of coefficient, while Portland had the smallest absolute value of coefficient. Austin is the only city in which lot size is consistently a significant variable in explaining variations in average monthly SFR water use at both scales. Lot size was excluded as a significant predictor in other cities probably due to the variable's positive correlation with tax assessed value. Maximum temperature is not a good predictor of average monthly SFR water use in any of the cities at either scale. The chosen predictors explain the variation of average monthly SFR water use best for Austin and Salt Lake City (R^2 ranges from 0.82 to 0.91), while they explain a moderate amount of variation (64%) in Portland and only 11–22% of variation in Phoenix. In all cases, the CT level analysis yielded higher R^2 values (4–11% higher) than the CBG level analysis, suggesting that CT level analysis can potentially mask the spatial heterogeneity of the data.

As shown in Table 4, the spatial error regression models yielded higher R^2 values than the OLS models, consistently yielding lower AIC values. The spatial autoregressive coefficients (lambda) of the spatial error regression models are all statistically significant across the four studied cities. The most dramatic improvement was made (highest decline in AIC values) for Phoenix where the model's explanatory power increased from 11% to 68% at the CBG scale, and from 22% to 69% at the CT scale. This is due to the fact that Phoenix has the highest lambda value (0.82 for CBG scale and 0.86 for CT scale) of the four studied cities. Also interesting was the changing sign of coefficient of building age. The variable had a negative sign in OLS, but the sign was flipped to positive and marginally significant ($0.05 < p < 0.1$) in the CBG scale spatial model. The sign remains stable for spatial regression models for all of the other explanatory variables.

3.2. Winter monthly SFR water use

As shown in Fig. 3, winter monthly winter water use is nearly half of monthly summer water use. The spatial patterns of winter water use follow those of annual and summer water uses, showing a similar spatial gradient from the central part of each city (low water use) to the periphery areas (high water use). The hotspots of high water use CBG remain the same. In all cases, there exist significant positive spatial autocorrelations, as measured by Moran's I index (I values range from 0.44 to 0.69). However, the Moran's I values are much lower than those of other seasons.

Building age is the only significant variable that explains the variation in winter water use across the four cities at both spatial scales

Table 4
Comparison of Ordinary least squares (OLS) and spatial regression models for explaining average monthly single family residential water use at Census Block Group and Census Tract scales by city.

Variables	Austin		Phoenix		Portland		Salt Lake	
	OLS	Spatial	OLS	Spatial	OLS	Spatial	OLS	Spatial
Census Block Group	$n = 375$		$n = 813$		$n = 335$		$n = 167$	
Lot size (10 m^2)	0.492	0.285						
Building age (year)	−0.160	−0.056	−0.078	0.087*	−0.046	−0.018	−0.228	−0.215
Assessed value ($10K)	0.534	0.574	0.259	0.950	0.096	0.068	0.736	0.725
% Impervious			−0.656	−0.256	−0.066	−0.052	−0.351	−0.297
Lambda		0.75		0.82		0.69		0.54
AIC	2279.91	2114.97	7139.48	6481.61	1413.85	1324.97	1052.17	1025.01
R^2	0.82	0.90	0.11	0.68	0.54	0.69	0.83	0.86
Residual's Moran's *I*	0.407	−0.070	0.618	−0.066	0.319	−0.039	0.265	−0.003
Census Tract	$n = 138$		$n = 309$		$n = 105$		$n = 59$	
Lot size (10 m^2)	0.208	0.146						
Building age (year)	−0.211	−0.125	−0.116	−0.125*	−0.084	−0.053	−0.234	−0.228
Assessed value ($10K)	0.527	0.546	0.459	0.240	0.136	0.092	0.725	0.714
% Impervious			−0.998	−0.817			−0.389	−0.338
AIC	778.55	740.77	2646.37	2435.76	403.93	379.10	330.87	323.66
Lambda		0.69		0.86		0.64		0.48
R^2	0.86	0.91	0.22	0.69	0.65	0.75	0.91	0.93
Residual's Moran's *I*	0.309	−0.009	0.514	0.037	0.296	−0.049	0.227	−0.007

Only the coefficients of the statistically significant factors ($p < 0.05$) are reported in the table, except marked as * significant at the 0.1 level. AIC = Akaike information criterion; R^2 for spatial models are Pseudo-R^2 values.

(Table 5). Like the case of annual water use, building age is negatively associated with winter water use and exhibits the least sensitive to change in annual water use in Portland. Tax assessed value is positively associated with winter water use and is significant in Austin and Phoenix at both spatial scales, but only significant in Portland at the CT scale. The variable is no longer statistically significant in Salt Lake City at either spatial scale. Similar to the case of annual water use, percent impervious surface is only significant in Phoenix. Maximum temperature is only significant in Portland at the CBG scale, and together with building age, the combination of the two variables explains 81% variation in winter water use at that scale. Compared to the case of annual water use, the chosen predictors explain less variation of winter water use in all cities (e.g., 10% less variation in Austin). In Salt Lake City, only building age becomes statistically significant, explaining <40% of variation in both scales. In all but one case, the CT level analysis yielded higher R^2 values (2–12% higher) than the CBG level analysis. In Portland, the CBG scale analysis better explains the variation of winter water use than the CT group scale analysis.

Similar to annual SFR water use, spatial regression models resulted in higher R^2 values than OLS models in winter water use. The increases in the model's predictive power range from 5 to 53%, with the highest increases for Phoenix (from 0.11 to 0.64 for the CBG scale and from 0.23 to 0.65 for the CT scale). The spatial autoregressive coefficients (lambda) of the spatial error model are all statistically significant across the four cities. Lambda is the highest in Portland at the CBG scale (0.89), while it is the highest in Phoenix at the CT scale (0.84). The coefficient of building age changed from negative to positive at the CBG scale analysis in Phoenix and Portland, and it is no longer significant in the spatial model (Table 5).

3.3. Summer monthly SFR water use

In all cases, there exist significant positive spatial autocorrelations (Fig. 4), as measured by the Moran's I index. Austin exhibits the highest positive spatial autocorrelation (I = 0.74), while Portland exhibits the lowest spatial autocorrelation (I = 0.60). Similar to annual and base

Table 5
Comparison of Ordinary least squares (OLS) and spatial regression models for explaining average winter (December–February) monthly single family residential water use at Census Block Group and Census Tract scales by city.

Variables	Austin		Phoenix		Portland		Salt Lake	
	OLS	Spatial	OLS	Spatial	OLS	Spatial	OLS	Spatial
Census Block Group	$n = 375$		$n = 813$		$n = 335$		$n = 167$	
Lot size (10 m^2)	0.248	0.122						
Building age (year)	−0.075	−0.025	−0.068	NS	−0.010	NS	−0.082	−0.081
Assessed value ($10K)	0.271	0.320	0.154	0.539				
% Impervious			−0.433	-0.230				
Tmax					9.815	9.700		
Lambda		0.76		0.80		0.89		0.55
AIC	1975.12	1766.61	6381.75	5803.8	649.15	257.08	829.23	797.19
R^2	0.72	0.87	0.11	0.64	0.81	0.95	0.29	0.46
Residual's Moran's *I*	0.510	−0.089	0.580	−0.055	0.716	−0.074	0.304	−0.014
Census Tract	$n = 138$		$n = 309$		$n = 105$		$n = 59$	
Lot size (10 m^2)	0.108	0.067						
Building age (year)	−0.101	−0.059	−0.094	−0.100	−0.049	−0.025	−0.094	−0.10
Assessed value ($10K)	0.253	0.278	0.285	0.149	0.037	0.036		
% Impervious			−0.634	−0.515				
Lambda		0.74		0.84		0.74		0.50
AIC	679.65	615.03	2343.78	2162.62	291.50	242.84	276.50	267.33
R^2	0.74	0.87	0.23	0.65	0.49	0.73	0.40	0.52
Residual's Moran's *I*	0.465	−0.023	0.475	0.035	0.471	−0.066	0.276	−0.013

Only the coefficients of the statistically significant factors ($p < 0.05$) are reported in the table, NA = not significant, OLS = Ordinary least squares; AIC = Akaike information criterion; R^2 for spatial models are Pseudo-R^2 values.

SFR water use maps, the locations of high and low SFR water use areas remain the same. Compared to annual and winter monthly SRF water use, spatial dependence is highest as demonstrated by the highest Moran's I values in three cities – Austin, Phoenix and Salt Lake City. The highest Moran's I value is found in Portland's annual water use map.

Tax assessed value (+) and percent impervious surface areas (−) are consistently significant predictors of SFR summer water use at both spatial scales (Table 6). Building age is a significant predictor in all cities but Phoenix. Lot size is positively related to SFR summer water use, and it is only statistically significant in Austin. Maximum temperature is not significant at all in any of the cities studied. Using the same set of variables, the variation is better explained at the CT level analysis than the CBG analysis (6–10% higher). Compared to the annual SFR water use, more variation in summer water use is explained in Austin and Salt Lake City. In Phoenix and Portland, similar variations were explained using a similar set of variables in both scales.

Like annual and base SFR water use, spatial regression models explain more variations in SFR water use than OLS models. The highest increase is found in Phoenix with >50% increase at both spatial scales. The spatial autoregressive coefficients (lambda) of the spatial error model are all statistically significant across the four cities. Lambda is the highest in Phoenix at both spatial scales (0.82 and 0.87 at the CBG scale and CT scale, respectively). The coefficients of all explanatory variables are unchanged at both scales of analyses.

4. Discussion

4.1. Drivers of seasonal SFR water use

When different seasons are compared, slightly different factors were selected for explaining the variations of SFR water use. Percent impervious surface area becomes much more important for explaining variations in summer monthly SFR water use, as it becomes a significant variable in all cities. This is related to the fact that summer SFR water use is highly associated with outdoor water uses. Outdoor water uses, such as lawn irrigation and swimming pools, are tightly coupled with the presence of green spaces in urban areas (Chang et al., 2010a, 2010b; Halper et al., 2012; Gober et al., 2013). While intuitive, this study finds further evidence that larger proportions of landscapes that do not require water are associated with lower water use. With increases in impervious surface areas, such as buildings or other non-vegetative surfaces (e.g., driveways or patios), irrigation water need decreases (Breyer et al., 2012). However, impervious surface area is also a significant factor for average and base monthly water use in Phoenix, suggesting that a high presence of impervious surface area could be an effective way of reducing SFR water use in an arid and hot environment. Alternately, we recognize that remotely sensed data could mis-identify native desert vegetation on properties as "impervious", due to similar spectral patterns of dirt/gravel and cement. If this is the case, the data indicates that native landscaping is associated with less water use (Lee et al., 2015).

While tax assessed value and percent impervious surface areas are significant predictors in both average annual and summer monthly SFR water uses, they are not significant predictors of base monthly SFR water use in Portland and Salt Lake City for the best fit models, two cities located in higher latitudes. This may be associated with relatively small variations in tax assessed values in both cities compared to the other two southern cities (Table 2). While the variation of impervious surface areas is the highest in Portland, Portland residents do not need to water lawns during the wet winter season (Straus et al., 2016). For all cities examined, the summer models at both scales had the highest R^2 values, with the winter models having the lowest. Winter SFR water use is largely but not exclusively associated with indoor water uses, which could be better explained by other household demographic or building structural characteristics (Willis et al., 2013, Liu et al., 2015; Yu et al., 2015).

4.2. Spatial influence on SFR water use

The presence of positive spatial autocorrelation suggests that neighboring CBGs are similar to each other in terms of water use amount (Figs. 2–4). The spatial error regression models resulted in higher R^2 than their ordinary least squares regression counterparts (Tables 4–6). The errors of the OLS regression models are not spatially random, so including the spatial error term as part of regression models improved regression models' capability to explain variations in SFR water use at both spatial scales in all seasons. The improvement of spatial regression models over OLS models was highest for Phoenix, which had significantly lower R^2 values in the OLS regression models than the other three cities (nearly additional 50% variation explained by spatial error

Table 6
Comparison of Ordinary least squares (OLS) and spatial regression models for explaining average summer (June–September) monthly single family residential water use at Census Block Group and Census Tract scales by city.

Variables	Austin		Phoenix		Portland		Salt Lake	
	OLS	Spatial	OLS	Spatial	OLS	Spatial	OLS	Spatial
Census Block Group	$n = 375$		$n = 813$		$n = 335$		$n = 167$	
Lot size (10 m^2)	0.704	0.448						
Building age (year)	−0.258	−0.104			−0.061	−0.338	−0.509	−0.473
Assessed value ($10K)	0.802	0.849	0.348	0.130	0.175	0.128	2.031	1.917
% Impervious	−0.170	−0.142	−0.920	−0.377	−0.120	−0.108	−0.863	−0.718
Tmax								
Lambda		0.74		0.82		0.64		0.58
AIC	2589.04	2440.73	7670.73	7003.9	1789.62	1711.71	1332.48	1301.98
R^2	0.83	0.90	0.11	0.68	0.53	0.67	0.86	0.89
Residual's Moran's *I*	0.376	−0.051	0.633	−0.073	0.307	−0.014	0.273	−0.009
Census Tract	$n = 138$		$n = 309$		$n = 105$		$n = 59$	
Lot size (10 m^2)	0.288	0.227						
Building age (year)	−0.354	−0.248			−0.086	−0.047	−0.509	−0.465
Assessed value ($10K)	0.780	0.802	0.604	0.323	0.195	0.123	0.213	1.916
% Impervious	−0.289	−0.257	−1.415	−1.093	−0.097	−0.124	−0.886	−0.778
Tmax								
Lambda		0.61		0.87		0.62		0.62
AIC	871.37	847.09	2852.85	2629.11	521.89	494.40	424.89	412.75
R^2	0.89	0.92	0.21	0.70	0.63	0.75	0.93	0.95
Residual's Moran's *I*	0.246	0.002	0.533	0.042	0.333	−0.023	0.275	−0.001

Only the coefficients of the statistically significant factors ($p < 0.05$) are reported in the table. OLS = Ordinary least squares; AIC = Akaike information criterion; R^2 for spatial models are Pseudo-R^2 values.

models). This shows that while there are spatial influences on SFR water use in all four cities, they are most pronounced in Phoenix. This also suggests that the current set of explanatory variables for Phoenix may have omitted important spatially-varying variables in our analysis. Notably, the inclusion of pool and other sociodemographic and behavioral characteristics (Wentz and Gober, 2007; Jenerette et al., 2011; Wentz et al., 2016) could help improve the model's explanatory power.

The spatial patterns we observe in the four cities might be explained by the urban spatial structure of each city, which mirrors the history of urban development. For example, the oldest single family residential properties in CBGs or CT are located in proximity to each other, i.e. “the older parts of town”. Newer developments have occurred on the peripheries of the older neighborhoods. It is also possible that other characteristics that determine water use, such as landscaping preferences and may be clustered spatially in cities. We were unable to measure preferences in this current study, but it is likely that residents that desire certain landscaping features may self-select into neighborhoods that meet their needs and desires (Wentz et al., 2016). If this were the case, we would again expect to see spatial clustering of high water use areas in cities. Additionally, neighborhoods that are close to public green space or pools are found to use less household water than those that are farther away from public spaces (Halper et al., 2012; Halper et al., 2015). Our study offers strong evidence that understanding urban water use requires an understanding of spatial patterns in cities

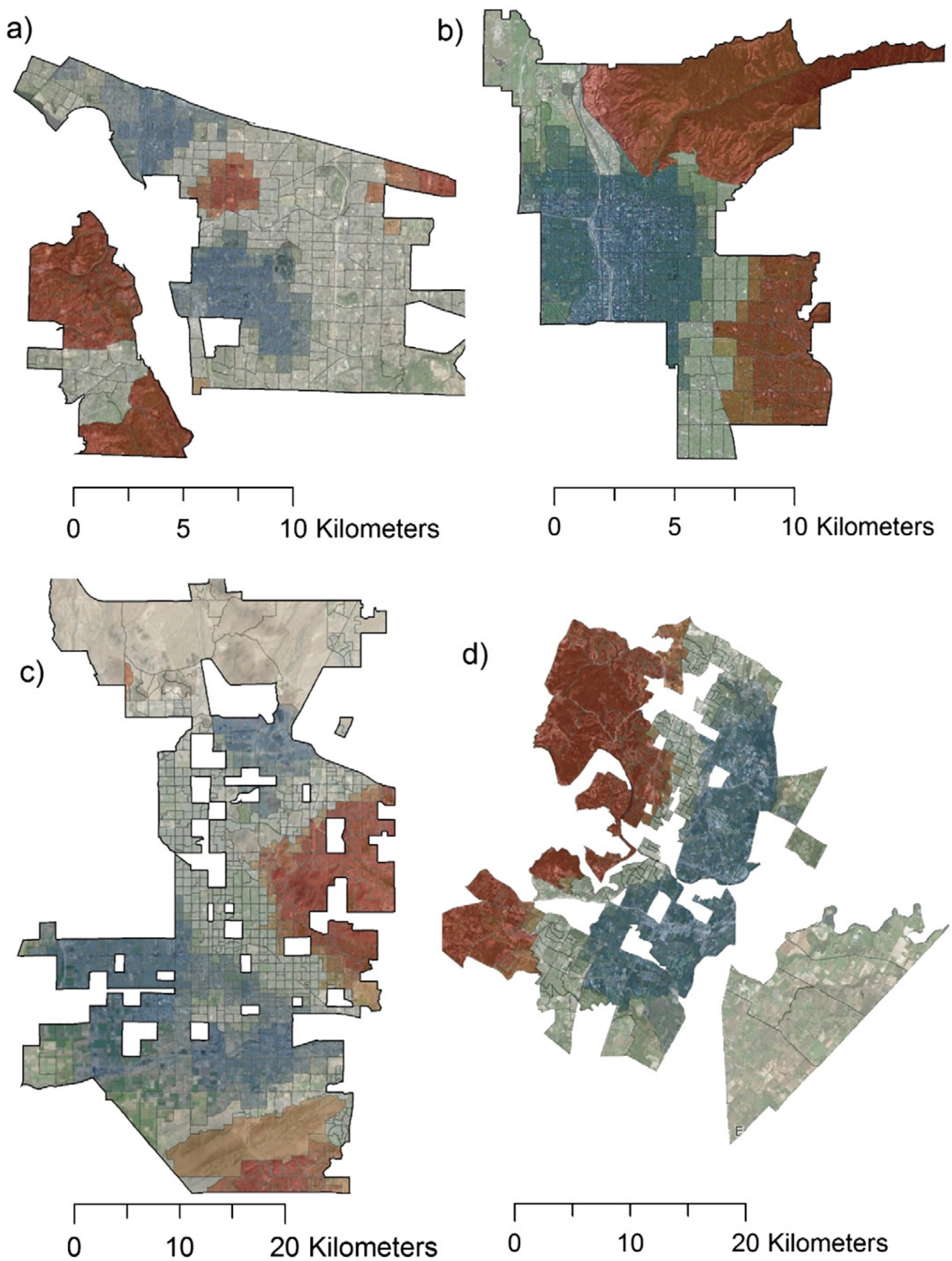

Fig. 5. Hotspots (red) and cold spots (blue) of summer (June–September) household water use at the census block group scale based on the Getis-Ord Gi* statistic - a) Portland, Oregon; b) Salt Lake City, Utah; c) Phoenix, Arizona; and d) Austin, Texas.

(Domene and SaurÍ, 2006; Wentz and Gober, 2007; Chang et al., 2010a; Lee et al., 2015). As shown in Fig. 5, there is a strong spatial clustering of high and low water use areas in each city.

4.3. Building less water intensive cities

The evidence in our study indicates that recent single family housing development is more water intensive, i.e. we are building water intensive cities. The strongest evidence to support this claim is that the CBGs or CTs with the oldest housing are associated with lower water use. There are several potential explanations, for example, old downtown areas are typically denser with small houses and have more impervious surface areas, which result in the reduction of SFR water use. Newer suburban areas are occupied with larger houses and have larger gardens, which increase SFR water use. Our findings are consistent with other studies in Europe (Domene and SaurÍ, 2006), Australia (Troy et al., 2005; Rathnayaka et al., 2014) and other western US cities (Harlan et al., 2009; Polebitski et al., 2011; Ouyang et al., 2014; Mini et al., 2014). These findings suggest that special care should be put into the permitting and design of new single family residential construction so that newer buildings are less water intensive. This could include reductions in lot size, reduced vegetative cover, and requirements for higher efficiency appliances (Stoker and Rothfeder, 2014). In order to accomplish these design and permitting changes, there needs to be better integration of land use planning and water planning (Gober et al., 2016).

4.4. Influence of spatial scale

While different factors potentially explain the variability of SFR water use at different scales, this is not the case for our current study. The same sets of variables were selected for explaining most of the variations in average monthly and seasonal monthly SFR water uses across scales. This is likely due to a relatively small set of independent variables used in our analysis. The exception was average annual and winter monthly water uses in Portland where percent impervious surface area is not a significant predictor in annual monthly water use, and tax assessed value was added in winter monthly water use, respectively, in Census tract level analysis. In general, the CT scale models had higher predictive accuracy than their CBG counterparts. This is closely associated with modifiable areal unit problem in spatial analysis (Openshaw, 1983; Wong, 2009); different statistical results could be derived from the choice of different spatial units (aggregation or zoning) or scales. Household water use could be specific to each location, but when individual households are grouped together at a certain spatial level, water use patterns could be substantially different. Our findings are similar to those of other multi-scale studies in water use (Ouyang et al., 2014; Hong and Chang, 2014) as changing analysis to a coarse scale could remove local noises and spatially heterogeneous patterns in water use within a city, thus increasing a model's explanatory power. Nevertheless, such model noise might not be nuanced at all as they could reveal a potential misspecification error by omitting important variables in the chosen model. The only exception is the winter CBG model in Portland, which had a higher R^2 value than its CT counterpart. In terms of spatial water policy, larger spatial units (i.e., CT) appears to become more important than finer spatial units (i.e., CBG) because CT is likely to encompass the greenness of the area (e.g., urban parks), public facilities and attitudes associated with water use (e.g., municipal pools, and landscape preferences).

4.5. Implications for urban water conservation and management

Our analysis has several implications for urban water conservation and management. First, we identified the hotspots of high water use areas within each city, which can be specifically targeted for further water conservation and spatially distributed water demand within the city (Polebitski et al., 2011). Considering the spatial disparity of SFR water use within each city, urban water managers impose different demand management strategies in different places, such as differing water prices or Block rate structures. Additionally, our study also suggests that there are windows of opportunity for urban water managers and urban planners to work together to achieve water conservation and sustainability (Gober et al., 2013), especially in the design and permitting of new construction. The four cities all show some potential for further reduction in water use by manipulating landscape characteristics (e.g., increasing non-vegetative surfaces) or building code (higher density building with smaller lot sizes). These new landscape planning and development strategies can be also used for effective climate adaptation, particularly for hot and dry cities in the southwestern USA.

While increasing impervious surface areas could reduce summer water use as evidenced by other studies (House-Peters and Chang, 2011b; Gober et al., 2012; Middel et al., 2012; Lee et al., 2015), higher impervious areas could also exacerbate existing urban heat island effects and reduce other ecosystem services in arid cities (e.g., in Phoenix, see references Jenerette et al., 2011; Wentz et al., 2016) and induce higher peak runoff and frequent localized flooding in the wet season (e.g., in Portland, see references Chang, 2007, Chang et al., 2010b). To minimize potential negative consequences of increasing impervious surface areas on urban water and ecosystem services, planners and decision-makers need to consider best management practices such as stormwater planning, porous pavement, green infrastructure (Pennino et al., 2016).

5. Conclusions

We investigated the spatial patterns of annual and seasonal SFR water use in four representative western US cities to identify the major determinants of SFR water use at two different spatial scales and answer the research questions laid out in the beginning of the paper. The main findings are as follows:

- There exist strong spatial gradients of water use across the four cities regardless of the time of the year. Water use in hot dry Phoenix is most intense, while mild, wet Portland uses the least water. Old downtown areas show less water use than newer suburban areas. The hotspots of high water use largely remain the same over the seasons.
- Tax assessed value and building age are the main determinants of SFR water use across the four cities regardless of scale. Impervious surface areas become an important variable for summer water use in all cities, and it is important in all seasons for an arid environment such as Phoenix.
- The selected variables better explain the spatial variation of SFR water use at a coarser spatial scale. This is associated with the fact that a coarser level of analysis potentially masks detailed local spatial variability.
- In all cities, seasons, and spatial scales, spatial error regression models better explain the variations of SFR water use. This is associated with the fact that SFR water use exhibits strong spatial dependence and has neighboring effects.

The findings of the current study offer insights on the major determinants of SFR water uses across different seasons and spatial scales. Urban water resource managers and city planners use such information to better form urban water policy and spatial planning to identify high water use neighborhoods to achieve water sustainability. Future research areas include the examination of the other determinants of SFR water uses in other cities facing similar climate challenges to draw broader conclusions.

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