SPATIAL VARIATIONS OF SINGLE-FAMILY RESIDENTIAL WATER CONSUMPTION IN PORTLAND, OREGON[1]

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Abstract: Although water demand theories identify price structures, technology, and individual behavior as determinants of water demand, limited theoretical or empirical evidence suggests a link between urban development patterns and water use. To assess the role of urban development patterns on water demand, we used GIS and statistical models to analyze single-family residential water consumption in the Portland, Oregon, metropolitan area. Our results show that residential water consumption per household at the census block group scale is best explained by average building size, followed by building density and building age, with low water consumption areas clustering together and typically located in high-density and older neighborhoods. Accounting for spatial dependence among residuals, explanatory variables explain up to 87% of variations in water consumption. Our results help to develop a water demand framework that incorporates existing factors with urban development policies to more effectively manage limited water and land resources. [Key words: Portland (Oregon), water consumption, urban development, spatial analysis, water management.]

There has been a growing interest in the sustainability of water resources in major metropolitan areas throughout the world. This interest stems from ongoing population growth and potential climate change that are posing multiple challenges for urban water resource managers (Morehouse et al., 2002; Ruth et al., 2007; Wentz and Gober, 2007; Kenney et al., 2008; Praskievicz and Chang, 2009). In order to cope with increasing water scarcity, many urban water managers have introduced water conservation policies and technologies as well as more sophisticated water demand modeling so that conservation programs can be more effectively targeted to specific consumer classes. As a result, many U.S. cities (e.g., San Francisco, Seattle, Denver, Los Angeles) were able to stabilize water demands over the past few decades despite significant population growth (Cooley and

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Gleick, 2009). Whereas conservation programs have been somewhat effective in reducing water consumption per capita, opportunities for future conservation may be enhanced, particularly if the structural dimensions of the new developments are also considered (Saurí, 2003; Domene et al., 2005).

Indeed, the structural features of residential developments, such as neighborhood density, lot size, and outdoor area, have been closely associated with water consumption. In a comparative study of two neighborhoods in Sacramento, Allen (1999) found that per capita water consumption was higher in a low-density development neighborhood than in a high-density neighborhood. In previous studies, researchers found that water consumption was affected by dwelling type (Martinez-Espineira, 2002; Troy and Holloway, 2004; Schleich and Hillenbrand, 2009), land use (Day and Howe, 2003; Durga Rao, 2005), neighborhood density (Balling et al., 2008), and the presence of gardens or other landscape features (Domene and Saurí, 2006; Wentz and Gober, 2007; see Table 1 for details). While these studies point to a need for examining structural variables in predicting water consumption, the implications for land-use planning are only beginning to take shape (Page and Susskind, 2007; Woltjer and Al, 2007).

In recent years, the focus of land-use planners on urban spatial structures has gained considerable attention, although much of this work has not dealt with water resource planning, but rather on landscape ecology (Yeh and Li, 2001; Yang and Lo, 2002; McGarigal, 2004), transportation efficiency (Song and Knapp, 2003; Metha, 2007), and community design (Randall and Baetz, 2001; Ewing et al., 2005; Clifton et al., 2007). The focus of these earlier studies is on reducing low-density, auto-dependent development through developing alternative forms of urban growth. Using sets of "smart growth" principles, urban planning agencies are attempting to use existing research to change land-use patterns by creating more compact cites that encourage walking, biking, and the use of mass transit (Beatley, 2000; Barnett, 2007; Daniels, 2008). In addition, scholars argue that such compact patterns will use land more efficiently (increasing density); building homes, offices, stores, and parks within close proximity to one another (mixing uses); and that linking development with transportation infrastructure will enable metropolitan areas to accommodate growth without creating large consumption footprints or devastating local ecologies (Grimm et al., 2008; Conway, 2009). While several studies conclude that more compact cities will reduce auto dependence (NAS, 2009), improve air quality (Stone et al., 2007), and enhance ecological conditions (Farr, 2007; Alberti, 2008), little is known about the role of urban spatial structure in several natural resource challenges, including urban water management (House-Peters et al., 2010).

Hence, there is a need to understand the dynamics of water consumption as they relate to urban spatial structure and concomitant socioeconomic variables. Previous studies either focus on the influence of income on municipal water consumption (Moilanen and Schulz, 2002; Jansen and Schulz, 2006) or the effect of structural variables (Domene et al., 2005; Fox et al., 2009). A lesser known area of urban water management is how water consumption patterns vary spatially and how these variations are associated with structural, socioeconomic, or climatic variables (Balling et al., 2008). Most previous studies are based on either an individual household survey or geographically aggregated areas (Lee and Wentz, 2008), offering limited value for understanding the spatial complexity of water consumption at the neighborhood scale. Identifying factors affecting water consumption at a neighborhood level provides a spatially targeted water resource management and policy,

Table 1. Structural and Socioeconomic Variables Used for Explaining Variations in Urban Residential Water Consumption

Author(s) (year)	Study area	Independent variables: Structural	Independent variables: Socioeconomic
Agthe and Ballings (2002)	Tucson, Arizona	Number of bedrooms, building age, pools, indoor water saving devices	Water price
Balling et al. (2008)	Phoenix, Arizona	Pools, landscaping, lot size	Income
Bradley (2004)	Asian cities	Property type	Household size, economy, employment
Clarke et al. (1997)	Leeds, UK	Property type, property size	Income, ownership
Day and Howe (2003)	Sydney, Australia	Garden, land use	Water use behavior, demography
Domene et al. (2005)	Barcelona, Spain	Garden, water saving devices	Income
Durga Rao (2005)	India	Distance from city, land use/cover	Population density
Fox et al. (2009)	Stevenage, UK	Number of bedrooms, housing type, garden	
Huei (1990)	Taipei, Taiwan	Number of bedrooms	Household size, employment
Koo et al. (2005)	Seoul, Korea		Employment, population
Kenney et al. (2008)	Aurora, Colorado	Number of bedrooms, building age	Household size, income, age of owner, ownership, water price, water conservation
Liu et al. (2003)	China		Household size, income, water price
Martinez-Espineira (2002)	Spain	Housing type	Occupancy
Renwick and Green (2000)	California	Lot size, indoor water saving devices	Price, income
Schleich and Hillenbrand (2009)	Germany	Housing type	Household size, income, water price, age of population
Syme et al. (2004)	Perth, Australia	Garden	Income, conservation attitude, lifestyle
Troy and Holloway (2004)	Adelaide, Australia	Housing type	Household size,
Tinker et al. (2009)	Austin, Texas	Building size, lot size, appraised value, pools	

which can be coordinated with urban land-use planning. Whereas residential water consumption can be subdivided into various indoor and outdoor water consumption categories (e.g., cooking, washing, gardening) with different price elasticities (Mayer et al., 1999; Arbués and Villanua, 2006; Schleich and Hillenbrand, 2009), we did not consider these differences because our data represent the total amount of water consumption by single-family residential households.

In this study, we apply three statistical regression techniques to assess the role of spatial structures on residential water consumption at the census block group level in Portland, Oregon. We attempt to explain the variation in water consumption by single-family residential (SFR) households in block groups in terms of density, physical, and socioeconomic characteristics that differ across census blocks. Based on water billing data provided by the Portland Water Bureau (PWB), existing tax-lot records, and U.S. Census demographic information, we attempt to single out the importance of spatial structure in understanding water consumption patterns. This research is based on a collaborative effort between an urban university and the local water provider to better understand the spatial determinants of SFR water consumption patterns and to elucidate spatially explicit potential water conservation strategies.

STUDY AREA

Situated at the northern end of the Willamette Valley, the Portland metropolitan area (PMA) has grown rapidly from a network of agricultural settlements containing just over 500,000 inhabitants in 1950, to more than 1.4 million in 2005, and is projected to grow by an additional 680,000 between 2005 and 2030 (Metro, 2009). The region is unique, however, because it contains an urban growth boundary (UGB) that is managed by a regionally elected government known as Metro, the only one of its kind in the United States. With the expansion of the UGB in 2004 and the requirement to have a 20-year land supply included within it, the Portland area will experience infill growth as well as growth in newly added UGB additions as approved by Metro.

The City of Portland is supplied by water originating in the 264 km^2 Bull Run Watershed and stored in reservoirs located east of the metropolis. The PMA overall, however, includes 24 individual water providers from cities to special districts (Fig. 1), of which the Portland Water Bureau (PWB) is the largest. The Bureau is responsible for the administrative and technical operations of providing water to approximately 860,000 Oregonians in their retail and wholesale service areas. These combined service areas provided water to approximately 60% of the PMA in 2008. In 2006–2007, the Bureau directly served more than 168,000 residential households (both single- and multifamily residences) and approximately 20,000 commercial and industrial customers (Portland Water Bureau, 2008). Residential water consumption comprises approximately 41% of total water consumption by retail customers in Portland. Another aspect of the water system which is rarely found elsewhere is the fact that water is delivered from the watershed to the urban area's reservoirs by force of gravity. This enables PWB to provide water at low rates to customers thanks to minimal pumping costs. Cheap water has encouraged water-intensive industries to locate in the Portland area. While per capita water consumption fell after the water shortage of 1992, other factors such as land use, conservation programs, and rate structures continued to influence further reductions in per capita water consumption ever since. At some point the Water Bureau would expect to see per capita water consumption level off, but the effects of continued infill and redevelopment, as well as wholesale contracting, is expected to result in an increase in water demand over time.

The 2002 Climate Change Study (Palmer and Hahn, 2002) indicated that reductions in yield from the Bull Run surface water source are likely to increase water stress over time that will need to be met by using of Portland's secondary groundwater source, or by

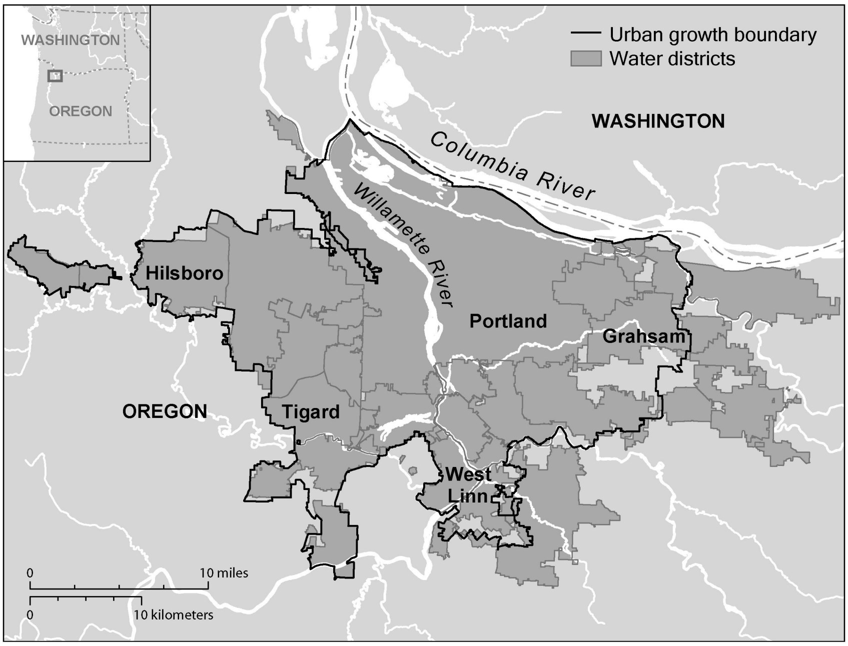

Fig. 1. Location of 24 water providers in the Portland metropolitan region.

reduced wholesale contracting over the longer term. The increase in the number of people in the region and the additional challenges of anticipated climate variability due to climate change impacts on the hydrology of the Portland area will make understanding the role of urban patterns on water consumption an essential step towards ensuring sufficient water supplies for future growth. Moreover, Portland, like many other cities in the country, has only modest knowledge of the specific impacts of different land-use patterns on water demand changes over time, creating an administrative and operational separation between land-use planning and water management (Shandas and Parandvash, 2010).

DATA

We used PWB's 2005 billing records for single-family residential (SFR) water consumption to determine factors affecting the total consumption of all SFR units at the census block group level. Individual households were geocoded in ArcMap 9.2 (ESRI, 2007) using address data and linked to tax-lot data provided by Metro. The integration of tax-lot and billing data provided a dataset from which we could test the role of structural independent variables (lot size, building size, building density, and building age) on water consumption. To accomplish this, we aggregated the individual household billing data into census block groups (U.S. Bureau of the Census, 2007) for all areas throughout the Portland region, except for the central-city CBD and industrial and commercial areas. We excluded downtown Portland because of the high density of multifamily residential housing located there. Additionally, census blocks that contain less than 25% residential areas or less than 40 residential units are omitted from the analysis, which leaves 398 census blocks in the study area. Aggregating the data into census blocks has three advantages. First, we are able to include several sociodemographic variables and test the extent to which social and structural variables contribute to water consumption. Second, density of buildings was established by calculating the number of SFR developments with the area zoned as SFR in each block group. Finally, from an analytical perspective, aggregating households into census block units provides a continuous surface for assessing the spatial variations of water consumption across the metropolitan region. Once the tax-lots are aggregated to census blocks, we can integrate structural attributes, sociodemographics, and water consumption data. These data were then normalized by household so that we could create comparable units across all block groups. Water price was controlled because all customers are in the PWB retail service area and have the same water rates. Furthermore, due to the relatively homogeneous topography, there is less than a 5° C temperature difference across the study area (Hart and Sailor, 2007). As a result, water rates and weather are likely to affect all customers similarly.

CHOICE OF INDEPENDENT VARIABLES

We considered a number of variables that are expected to affect water consumption. Variables such as average building size, average number of houses per acre (building density), average number of rooms, and average age of the house (building age) reflect the land-use characteristics and development history of the census block group. They also provide some indications of the economic status of the households in each block group. Average income per household, average number of people living in a house (household size), average building age, and average percentage of households with college education indicate the socioeconomic characteristics of the households. Initially, the correlation between water consumption and each variable was inspected to determine the direction and magnitude of correlations (Fig. 2). Average household size is the only variable that is not significantly related to water consumption. All other structural and socioeconomic variables are strongly associated with water consumption at the .05 significance level. Although building density and average building age are negatively correlated to water consumption, all of the other independent variables are positively correlated to water consumption. These independent variables along with water consumption were used to develop multiple regression models. Note as well that some independent variables are also correlated to each other. For example, average income, education, and average age of household are correlated with average building size ($r = .69$, .73, and .48, respectively), suggesting that there could be a multicollinearity problem in developing regression models.

STATISTICAL MODELS

After selecting the explanatory variables, we used three statistical models to explain the variations in SFR water consumption at the census block group level. Initially, a linear stepwise ordinary least square (OLS) regression model is used to estimate the relationship between water consumption and independent variables. Stepwise regression models select significant independent variables, removing redundancy in regression models. Second,

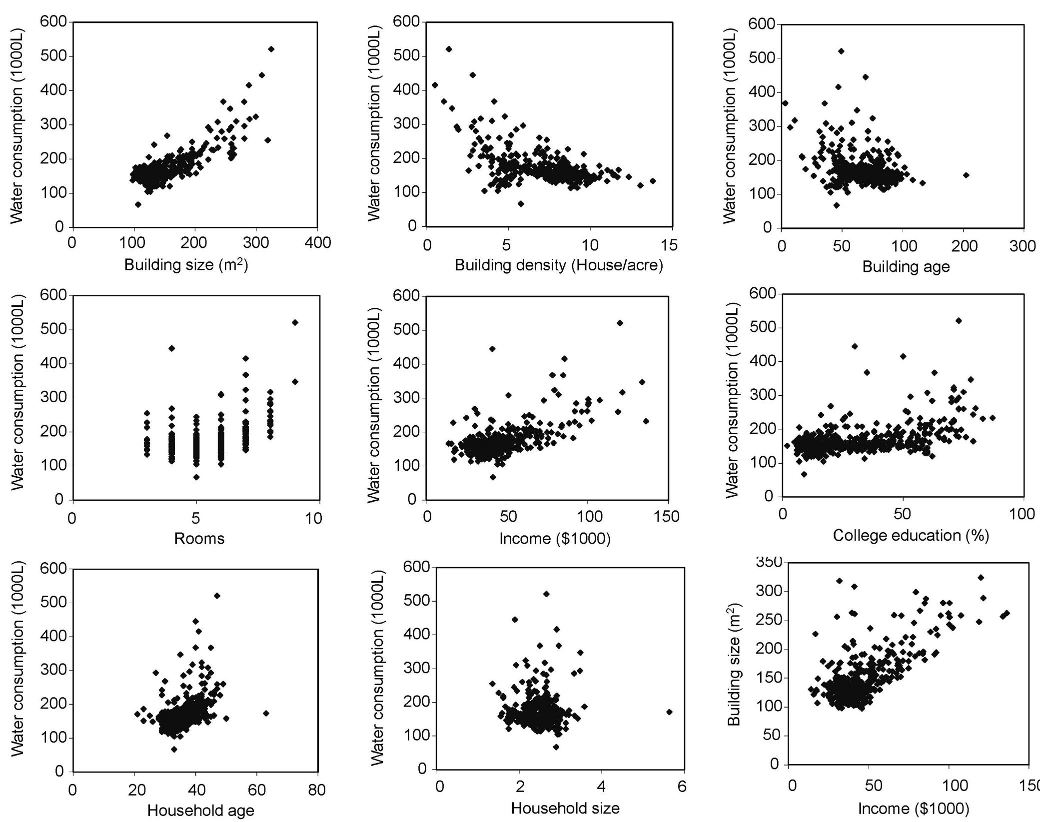

Fig. 2. Relation between average water consumption per household and structural (average building size, average building density, average building age, average number of rooms) and sociodemographic (average income, % college education, average household age, average household size) variables.

we used piecewise linear regression models to accommodate for any regime shifts in the relationship between dependent and independent variables so that we could better estimate the effect of these independent variables on water consumption. Third, we used Moran's I to measure the direction and strength of spatial autocorrelation and spatial regression models to correct any spatial bias in estimating water consumption. Based on the comparison of the results between OLS regression models and spatial regression models, and between piecewise linear regression models and spatial regression models, we assess the extent to which one model can predict water consumption more accurately than the other.

Piecewise Linear Regression Model

There is ample literature that focuses on the treatment of structural or temporal regime shift in a regression model. Bookstein (1975), Bacon and Watts (1971), Ertel and Fowlkes (1970), Watts and Bacon (1974), Tishler and Zang (1981), Gujarati (2003), and Montgomery et al. (2006) represent studies using spline functions or piecewise linear regression. Typically, the point of change in the structure is known empirically or theoretically. Given the point of change, also called the knot, one can apply linear models to each segment along with constraints for continuity. The piecewise linear model has the advantage of simplicity of interpretation of the coefficients and simultaneously reflects the changes in the slope that otherwise need to be estimated with nonlinear models.

Following Bacon and Watts (1971) and Watts and Bacon (1974), we used a transition function to determine the point of regime change implicitly. The model is similar to the piecewise linear form. It is set up so that a transition function is used instead of the dummy variable and the knot is determined as a parameter in the nonlinear regression model. Three nonlinear regression models are used to estimate the knots for building size, building density, and income variables. The knots are estimated as 4 houses per acre for building density, 150 m^2 for building size, and $45,000 for income.[3] These knots are used in a multivariable piecewise linear model to explain the variations in water consumption across the blocks.

Spatial Autocorrelation

Spatial autocorrelation refers to whether adjacent regions exhibit similar or dissimilar patterns. One of the most widely used indices of spatial autocorrelation is Moran's I, a global measure of spatial autocorrelation. We used this to identify the degree of spatial dependence on residential water consumption and explanatory variables (O'Sullivan and Unwin, 2003). Whereas Moran's I is useful in detecting global spatial correlation, it does not show where high or low water consumption census block groups are clustered or dispersed. Local Index of Spatial Autocorrelation (LISA) analysis calculates a spatial autocorrelation value for each unit (i.e., census block group) by explaining the extent to which an

[3]The housing industry in the United States uses the British (standard) measurement system. Lot sizes are measured in square feet or as a fraction of an acre, where each acre is 4,046.9 m^2. We have used British units because the number of houses per acre has been used as proxy for urban housing density in urban planning. However, we have converted house size measured in square feet to square meters for direct comparison with the international literature.

TABLE 2. Regression Coefficients, Standard Errors, and Test Statistics for an Ordinary Least Square (OLS) Regression Model and a Spatial Error (SE) Regression Model of Census Block Group Single-Family Residential Water Consumption per Household in Portland[a]

	Coefficient		Standard error		t-statistic	Z-value
Variable	OLS	SE	OLS	SE	OLS	SE
Constant	101.834	75.475	7.869	13.056	12.901	5.781
Building size	0.783	0.942	0.033	0.047	23.361	20.166
Density	– 4.904	– 6.071	1.010	1.013	– 4.858	– 5.994
Years built	– 0.171	0.009	0.109	0.105	– 1.560	0.082
Lambda		0.702		0.042		16.723

[a]N = 398, R^2 = .71 (OLS), 0.82 (SE); Log likelihood = –1,843.36 (OLS), –1,772.88 (SE).

individual group resembles its neighboring groups. This provides an evaluation of where unusual interactions occur, isolating either "hot" spots (areas of high local autocorrelation) or "cold" spots (areas of low local autocorrelation; Anselin, 1995). This will provide more detail on the regional water consumption around the metropolis and further identify census block groups based on their water consumption similarities or differences.

Spatial Regression

Compared to the OLS regression models, spatial regression models incorporate spatial dependence in the form of lag or error dependence (Ward and Gleditsch, 2008). In other words, spatial autocorrelation is allowed and accounted for explicitly by dependence among errors and/or dependent variables. In spatial error models, the error terms across different spatial units are correlated, while in spatial lag models the dependent variable is affected by the independent variables in adjacent places. Both models thus remove any biased trends in spatially dependent data. Spatial regressions have been applied in water quality studies in coastal areas (Ye et al., 2007) and inland water bodies (Chang, 2008) as well as a county water consumption study in Oregon (Franczyk and Chang, 2009). Spatial autocorrelation and regression were performed using GeoDa software available at https://www.geoda.uiuc.edu/ (Anselin et al., 2006).

RESULTS

Ordinary Least Square Regression

The stepwise OLS regression model predicts up to 71% of the water consumption in all census block groups (Table 2). Specifically, the results show a rather strong relationship between consumption and building size, which corroborates previous studies for the same region (Shandas and Parandvash, in press). However, the relation between density and consumption, although significant and negative as expected, is relatively weaker than the one between building size and water consumption, as indicated by a lower statistical test

Table 3. Regression Coefficients, Standard Errors, and Test Statistics for a Piecewise (PW) Regression Model and a Spatial Error (SE) Regression Model of Census Block Group Single-Family Residential Water Consumption per Household in Portland[a]

	Coefficient		Standard error		t-statistic	Z-value
Variable	PW	SE	PW	SE	PW	SE
Constant	288.570	248.106	16.556	18.646	17.430	13.306
Building size	0.194	0.470	0.079	0.090	2.446	5.233
Building size > 150 m^2	0.705	0.584	0.105	0.110	6.717	5.303
Density	– 34.366	– 34.320	3.443	3.060	– 9.980	– 11.216
Density>4	32.594	32.002	3.631	3.300	8.977	9.698
Years built	– 0.235	– 0.194	0.093	0.092	– 2.511	– 2.110
Lambda		0.700		0.042		16.637

[a]N = 398, R^2 = .79 (PW), 0.87 (SE); Log likelihood = –1,777.06 (PW), –1,713.55 (SE).

value (–4.858) compared to building size (23.361). Age of building, unlike other studies, is not significant (p = .12).

Further examination of the scatter plots of each independent variable with block group-level water consumption shows that the relationships between water consumption and building structural variables are not linear. In other words, the magnitude of changes in water consumption depends on building size or building density (Fig. 2). For example, in the lower density range, the negative relationship between water consumption and density is much stronger. Similarly, building size shows a similar but opposite relationship with water consumption. In the lower range, change in building size does not have a strong effect on water consumption, but in the upper ranges there is a steep change in water consumption as building size increases. To accommodate such regime shifts, piecewise linear functional forms are used to better estimate the effect of these variables on water consumption.

Piecewise Linear Regression

Based on the scatterplots of the variables, a piecewise linear model with predetermined knots for size and density was estimated as described earlier. The results indicate a statistically significant structural change in size and density. Income, although showing a significant nonlinear relationship with water consumption (Fig. 2), was omitted by the stepwise regression model because inserting the variable into the regression model does not significantly improve the model prediction. This is due to the fact that it is highly correlated to building size. As shown in Table 3, the piecewise functional form explains 79% of the variations in consumption, and 8% additional variation is explained by the model compared to the OLS regression model. The coefficient for building size range below 150 m^2 is significant and shows an increase of 194 liters per household (0.194 * 1,000 liter) for every 1 m^2 change in average building size of the census block group. For building size above 150 m^2, the relationship between size and water consumption is more significant (higher statistical test value) and indicates a 899 [(0.194 + 0.705) * 1,000] liter change in water consumption per household for every 1 m^2 change in average building size. The results also show that a unit increase in density (i.e., an average increase of one house per acre) reduces annual consumption by 34,320 liters per household below the threshold of 4 houses per acre. The effect of density increase in the range above the threshold is more moderate, resulting in only a decrease of 2,318 liters (–34,320 + 32,002) per household. The threshold designates an average lot size of 1,011.7 m^2.

Global and Local Spatial Autocorrelation

There exists a moderate positive spatial autocorrelation in water consumption (Moran's I = 0.54), suggesting that residential water consumption patterns are not randomly distributed across the study area. It is very unlikely that adjacent values of water consumptions (clustered pattern) are the result of random spatial processes. As shown in Figure 3, census blocks with similar water consumption rates are clustered together, suggesting that water consumption patterns can be grouped by different neighborhoods. The existence of spatial dependence provides a rationale to use spatial regression to better understand water consumption patterns.

Figures 4 and 5 display LISA maps and Moran's scatterplots, respectively. The slope of the line in Moran's scatterplots is global spatial autocorrelation, namely Moran's I. There exists very strong positive spatial autocorrelation for building size (Moran's I = 0.73), building density (0.74), and building age (I = 0.76). In these scatterplots, the average water consumption (or building size, density, age) of one's neighboring census block (defined as Rook's distance) is shown on the vertical axis, while the horizontal axis displays the value (consumption or building structural variables) of each census block. Both X- and Y-axis values are standardized to have means of 0 and variances of 1. The observations in the first and third quadrants illustrate that a census block and its neighbors have higher (or lower) than average values of water consumption (or housing density). The observations in the second and fourth quadrants show that a census block and its neighbors have dissimilar characteristics.

The LISA maps confirm these cases as they illustrate hot (darker shaded areas) and cold spots (lighter shaded areas) of water consumption and building structural variables. Black areas indicate high water consumption (building structural variables) census blocks surrounded by census blocks with high water consumption (building structural variables; observations in the 1st quadrant), while light grey areas indicate low water consumption (building structural variables) census blocks surrounded by census blocks with low water consumption (building structural variables; observations in the 3rd quadrant). Dark grey areas show high water consumption (building structural variables) census blocks surrounded by blocks with low water consumption (building structural variables), while medium grey areas show low water consumption (building structural variables) blocks surrounded by blocks with high water consumption (building structural variables). For water consumption, hot spots are clustered in the northwestern part of the city, while cold spots are located in northern and eastern parts of the city. The building size map shows similar patterns with water consumption. In contrast, building density, hot spots are dominant in the east-central part of the city, while cold spots are concentrated in the western and far eastern parts of the city. By overlaying these two maps, we can spatially corroborate the strong negative correlation between water consumption and building density. The building age LISA maps are very similar to building density LISA maps.

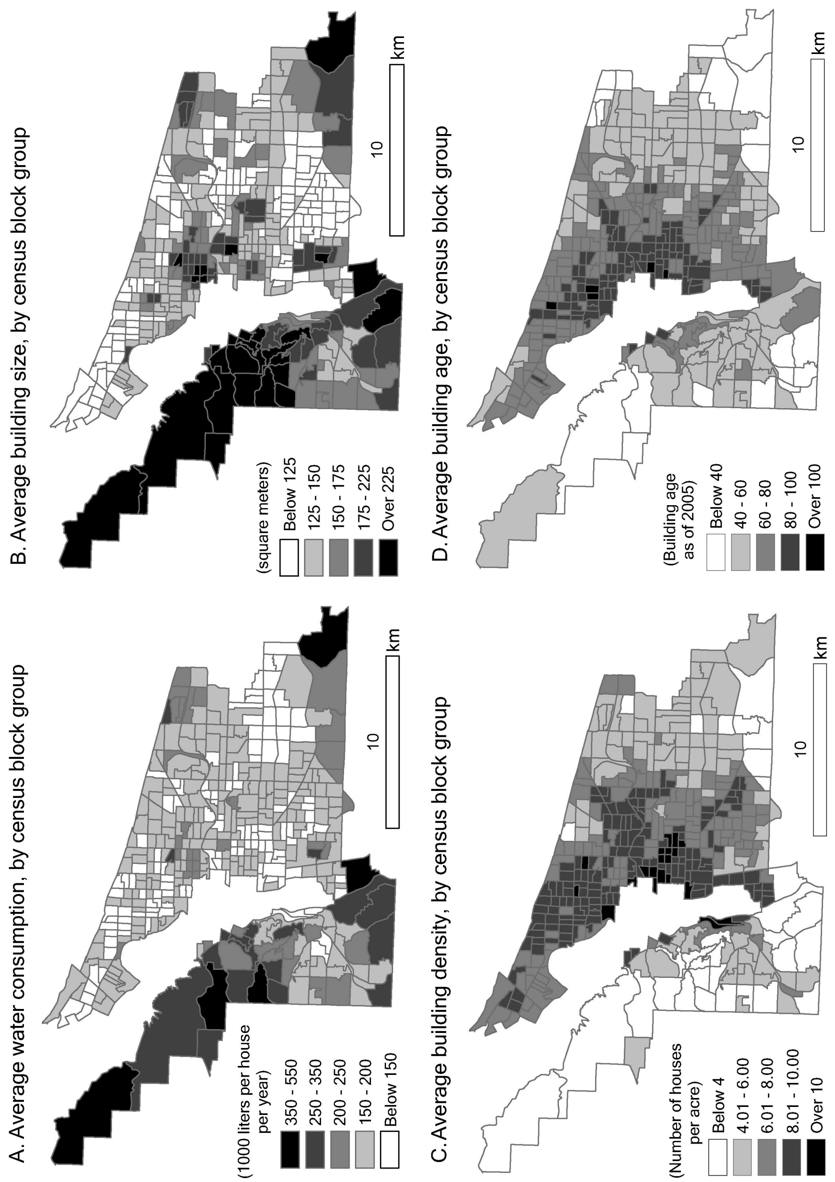

Fig. 3. Spatial patterns of (A) water consumption, (B) building size, (C) building density, and (D) building age by census block groups in Portland, Oregon.

Spatial Regression Models

Table 2 summarizes the results from a spatial error (SE) regression model and a standard OLS regression model. Several differences are evident between the two regression models, including the signs of the coefficients remaining the same in the SE regression model, but the magnitudes of these coefficients differing from the OLS regression model. The lambda value (0.702) in the SE regression model is statistically significant, confirming that spatial errors are not randomly distributed over space. SE regression models have higher standard error and lower test statistic values for building size and density than OLS regression models, suggesting that not correcting spatial dependence in building size and density overestimates the influence of these variables. Building age, although still not significant, becomes less important in the SE regression model as demonstrated by lower Z-value.

Table 3 compares the results from the piecewise regression model with an SE regression model using the same independent variables. As shown in this table, the lambda value (0.700) in the SE regression model is still significant, suggesting that there is strong spatial autocorrelation. The SE regression model has higher standard error and lower test statistic values for size than the piecewise regression model, suggesting that not correcting spatial dependence still overestimates the influence of housing size (although not significant). The standard error and the test statistic value for density and building age, however, are slightly lower in the SE regression model. In general, the SE regression model has a better fit than the piecewise regression model as indicated by lower Akaiki information criterion, but the difference in values of both models are very minor (3,566.12 in the PW regression model vs. 3,439.09 in the SE regression model). The results of this comparison suggest that a further refinement that takes into account spatial relationships among independent variables increases a model's ability to explain the variations in water consumption.

DISCUSSION AND CONCLUSIONS

This analysis shows that SFR water consumption is mostly explained by key building structural variables, namely building size, building density, and building age. While income and education are useful predictors of water consumption, because these socioeconomic variables are correlated with building size, it was found that structural variables can be used as proxies for these socioeconomic variables in Portland. Unlike building structural variables that are derived from individual household data, socioeconomic data are estimated from data measured at the census block group level—thus the variations within census block groups may have been masked. This suggests that building structural variables typically available in a GIS format from tax assessor's records can be used to predict residential water consumption levels when socioeconomic data are not available. It would be interesting, however, to investigate whether this is truly the case if comparable socioeconomic data were available from a survey.

One surprising finding of the study is the negative relationship between the age of building and water consumption. At first glance, this seems counterintuitive. This is probably because older houses are smaller and during the housing boom most of them were remodeled with more water-efficient fixtures and appliances. The passage of the Energy Policy Act of 1992 established national efficiency standards for toilets, faucets, and showerheads.

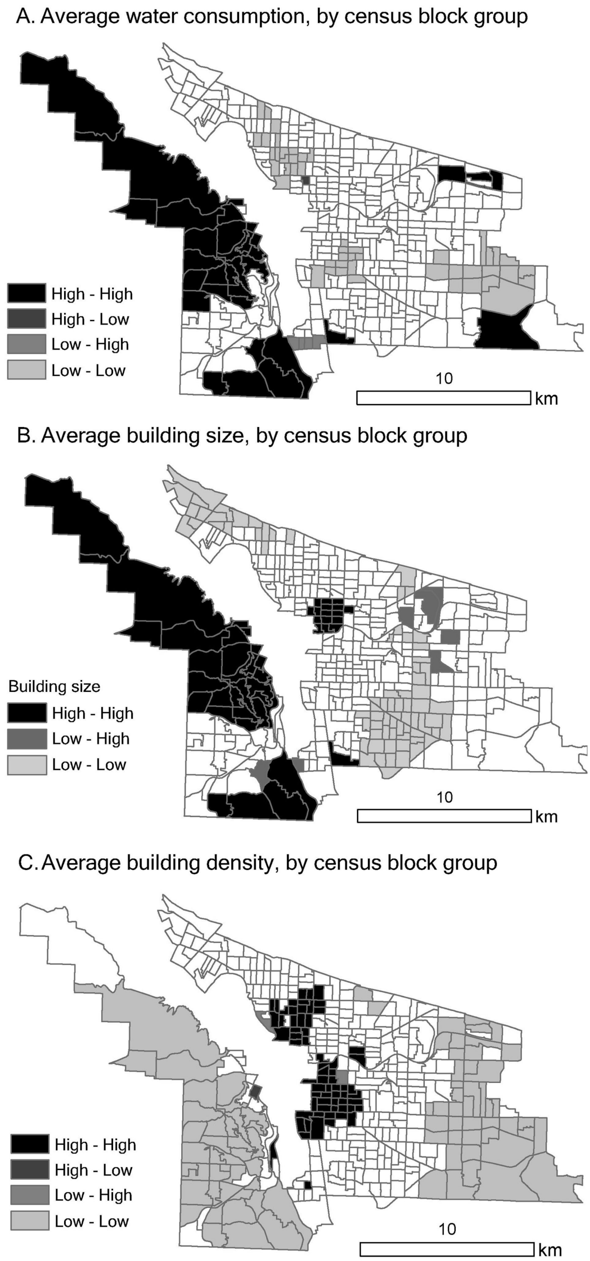

Fig. 4. Local Index of Spatial Autocorrelation (LISA) cluster maps for (A) Average water consumption. In census block groups shaded dark, high rate of water consumption census block groups are significantly correlated with high rates of water consumption in surrounding census block groups; in census block groups shaded light, low rate of water consumption census block groups are correlated with low rates of water consumption in surrounding census block groups. (B) Average building size. (C) Average building density. (D, next page) Average building age. Significance level, $p < .05$; spatial weights matrix based on rook's distance; test for spatial randomness based on 999 iterations.

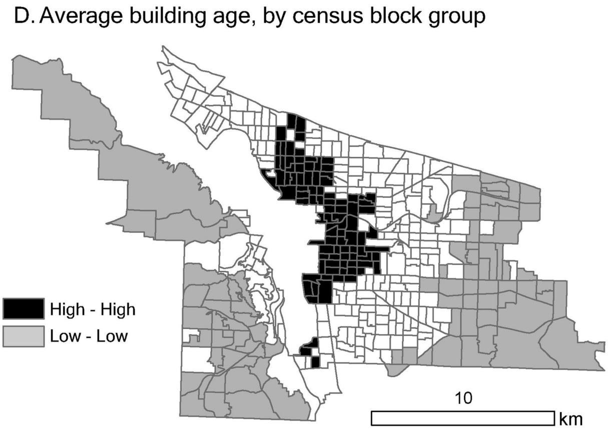

Fig. 4. D.

As toilets, washing machines, showers, and bathtubs account for approximately two-thirds of household indoor water consumption (Mayer et al., 1999), it is reasonable to assume that, since for the most part older houses have been remodeled and their old fixtures been replaced with new efficient ones and urban homes generally have smaller lots, they are likely to use less water than houses built in suburban areas. Additionally, older neighborhoods are more likely to have a mature tree canopy than newer suburban neighborhoods, which leads to a reduction in outdoor water consumption.

Indeed, the bulk of water consumption in metropolitan Portland occurs during summer, which most likely corresponds to outdoor use. Therefore, changes in urban density have significant implications for outdoor water conservation. In this study, the effect of change in density on water consumption can be explained by the fact that the blocks with larger average lot sizes are located in more affluent neighborhoods, as shown by the statistically significant correlation between lot size and income ($r = .68$, $p < .01$). Houses with bigger lots in the affluent neighborhoods typically have more elaborate water-intensive landscapes (e.g., grass lawns) than those in less affluent neighborhoods. Moreover, although not common, certain affluent houses in suburban neighborhoods have swimming pools, which consume additional outdoor water supplies. Wentz and Gober (2007) reported similar findings in their study of Phoenix: areas of higher density include smaller lot sizes with yards that usually do not contain lawns. This suggests that an increase in density in already dense areas does not appear to further reduce outdoor water consumption.

It was also found that no simple nonlinear relationships exist between structural variables and SFR water consumption. Accordingly, a piecewise linear regression model that breaks building size and building density into two ranges better explains the variations in census block group water consumption than an OLS regression model. Additionally, the relationships between water consumption and these structural variables show distinct spatial patterns. The hot spots of water consumption are typically coincide with the hot spots of building size and cold spots of building density and age. Building size above 150 m^2 and building age become less significant in the SE regression model, suggesting that census blocks with similar building sizes and ages are not randomly distributed across

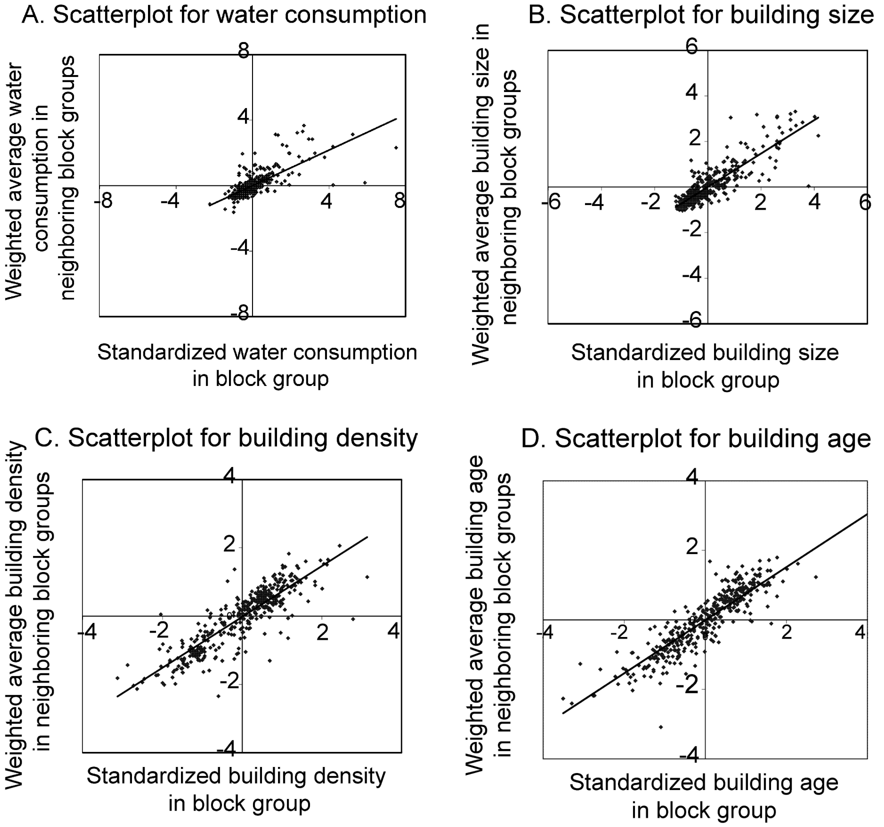

Fig. 5. Univariate Moran's scatterplots for (A) Average water consumption. This scatterplot shows the water consumption of a census block group on the horizontal axis and the weighted average of water consumption in neighboring census block groups (spatial lag of water consumption) on the vertical axis. Both variables are standardized. The distribution is shown in four quadrants to indicate positive and negative spatial autocorrelation. (B) Average building size. (C) Average building density. (D) Average building age. Each circle represents each census block group. The slope of the regression line is Moran's I.

urban space. This finding suggests that incorporating the spatial dimension into water resource planning is needed to better predict water consumption patterns. Census blocks with similar housing sizes and ages can be grouped together for integrated water and land-use planning.

As smart growth strategies become further ingrained into the options available to land-use planners, we will need better information about the relationship between urban spatial structure and water consumption. For example, in 1973 Oregon became the first state to implement urban growth boundaries (UGBs). In Portland, a new planning agency was created—Metro—and charged with regulating the spatial organization of the entire metropolitan region (Metro, 2009). Such approaches, while novel and unprecedented, seem to have reinforced urban water conservation efforts.

In coming decades, more infill development is expected to occur in Portland as the UGB is likely to expand to accommodate population growth. Some of these new infill developments will exemplify smart growth. At the same time, suburban areas may continue their relatively low-density development, typically requiring lawn irrigation during the summer. Ironically, water in these new development areas is currently provided by small local water providers that are constantly searching for new sources of water. With projected climate change and population growth, their water provisioning systems may increasingly become stressed in the future. Hence there are potential opportunities for future water conservation in these new development areas. Given the results of this study, land-use planning can be essential to developing viable climate adaptation strategies, and making urban communities more resilient vis-à-vis potential water stress induced by climate change. For example, one strategy to reduce water demand from lawn irrigation includes planting native vegetation. Implementing such strategies require behavioral changes as well as neighborhood design changes. Our research demonstrates that a spatially targeted approach would be useful for further conservation of water in low-density, new suburban neighborhoods. Water resource planners and land-use planners should consider better coordination of their respective efforts to ensure the sustainability of urban water resources.

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