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Spatial patterns and policy implications for residential water use: An example using Kelowna, British Columbia

Johannus (John) Janmaat *

Department of Economics, I.K. Barber School of Arts and Sciences, University of British Columbia, 3333 University Way, Kelowna, British Columbia, Canada V1V 1V7

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ABSTRACT

The front yard makes a powerful visual statement about the occupants of the residence. As visible statements, yards are likely to induce a behavioral response on the part of neighboring residents. As an example, residents may strive to keep their yard as green and lush as their neighbors. For Kelowna, British Columbia, a highly significant positive spatial lag for summer water use implies some degree of spatial emulation in water using behavior. Other variables such as lot size, building size, assessed value, presence of a pool, etc. impact on water use as expected. The presence of a spatial lag implies a spatial multiplier for water saving innovations. If local water managers and policy makers can influence the spatial pattern of water saving innovations, they may be able to increase the size of the multiplier effect. Similar spatial policies may also be applicable to other socially influenced behaviors that leave a spatial signature, such as protecting ecologically significant habitats in urban areas.

1. Introduction

British Columbia's Okanagan Valley is one of the driest watersheds in Canada [39]. Over 100,000 residents living in its largest city, Kelowna, are supplied by five different water providers (see Fig. 1). The providers have different pricing structures and engage in a mixture of individual and cooperative

* Tel.: +1 250 807 8021.
E-mail address: john.janmaat@ubc.ca

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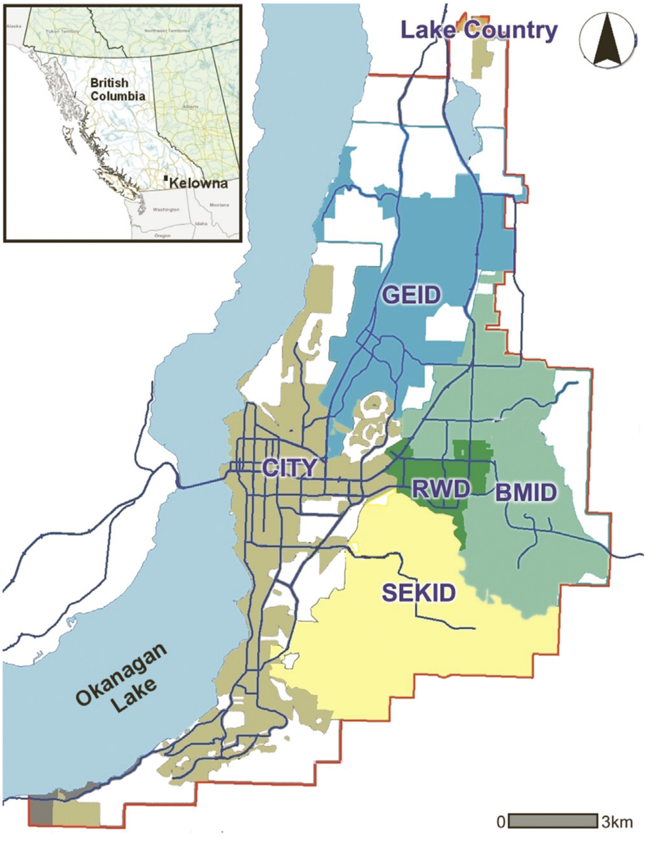

Fig. 1. City of Kelowna Water Providers. Glenmore Ellison Improvement District (GEID), the City of Kelowna (CITY), Rutland Waterworks Department (RWD), Black Mountain Irrigation District (BMID) and South East Kelowna Irrigation District (SEKID).

efforts to encourage water conservation. Of the five, only CITY and RWD charge by volume, and these two price differently.

Okanagan summers are hot and dry, with peak summer water use (largely for landscaping) about five times winter use. Fig. 2 plots average monthly residential water use (1998–2008) for all single family households and for the top and bottom quartiles of summer water use. For the top quartile, peak summer use is about eight times average winter use, while for the bottom quartile the factor is around two. An important water conservation challenge is containing the summer peak. Therefore, finding those factors that contribute to water use, particularly outdoor water use, can help identify strategies to encourage greater water conservation.

By visual inspection, membership in water use quartiles has a strong spatial pattern (Fig. 3). This paper explores the determinants of this spatial pattern, and discusses policy implications of the results. It is among the first to use spatial econometric methods to test for the presence of spatial correlation in water use among residential water consumers. Much of the variation in water use is due to differences in home age, home size, lot size and similar features which are themselves spatially correlated. This correlation stems in part from the history of development, where neighborhood features largely reflect zoning laws, building codes and population tastes dominant when development took place. However, after controlling for these effects, there remains a strong spatial correlation for summer water use.

While the data cannot conclusively separate the influence of unobserved spatial shocks from that of imitation behavior, the presence of substantial imitation creates a policy opportunity. Spatial

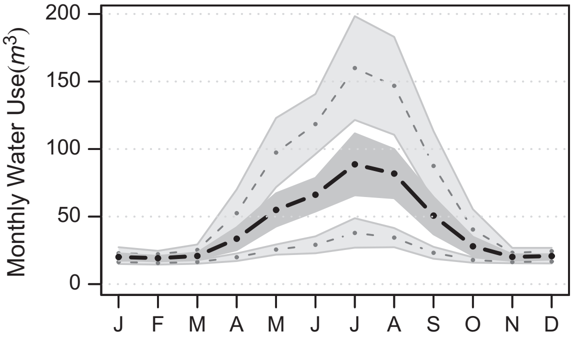

Fig. 2. Monthly average (1998–2008) household water consumption, for all households and for high and low summer use quartiles. Bands identify two standard deviations.

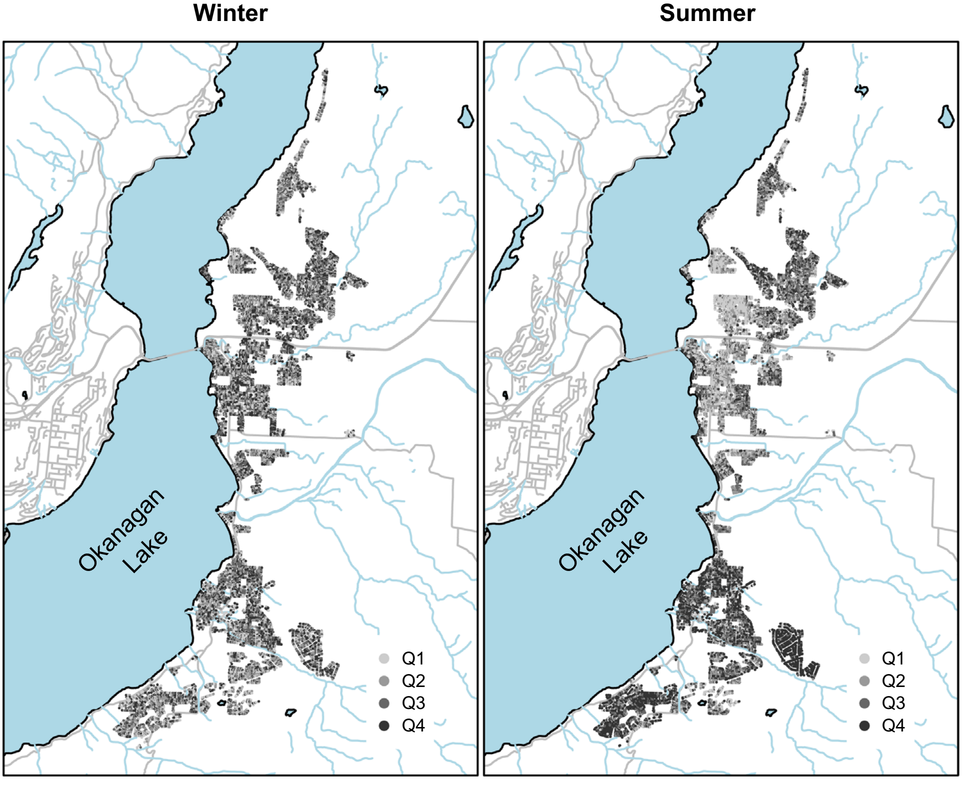

Fig. 3. Spatial distribution of Kelowna households with water consumption data. In each panel, households are divided into water consumption quartiles. For the winter panel, quartiles formed by sorting on average monthly consumption for December, January and February. For the summer panel, sorting on average monthly consumption for June, July and August.

correlation means that water saving innovations have a 'cascade' effect, with the total impact of that cascade depending on the distribution of the initial innovations. We show that careful choice of the location of these innovations can significantly impact on the total spillover water savings. To the best of our knowledge, this is the first analysis to examine spatially optimizing water conservation interventions and further to examine the implications on the optimal choice of having incomplete information about the spatial process.

The remainder of the paper is organized as follows. In the next section related literature is reviewed, highlighting that spatial methods have only seen limited application to residential water consumption. We then present the spatial econometric model and discuss its application. After this we describe the data, present a selection of summary statistics, and discuss the expected relationships. Next we present the results. This is followed by a simple model that shows how spillover water savings operate, where the scale of the spillover is chosen to reflect the estimation results. We follow this by a discussion and conclusion.

2. Background

Residential water demand has been well studied (see [6] and more recently [44] for review articles). This research consistently finds that the demand for water is strongly price inelastic. Where dynamic effects are studied, that price elasticity increases as water users have time to adjust. Other common findings include that water use increases with increasing income (sometimes proxied by property value), household size and water using features like pools and bathrooms. One interesting meta-analysis involving the results of 64 previous studies, Dalhuisen et al. [12], reports that price elasticity tends to be different (possibly higher) in the arid western US, compared to other areas. However, this result is highly sensitive to the functional form used. This does suggest that outdoor water use, which dominates in the arid west, may be different from indoor use. However, beyond considering differences between regions, this work has not considered space.

Some research that considers water use rather than water demand has found evidence of spatial patterns. Using data for 6788 households in Melbourne, Australia, Aitken et al. [1] find that in addition to assessed value and number of occupants, water use can also be clustered into similar spatial neighborhoods. For Adelaide, Australia, Troy and Holloway [41] also find evidence for area effects. However, neither of these use spatial modeling. Wentz and Gober [43] use geographically weighted regression (GWR) to examine household water use for Phoenix, Arizona. The usual variables, household size, lot size, having a pool, landscaping, etc. have the usual effects. GWR extends regression models by allowing parameters to smoothly change over space. The GWR fit is superior to the fit with fixed parameters, suggesting that the way households respond to the exogenous variables varies over space and is similar for those closer together. Franczyk and Chang [13] use spatial regression methods to fit a model for county level water use in Oregon state, finding that models with spatial lag and spatial error effects perform better than a simple OLS model. Ramachandran [36] uses tests for spatial dependence (e.g. Moran's I) to test for household level spatial water use patterns during water restrictions for Ipswitch, Massachusetts. Some weak evidence for a neighborhood effect is found, particularly when disaggregated by lot size. However, an explicit spatial regression model is not used.

Landscaping is an important determinant of outdoor residential water use, and spatial landscaping patterns will induce spatial water use patterns. Landscaping choices are also public statements, and therefore will reflect complex social influences (for example [18,42,20,14], and references therein), which may or may not generate spatial patterns [19]. Using a detailed inventory of front yard landscaping features for a Montreal neighborhood, Zmyslony and Gagnon [46] found highly significant spatial clustering. In a slightly later study [47], they also find a correlation between landscaping choices and building features. Henderson et al. [16] also find clustering of lawn alternatives in Guelph, Ontario, but suggest this may be a response to physical features of the yard. In contrast, Kirkpatrick et al. [19] find no evidence of spatial correlation in landscaping choices for Hobart, Tasmania, Australia. Using a contingent ranking style approach, Iverson et al. [17] find that individual preferences are dominated by neighborhood characteristics, suggesting that efforts to change landscaping choices should focus at the neighborhood level.

Recognizing that place matters is not particularly novel, and modern computational technologies have enabled solving models that were previously impossible. There are now a number of surveys that can be consulted to see the variety of models which have been analyzed using spatial methods [4,5,21]. Spatial econometric models attempt to empirically account for the presence of network interactions between economic agents [11]. Hedonic property models are now as incomplete without a test for spatial correlation as time series regressions are without a test for autocorrelation. Some recent examples with a focus on environmental issues include the following. Zabel and Guignet [45] examine the impact of leaking underground petroleum storage on property prices, finding that publicized sites have a significant impact. Nelson [27] finds a significant premium for lakefront and ski hill access for properties near Deep Creek Lake, Maryland. Pandit et al. [30] show that in Perth, Australia, broad leaf trees along the street contribute significantly to property values, while trees elsewhere on the lot do not do so. They argue that planting broad leaf trees along streets can contribute to social welfare. Netusil [28] show that publicly owned streams and wetlands command a significantly larger price premium for closer properties than do those privately owned, possibly due to uncertainty about future land uses. In studies such as these spatial effects are commonly found. However, the impact varies and typically including spatial lag and spatial error terms is intended to refine parameter estimates. In what follows we estimate one of the first spatial econometric models for household level water consumption. We also demonstrate that the presence of a neighbor effect implies that spatially explicit policies to encourage water conservation can be more cost effective than those which are not.

3. Model

The theory and estimation of spatial econometrics have been well documented elsewhere (with Anselin [2] among the first), and readers are referred to sources such as LeSage and Pace [21] for a more rigorous presentation.

The basic ordinary least squares model is

$$\mathbf{y} = X\boldsymbol{\beta} + \mathbf{u} \tag{1}$$

where for our purposes $\mathbf{y}$ is a vector of average summer water use, X is a matrix of independent variables, $\boldsymbol{\beta}$ is a vector of coefficients, and $\mathbf{u}$ is a disturbance vector. Spatial effects can be incorporated both as spatially lagged dependent variable effects and as a spatially autoregressive disturbance vector. With both of these effects, the regression model becomes

$$\mathbf{y} = \rho W_1 \mathbf{y} + X\boldsymbol{\beta} + \mathbf{u} \tag{2}$$

$$\mathbf{u} = \lambda W_2 \mathbf{u} + \boldsymbol{\epsilon} \tag{3}$$

where W_1 and W_2 are spatial weights matrices and $\boldsymbol{\epsilon}$ is an independently and identically distributed (iid) disturbance vector. When $W_1 = 0$ and $W_2 \neq 0$, then this becomes a spatial autoregressive (SAR) model, while when $W_1 \neq 0$ and $W_2 = 0$ it is a spatial lag (LAG) model. If both W_1 and W_2 are nonzero, then it is a spatial autoregressive moving average (SARMA) model. The spatial weights matrices W_1 and W_2 incorporate the spatial connections between the observations. While in principle W_1 and W_2 can be different, for what follows we assume they are equal.

The spatial regression model (Eqs. (2) and (3)) is essentially a system of simultaneous equations with an autocorrelated error. The reduced form for Eq. (2) is

$$\mathbf{y} = (I - \rho W)^{-1} X\boldsymbol{\beta} + (I - \rho W)^{-1}\mathbf{u} \tag{4}$$

Eliminating $\mathbf{u}$ using its definition in Eq. (3) yields

$$\mathbf{y} = (I - \rho W)^{-1} X\boldsymbol{\beta} + (I - \rho W)^{-1}(I - \lambda W)^{-1}\boldsymbol{\epsilon} \tag{5}$$

With sufficient information or assumptions about the distribution of $\boldsymbol{\epsilon}$, maximum likelihood (ML) can be applied. However, ML solvers can have difficulty in converging. Generalized method of moments (GMM) solvers are typically more stable, and do not require the same distributional assumptions that ML does.

The matrix W represents the relationship between neighbors. For the present problem, W should capture the relationships that affect ones decision, with the size of the weight reflecting the strength of the influence. In our case, we expect that residents observe their neighbor's yards, and that their own behavior is affected. The weights matrix will therefore show a greater influence from closer neighbors. These relationships are difficult to observe and beyond this ad-hock description there is no consistent theory to predict relationship structures. Thus, empirical researchers are frequently left to simply compare alternatives [33]. Estimates were generated for several k nearest neighbor structures, sphere of influence, and a range of inverse distance forms (detailed results available on request). We will use an inverse distance squared weighting matrix with a 100 m distance bound for our estimations, which was chosen through a somewhat ad-hoc examination of significance tests and examination of parameter estimates.

Estimation procedures typically require a weights matrix that is row standardized. This enables solutions to be found, but in effect imposes the assumption that the total influence of all ones neighbors is the same. More neighbors, each has less influence, but the total influence is unchanged. This assumption implies that each person is embedded in a network where total link strength is the same, irrespective of the number of links. For our predictions we examine the impact of a change to this assumption.

Finally, as pointed out by Manski ([25], see also [9]), there is an identification problem in linear models of social influence. Manski described three elements that can contribute to an observed neighbor relationship. Local correlations may be due to contextual factors, a result of unobserved correlations between neighbors, and an endogenous peer effect. Separating the endogenous peer effect from the contextual and correlated effects relies on knowing the form of the social network and having sufficient individual and neighborhood information to identify each effect. For the cross sectional data used in this paper, neighbor average values for the exogenous variables can capture the contextual effect [15]. The spatial Durbin model,

$$\mathbf{y} = \rho W\mathbf{y} + X\boldsymbol{\beta} + WX\boldsymbol{\gamma} + \mathbf{u}$$

provides a way to account for at least the contextual effect, under the assumption that the relevant contextual variables are in X. We find that spatial lag effects remain when the Durbin model is fit by ML, but are unable to solve the Durbin model with GMM.

4. Data

Water use records were provided by the city of Kelowna, for those served by the city water utility (CITY). Supplemental data was generated using GIS layers also provided by the city, and from assessment authority records purchased from Landcor™, the marketing arm of the British Columbia Assessment Authority. The data for which city water records, GIS data and assessment data could be matched included 11,289 observations. When restricted to observations with at least four neighbors within 100 m, 10,976 observations remained. Table 1 reports summary statistics for these 10,976 observations.

For the sample, mean summer (June, July, August) water use is 3.89 times mean winter (December, January, February) water use. There are extreme outliers in all seasons. We use mean monthly summer water use as the dependent variable in the regressions reported below.

Total assessed value ranges from around $200,000–$8.6 million. The average of $577,200 emphasizes that the city water utility does not deliver water to many low income people with single detached homes. The sample does not include households supplied by the other four water providers. As these tend to be further from the lake and/or have a more working class history, lower value single family homes are more likely in these other areas. In the regressions we include assessed value, which we assume is a proxy for income, and as such expect water use to be increasing in assessed value, likely at a decreasing rate.

The average Kelowna house is about 31 years old, occupies a lot that is almost 0.1 ha in area, with a building that has about 203 m^2 of living space (2185 ft^2). We expect summer water use to be increasing in lot size, as there is more area to irrigate. Indoor water use is expected to increase with the area of living space and with age. The latter effect may eventually decrease, as the oldest homes are more likely to be renovated, and through renovation have water using fixtures updated [26].

Number of bedrooms and bathrooms, and presence of a pool, are all expected to increase water use. More bedrooms likely indicates more occupants, and more bathrooms mean more water using fixtures. Pools are water using, and therefore having one should result in more water being used.

Table 1
Summary table. The coefficient of variation is calculated as the standard deviation divided by the mean.

Variable	Min.	Mean	Max.	Coefficient of variation
Annual water use (m^3/mo)	1.083	38.36	329.20	0.532
Summer water use (m^3/mo)	1.000	73.51	788.70	0.658
Winter water use (m^3/mo)	1.000	18.89	478.70	0.718
Total assessment ($,000)	199,400	577,200	8,653,000	0.657
Age (years)	1	30.83	95	0.570
Lot size (m^2)	165.2	974.6	7807.0	0.571
Finished area (m^2)	40.88	202.99	955.97	0.410
Slope (deg.)	0.0003	3.382	32.55	1.282
Elevation (m)	342.3	392.3	616.0	0.167
Bedrooms	1	3.527	12	
Bathrooms	1	2.471	6	
Pool		0.1035		
Prime view		0.0823		
Near agriculture ($<$ 100 m)		0.0343		
Near GEID ($<$ 100 m)		0.0212		
North aspect (-45° to 45°)		0.1491		
East aspect (45°–135°)		0.1233		
South aspect (135°–225°)		0.2509		

Having a prime view should have no direct relationship with water use. However, it may capture effects not well captured by assessed value, slope, elevation or aspect. We have no specific expectation for the impact on water use of prime view.

Water use is expected to decrease in slope, as lots that are more sloped likely have less lawn and more natural space, the latter requiring less water. The effect of elevation is uncertain. All else equal, increasing elevation reduces temperature, and thereby should reduce water use. However, in Kelowna the lowest elevation properties are on flat land near the lake, where the water table is high and there is a cooling effect. Therefore, the sign for elevation is ambiguous. Given that Kelowna is at 49.88° north latitude, lots with a more southerly aspect are expected to use more water.

Finally, two additional neighbor influences are considered. Agriculture in the Okanagan requires irrigation, and therefore properties that are close to agriculture are more likely to see regular watering. We expect that this will encourage households to also irrigate, increasing water use. Similarly, properties near the boundary with GEID may be influenced by the fact that GEID customers pay a flat rate for water. Thus, if zero marginal cost means that GEID customers use more water outdoors, and if Kelowna residents are influenced to be like their neighbors, then water use would increase as we near the boundary with GEID.

5. Results

To get to a discussion of spatially explicit residential water conservation policy, the analysis proceeds through a sequence of steps. First, a set of tests are presented that establish there is a strong case for spatial structure in the data. Using these test results, we argue that it is reasonable to assume an inverse squared distance spatial weights matrix with a 100 m distance bound. Next, using this spatial weights matrix we estimate a set of regression models, and demonstrate that there is strong evidence for a spatial lag process in the data. We then construct a simple example to illustrate that when a spatial lag process similar to that found in the data exists, spillover water savings can be maximized by careful choice of the location of water saving innovations. Finally, we explore how sensitive this optimal choice is to incomplete knowledge about the spatial process.

5.1. Spatial structure

Table 2 reports spatial structure tests on the residuals of an OLS regression of summer water use for nine inverse distance spatial weights matrices. Moran's I was strongly significant for all cases and

Table 2
Spatial structure tests. Test statistic (θ) and significance level reported for robust tests for spatial error, spatial lag, and both spatial error and spatial lag (SARMA). Estimates of spatial lag (λ) and spatial error (ρ) parameters reported as appropriate. Inverse distance spatial weights, with square root, linear and square of distance, distance bound at 50, 100 and 200 m.

Weights	Spatial error			Spatial lag			SARMA			
	θ	P	λ	θ	P	ρ	θ	P	ρ	λ
$1/\sqrt{d_{200}}$	597.4	0.0000	0.612	263.9	0.0000	0.477	1884.3	0.0000	0.467	0.200
$1/d_{200}$	343.0	0.0000	0.573	251.3	0.0000	0.487	1663.4	0.0000	0.482	0.112
$1/d_{200}^2$	0.1	0.7432	0.360	272.4	0.0000	0.479	899.9	0.0000	0.492	–0.187
$1/\sqrt{d_{100}}$	38.2	0.0000	0.407	245.8	0.0000	0.467	986.5	0.0000	0.474	–0.110
$1/d_{100}$	12.9	0.0003	0.382	229.7	0.0000	0.475	929.3	0.0000	0.484	–0.157
$1/d_{100}^2$	11.4	0.0007	0.279	251.9	0.0000	0.475	680.4	0.0000	0.497	–0.273
$1/\sqrt{d_{50}}$	1.3	0.2536	0.228	54.8	0.0000	0.375	172.2	0.0000	0.394	–0.193
$1/d_{50}$	2.1	0.1436	0.219	51.0	0.0000	0.376	172.3	0.0000	0.396	–0.200
$1/d_{50}^2$	5.1	0.0241	0.185	54.7	0.0000	0.346	152.1	0.0000	0.371	–0.188

is not reported. The full data set contains 11,289 observations. For 50, 100 and 200 m bounds, there are 4433, 10,976 and 11,205 usable observations that have at least four neighbors within the distance bound. A serious forest fire occurred near Kelowna during 2003 [34], and all analysis were also conducted without 2003 data. No changes of note occurred.

Results for Lagrange multiplier tests that are robust to the alternate error structure, and a joint test for both forms [3] are reported in the table. When estimated independently, the size of the spatial error parameter (λ) varies inversely with the power on distance and is increasing in the distance band width. The significance test is somewhat inconsistent. When the spatial lag (ρ) is estimated, the test is always highly significant. The value of ρ increases as the distance bound increases from 50 to 100, but changes little thereafter. When the tests are performed jointly (SARMA), the lag parameter is little changed while the error parameter often changes sign and is generally less stable.

We do not have an explicit theory of how neighbors influence each other in this setting, beyond neighbors noticing each others' water use. Given that ρ is relatively stable when the distance bound is increased beyond 100 m, a distance bound of 100 is chosen. To more aggressively limit neighbor influence, inverse squared distance is used. The average lot covers 974.6 m^2, or if square is 31.2 m on a side. A 100 m distance bound would seem to capture a large enough number of neighbors, an average of 19.76, so that those who are significant are likely included. However, it is narrow enough that it does not include an unreasonable number of neighbors. Using inverse distance squared also results in the influence of neighbors falling off rapidly with distance, making closer neighbors more influential.

5.2. Regression results

Spatial lag and spatial Durbin models were also estimated using maximum likelihood. The spatial lag parameter estimates range between 0.183 and 0.502, averaging 0.337 for the spatial lag specification. For the spatial Durbin form, the spatial lag parameter estimates run from 0.164 to 0.578, with an average of 0.326. Estimation issues with the Durbin form prevented the full set of variables being included in the model, and in all cases a Shapiro–Wilkes [37] test for normality of the residuals was strongly violated, rendering the assumptions of the maximum likelihood estimation suspicious. The GMM estimator used here instruments for *Wy* using *WX*. Including *WX* as a regressor will therefore fully capture the effect represented by the prediction of *Wy*, making it impossible to solve the Durbin form of the model. However, on account of the distributional concerns, we report only the GMM results.

Given the results in Table 2, regressions were run with a spatial error alone (SAR), a spatial lag alone (LAG), and with both a spatial error and a spatial lag (SARMA). Regression results are shown in Table 3. Robust standard errors to allow for heteroskedasticity are reported for the LAG and SARMA estimations, as implemented in spdep [8]. GMM is used for the spatial models as the combination of a large sparse weights matrix and fairly high collinearity between some of the variables prevented maximum likelihood based approaches from converging. Using GMM also relaxes the normality assumption that is necessary for maximum likelihood, which is appropriate given that a Shapiro test for normality is rejected for all the models. Relaxing the normality assumption does mean that conventional t tests cannot be conducted for the spatial error parameter λ, and other tests based on the normality assumption likewise cannot be conducted. As such, only a few regression diagnostics can be reported.

For summer water use, June, July and August, there is a strong and highly significant spatial lag. With $\rho = 0.497$ in the SARMA model, almost half of the weighted average water use of the neighbors of an average household is part of the predicted use of that household. With the assumptions outlined earlier, this estimate for ρ means that a water saving impact at a particular house in effect generates about the same savings again elsewhere throughout the CITY service area, through neighbor influences.

Table 3
Average summer household water use regression results. Values in bold are significant at at least $\alpha = 0.01$. Assess value in millions of dollars, lot size and building area in hectares, age in decades, and elevation in kilometers above sea level.

Variable	OLS		GMM SAR		GMM LAG		GMM SARMA	
	$\hat{\beta}$	P-val	$\hat{\beta}$	P-val	$\hat{\beta}$	P-val	$\hat{\beta}$	P-val
Intercept	**2.8226**	**0.000**	**2.8243**	**0.000**	**1.4258**	**0.000**	**1.3728**	**0.000**
Beds 2	−0.0633	0.168	−0.0713	0.111	−0.0805	0.076	−0.0739	0.092
Beds 3	0.0159	0.726	−0.0039	0.929	−0.0241	0.593	−0.0149	0.731
Beds 4	0.0037	0.937	−0.0147	0.744	−0.0319	0.487	−0.0230	0.603
Beds 5	0.0288	0.546	0.0109	0.815	−0.0009	0.985	0.0073	0.872
Beds 6	−0.0091	0.870	−0.0250	0.646	−0.0222	0.688	−0.0076	0.887
Beds 7	0.0227	0.766	0.0331	0.656	0.0500	0.503	0.0493	0.492
Beds 8+	−0.1990	0.073	−0.1556	0.149	−0.1148	0.431	−0.1276	0.370
Baths 2	**0.1122**	**0.000**	**0.1021**	**0.000**	**0.0885**	**0.000**	**0.0873**	**0.000**
Baths 3	**0.1596**	**0.000**	**0.1397**	**0.000**	**0.1120**	**0.000**	**0.1132**	**0.000**
Baths 4	**0.1580**	**0.000**	**0.1377**	**0.000**	**0.1194**	**0.000**	**0.1225**	**0.000**
Baths 5	**0.1494**	**0.000**	**0.1381**	**0.001**	**0.1274**	**0.004**	**0.1266**	**0.003**
Baths 6+	−0.0938	0.169	−0.0869	0.193	−0.0760	0.320	−0.0769	0.287
Assessed	**0.1870**	**0.000**	**0.2135**	**0.000**	**0.1001**	**0.016**	**0.0835**	**0.026**
Assessed^2	**−0.0857**	**0.000**	**−0.0873**	**0.000**	**−0.0678**	**0.000**	**−0.0622**	**0.000**
Age	**0.0791**	**0.000**	**0.0823**	**0.000**	**0.0555**	**0.000**	**0.0494**	**0.000**
Age^2	**−0.0154**	**0.000**	**−0.0151**	**0.000**	**−0.0099**	**0.000**	**−0.0089**	**0.000**
Lot *ha*	**6.1299**	**0.000**	**5.6610**	**0.000**	**3.2875**	**0.000**	**3.1849**	**0.000**
(Lot *ha*)^2	**−10.7936**	**0.000**	**−9.7849**	**0.000**	**−6.1315**	**0.000**	**−6.0418**	**0.000**
Bld *ha*	**0.1982**	**0.000**	**0.1760**	**0.000**	**0.1393**	**0.000**	**0.1343**	**0.000**
(Bld *ha*)^2	**−0.0195**	**0.000**	**−0.0169**	**0.000**	**−0.0123**	**0.011**	**−0.0121**	**0.011**
Pool	**0.1380**	**0.000**	**0.1225**	**0.000**	**0.1142**	**0.000**	**0.1159**	**0.000**
View	0.0132	0.477	−0.0052	0.800	−0.0197	0.275	−0.0094	0.550
Aspect N	**−0.0479**	**0.005**	**−0.0450**	**0.016**	**−0.0469**	**0.005**	**−0.0446**	**0.002**
Aspect S	−0.0088	0.571	−0.0164	0.319	−0.0147	0.315	−0.0092	0.479
Aspect W	**−0.0350**	**0.014**	−0.0288	0.068	−0.0235	0.082	**−0.0238**	**0.041**
Assess × lot	**1.0258**	**0.000**	**1.0220**	**0.000**	**0.8885**	**0.000**	**0.8287**	**0.000**
Assess × Bld	0.0136	0.202	0.0117	0.276	0.0109	0.404	0.0114	0.351
Near Agr	0.0400	0.109	0.0556	0.075	−0.0002	0.995	−0.0024	0.904
Near GEID	−0.0231	0.461	−0.0266	0.505	−0.0357	0.246	−0.0343	0.157
Slope	**−0.0250**	**0.000**	**−0.0240**	**0.000**	**−0.0171**	**0.000**	**−0.0162**	**0.000**
Elevation	**0.9193**	**0.000**	**1.0973**	**0.000**	**0.4340**	**0.000**	**0.3826**	**0.000**
λ			0.2787				−0.2731	
ρ					**0.4746**	**0.000**	**0.4970**	**0.000**
SSE	2352.6		2360.0		2183.8		2099.2	
cor $(y, \hat{y})$	0.6027		0.6019		0.6394		0.6578	
R^2	0.3632		0.3612		0.4089		0.4318	

The individual parameter estimates are largely in line with expectations. Note that in general we expect the parameter estimates for the LAG and SARMA models to be smaller than for the OLS and SAR models, as some of the influence of the independent variables will propagate through the spatial lag process. Also, the variables have been scaled to generate conveniently sized parameters. Thus, assessed value is in millions of dollars, lot size and building size in hectares, age in decades, and elevation in kilometers above sea level. Univariate analysis suggested that the impact of the number of beds and the number of baths was not linear, so dummy variables were used to represent the different numbers of rooms.

The quadratic terms for assessed value, age, lot size and building size imply that the water use function is curved. For assessed values above about $900,000, water use falls with further increases in assessed value, all else equal. Only 5.4% of homes are assessed above this, so few homes fall into the area where water use is declining. For houses more than 2.72 decades old, water use declines with further age. This is consistent with older homes more likely renovated than middle aged homes [26]. Water use is increasing in lot area until lot area exceeds on average 0.276 ha. Only 1.6% of households fall into this range. Finally, for building size, water is increasing in building size over the entire relevant range.

The two neighboring use influence variables, near agriculture and near GEID, are not significant, and near GEID has the wrong sign. However, as there are only 233 near GEID observations and 376 near agriculture observations, the insignificance may be due to a lack of observations. The spatial lag term is strongly significant, both when the model is estimated only with a spatial lag process (LAG) and when it is estimated with a spatial lag and spatial error process (SARMA). As pointed out by Manski [25], this spatial effect need not reflect mimicry. Running a Durbin form of these models and solving by maximum likelihood does not eliminate the presence of a spatial lag effect. However, the data is inadequate to differentiate between a true endogenous effect and due to spatially correlated but unobserved shocks.

The winter results (available on request) confirm many of the summer results. In winter, lot size ceases to be significant, except where interacted with assessed value. This is consistent with summer use being driven by landscape watering, which is not needed in the winter. The diagnostic tests using different spatial weight matrices show evidence for a spatial process (Moran's I). However, the spatial effects are also far weaker, with the spatial lag parameter estimate, ρ, insignificant for both the LAG and SARMA specifications. Further, little explanatory power is added by including the spatial error structure.

The winter and summer results described were estimated assuming independence. In principle, a more sophisticated relationship could be modeled where summer water use impacts on winter water use. Such a model would enable testing if more prolific summer water use is associated with more prolific winter water use. Construction and evaluation of such a spatial simultaneous system is left to further work. That such a process may exist is suggested by the fact that there is a strong correlation between the summer and winter residuals for the SARMA regressions ($r=0.286$, $P<2.2\times10^{-16}$).

5.3. Prediction

The existence of a spatial lag process creates a policy opportunity, stemming from the fact that a water saving innovation at one place will have spillover effects on neighboring properties. This spatial spillover effect is analogous to the propagation of impacts from a shock in an autoregressive model. The aggregate spillover effect can be maximized by choosing where the innovations take place. To the extent that such choices are possible, policy makers can take advantage of the tendency to mimicry and encourage innovations that are optimally distributed.

The spatial regressions estimate the spatial lag term to lie between 0.45 and 0.50. We consider a stylized neighborhood of 49 identical residences on a 7×7 grid, with $\rho=0.5$ and $\lambda=0$. The prediction model that follows from the spatial regression is

$$\hat{\boldsymbol{y}}=(I-\rho W)^{-1}X\boldsymbol{\beta}+(I-\rho W)^{-1}\hat{\boldsymbol{\epsilon}} \tag{6}$$

when $\lambda = 0$ is imposed and the disturbance is estimated as $\hat{\epsilon}$. Define $\Delta\epsilon$ to be an innovation pattern, where elements of $\Delta\epsilon$ equal one for locations where an innovation occurs and zero elsewhere. With identical households, the impact of an innovation pattern $\Delta\epsilon$ is given by

$$\Delta\mathbf{y} = (I - \rho W)^{-1} \Delta\epsilon \tag{7}$$

with total impact as the sum of the elements of $\Delta\mathbf{y}$. The optimal innovation pattern $\Delta\epsilon^*$ is that pattern where $\mathbf{i}'\Delta\mathbf{y}$ is maximized.

Estimation requires choosing a spatial weights matrix. Prediction requires a spatial weights matrix and some further assumptions about how the spatial effects propagate. One question is whether the innovations interact with each other. We consider three cases: (a) raw, where innovations can build on each other, (b) trimmed, where all resultant impacts that exceed one are forced equal to one, and (c) scaled, where all resultant impacts are scaled back so that the largest impact is equal to one.

Another question is whether the row standardization used for estimation purposes is too strong a behavioral assumption. An alternative is to standardize the entire spatial matrix, which would allow households with more neighbors to have a greater propagation of spillover effects than ones with few neighbors. Finally, in this particular case where $\hat{\rho}$ was fairly stable for different distance weighting schemes, it is also interesting to examine how the aggregate spillovers and the optimal distribution of innovations varies as the weighting scheme is changed.

Using a 7×7 grid, we identified the spillover minimizing and spillover maximizing innovation pattern for various combinations of these alternative spatial structures. Since $\Delta\epsilon$ enters linearly, the relative impacts of innovations are scale invariant. We therefore explore the effect of different weighting matrices and different scaling processes on the distribution of innovations by exploring how total impact changes as the pattern of innovation across the neighborhood changes. For k innovations, a pattern of innovation is represented by setting k elements of $\Delta\epsilon$ equal to one while leaving the remaining values equal to zero. The number of unique combinations is $n(n-1)\ldots(n-k+1)$. A short segment of recursive code was written in R Development Core Team [35] that allows any arbitrary value of k to be examined. However, the rapid increase in the number of cases to explore meant that the grid was kept at 7×7 and the number of innovations as $k=2$ and $k=4$.

Twenty-four combinations of distance weighting, spatial weights normalization, and innovation scaling were examined to identify the spatial patterns that maximize and minimize aggregate water savings. Fig. 4 plots the spatial patterns that minimize aggregate water savings, while Fig. 5 plots those that maximize it. See Appendix Table A1 for details. In general, aggregate water savings are minimized when innovations occur near the edge. When innovations multiply each other's effect, then the minimum effect occurs when innovations are widely spaced. In contrast, when they do not build on each other, clustering the innovations near the edge minimizes the total spillover effect.

The situation is essentially the opposite when maximizing aggregate water savings. When innovations compound each other, then the optimum clusters them near the center of the space. However, if they do not, then it is optimal to provide more space between innovations.

The difference in the aggregate spillover can be substantial (see Appendix Table A1). The savings maximizing pattern typically at least doubles the savings from the initial innovations alone, while the savings minimizing pattern adds less than 50%. Choosing the best pattern commonly triples

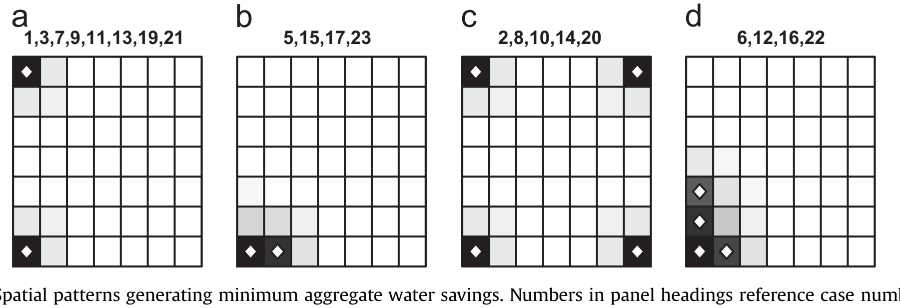

Fig. 4. Spatial patterns generating minimum aggregate water savings. Numbers in panel headings reference case numbers in Table A1. Innovations occur at black points with diamond inset. Shading reflects size of spillover innovation.

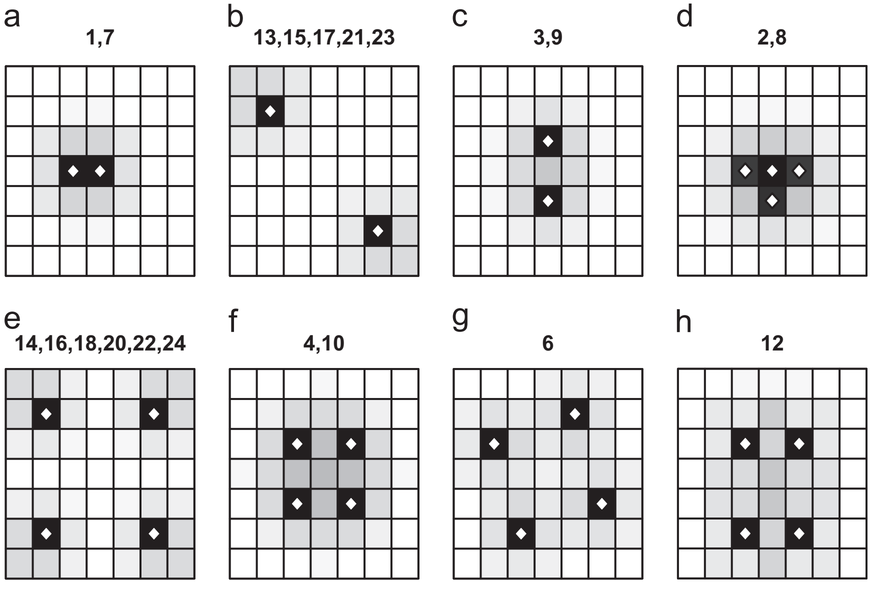

Fig. 5. Spatial patterns generating maximum aggregate water savings. Numbers in panel headings reference case numbers in Table A1. Innovations occur at black points with diamond inset. Shading reflects size of spillover innovation.

the spillover benefit relative to the worst pattern. Thus, if a manager can choose where the innovations occur, there is scope to choose a pattern that maximizes total water savings.

These results demonstrate that if a city manager can choose where water saving innovations occur, then provided they know how the spatial effects of those innovations are propagated, the manager can choose a spatial pattern that maximizes aggregate water savings. However, in reality managers are typically making choices absent definitive knowledge about these spatial propagation processes. The best pattern is that one which maximizes the aggregate spillover water savings, conditional on the spatial process being unknown.

Table 4 reports the relative impact of being wrong. Each row in the table contains the ratios of the water savings realized when the optimal spatial pattern for that structure is applied to the spatial structures identified by the column headings. As an equation, each entry is

$$\sum \mathbf{f}_A(Q_A \epsilon_E^*) / \sum \mathbf{f}_A(Q_A \epsilon_A) \tag{8}$$

where subscripts E and A indicate expected and actual, $\mathbf{f}_A$ is the scaling function that applies, and $Q_A = (I - \rho W)^{-1}$.

To interpret the table, consider the first row. All entries on this row are calculated assuming that the spatial weights matrix is matrix standardized, inverse squared distance, and innovations can compound each other (Raw). When this is the true spatial structure, spillover benefit is 100% of that possible. However, if it is not, then the actual gain is less than it could be. When the actual structure is row standardized with innovations scaled so that the maximum total innovation is equal to one (Scale), then the actual spillover benefit is only 68.3% of what it could be. Each row is likewise interpreted, but for the different assumed spatial structure. The overall result evident from Table 4 is that if one is unsure of the spatial structure, one is best off to assume that row standardization is an appropriate representation.

Finally, it must be borne in mind that the spatial weights matrix, the method of standardization and the way that innovations are compounded is intended to capture the essence of underlying social relationships that impact on behavior. Any choice of spatial structure implies a set of assumptions about the way people interact. The safest assumption to make, based on the results in Table 4, is that people are subject to the same total amount of influence from their neighbors, independent of the number of such neighbors they interact with. When this assumption is true, one does not need to

Table 4
Relative impact for incorrect spatial weights. Rows represent assumed spatial structure and columns are actual spatial structure. Row identities are identical to column identities. Table entries are the ratio of the water saving using the optimal spatial pattern for the assumed structure relative to the water savings if the optimal pattern for the actual structure had been used. Spatial weights are matrix or row standardized, and cumulative effects are raw, trimmed or scaled.

	$w_d = (1/d)^2$						$w_d = \sqrt{1/d}$					
	Matrix standard			Row standard			Matrix standard			Row standard		
Case	Raw 1	Trim 2	Scale 3	Raw 4	Trim 5	Scale 6	Raw 7	Trim 8	Scale 9	Raw 10	Trim 11	Scale 12
1	**1.000**	0.901	0.762	0.877	0.778	0.683	**1.000**	0.923	0.819	0.842	0.761	0.699
2	0.987	**1.000**	0.998	0.888	0.878	0.876	0.983	**1.000**	0.998	0.857	0.847	0.848
3	0.935	0.971	**1.000**	0.940	0.942	0.948	0.918	0.962	0.998	0.922	0.925	0.933
4	0.891	0.928	0.962	**1.000**	**1.000**	**1.000**	0.865	0.910	0.954	**1.000**	**1.000**	**1.000**
5	0.891	0.928	0.962	**1.000**	**1.000**	**1.000**	0.865	0.910	0.954	**1.000**	**1.000**	**1.000**
6	0.891	0.928	0.962	**1.000**	**1.000**	**1.000**	0.865	0.910	0.954	**1.000**	**1.000**	**1.000**
7	**1.000**	0.901	0.762	0.877	0.778	0.683	**1.000**	0.923	0.819	0.842	0.761	0.699
8	0.987	**1.000**	0.998	0.888	0.878	0.876	0.983	**1.000**	0.998	0.857	0.847	0.848
9	0.961	0.986	0.999	0.914	0.910	0.905	0.950	0.983	**1.000**	0.890	0.886	0.881
10	0.891	0.928	0.962	**1.000**	**1.000**	**1.000**	0.865	0.910	0.954	**1.000**	**1.000**	**1.000**
11	0.891	0.928	0.962	**1.000**	**1.000**	**1.000**	0.865	0.910	0.954	**1.000**	**1.000**	**1.000**
12	0.891	0.928	0.962	**1.000**	**1.000**	**1.000**	0.865	0.910	0.954	**1.000**	**1.000**	**1.000**

know if or how the innovations compound. However, if in reality people are influenced to a different degree if they have more or less neighbors, then the maximum additional spillover will be attained. Fortunately, the loss is relatively small, as compared to making any other assumption about the social relations.

To summarize, we began by testing a number of different spatial structures, and showed that for inverse distance style spatial weights, the spatial lag estimates are quite stable for distance bands of 100 m or larger. Using an inverse square distance spatial weights matrix, we estimated a set of spatial regression models for water use. Overall, the variables that predict water use are as expected. The regressions generate estimates for the spatial lag parameter that lie close to 0.5, which we use as the value for ρ to construct a set of predictions for different spatial patterns of water saving innovations. We show that the spatial pattern of innovations can have a substantial effect on the aggregate water savings, on account of the spillovers implied by the existence of a spatial lag process. Finally, we show that when one does not know how these spatial social effects impact on behavior, assuming that the total impact on each individual is about the same is relatively safe, compared to some other possible assumptions. This implies that the second best spatial pattern of innovations spreads the innovations widely around the community.

6. Discussion

We have shown that taking advantage people's tendency to mimic the behavior of their neighbors can enhance the effectiveness of water conservation efforts. There are an assortment of 'cash for grass' programs that pay residents a subsidy to remove grass and replace it with water conserving landscaping (see for example [38]). These programs generally allow anyone in a relatively large area to apply for a subsidy. The tendency to mimic implies that neighborhoods where one person chooses to convert their yard are more likely to see others do the same. Therefore, subsidy requests will tend to be spatially clustered. This limits the spillover benefits. Likewise, neighborhoods where no one has taken a chance on water saving landscaping are less likely to avail themselves of the subsidy. A community could take advantage of these neighbor effects by allocating subsidy dollars by neighborhood or some other spatial division. Similarly, program staff could directly target individual households in areas dominated by heavy water using landscaping. Introducing an innovation may lead to spillover mimicry which would not occur if the dominant pattern is not actively disrupted. Targeting efforts to support early adopters is a common strategy when policy seeks to encourage technology diffusion (see for example [40]).

The tendency to mimicry may also imply that complaint driven enforcement efforts should be spatially targeted. The neighbor effect means that people who are neighbors of households that violate water use restrictions are more likely to be violating these restrictions themselves. This suggests that where there are resources for some random inspections, inspection efforts should be targeted at neighborhoods where violations are rare and/or average water use is high.

There are a number of limitations to the current study. Chief among these is the fact that the mechanism for social influence is not known. The assumption that people are influenced principally by those who live in physical proximity is a strong assumption. Assuming that nearby houses are influential can be justified because home owners are likely to see their neighbors yards, and at least part of the spatial correlation can be attributed to such influences. However, other elements of a home owners social connections may be far more influential. Identifying the dominant social relations and how they interact with other variables such as the price of water is left for further work.

There are of course a number of additional variables that may be important. More detail about landscaping choices may help explain variations in water use. Correlations in landscaping may explain correlations in water use. However, as changing landscaping choices is already a policy target, the conclusions and policy advice of the present work still apply. Other variables such as soil type may also be important in explaining why households behave like their neighbors. Spatial patterns may also be a consequence of city regulations that in recent times have seen smaller lots and an emphasis on water conservation. Finally, there may also be an inherent selection bias, as home owners choose to move into neighborhoods that reflect their landscaping preferences, with residents who value water conservation likely to locate in neighborhoods with more water conserving landscaping.

The impact of landscaping choices goes beyond water use and aesthetics. Landscaping choices can be key contributors to habitats in residential areas. Several authors [22,24,23,32,31,29] have suggested incentive based policies that are spatially coordinated to enhance urban environments. Typically, these involve a higher conservation incentive near a critical habitat or where connectivity and patch size are important. Spatial correlations in land use or conversion probabilities may reduce or increase conservation costs. If owners respond positively to neighboring protection – perhaps enhanced through public recognition – then conservation costs may be reduced. Alternatively, if conservation of one parcel increases the risk of conversion of adjacent sites – residential development seeking to about a park or protected area – then spatial correlation may be increasing costs. This latter effect has been noticed in hedonic pricing studies [7,10].

7. Conclusion

Spatial econometric analysis finds strong evidence for spatial correlation in residential water use in Kelowna, British Columbia. This effect is in addition to the normal observation that more water is used on larger lots, by occupants of larger homes, and when there are more ways to use water (bathrooms, having a pool, etc.). There may be scope to maximize aggregate water savings by taking advantage of this spatial effect. Conditional on knowing the spatial process, the best pattern of innovations can generate more than three times the spillover water savings than the worst pattern. Geographically based targeting of water conservation incentives may be an effective tool because it can give more residents 'water conservation heros' as neighbors that they may emulate.

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Table A1
Minimum and maximum water savings as a function of spatial weights and innovation scaling. Weights matrix based on inverse distance squared or inverse square root distance, with row or matrix standardization. Innovation impacts are raw, trimmed to not exceed innovation size, or scaled to all lie below innovation.

No.	w_d	Scaling	k	Minimum		Maximum		Diff.	Ratios	
				Value	Mult.	Value	Mult.		Diff.	Mult.
Matrix standard										
1	$(1/d)^2$	Raw	2	2.953	1.477	5.022	2.511	2.069	0.7006	3.171
2			4	5.907	1.477	10.018	2.505	4.111	0.6961	3.156
3		Trim	2	2.895	1.445	4.772	2.386	1.877	0.6485	3.097
4			4	5.659	1.415	9.272	2.318	3.613	0.6384	3.178
5		Scale	2	2.777	1.389	4.529	2.265	1.752	0.6309	3.255
6			4	4.974	1.244	8.582	2.146	3.608	0.7254	4.704
7	$\sqrt{1/d}$	Raw	2	2.884	1.442	5.255	2.628	2.371	0.8221	3.682
8			4	5.769	1.442	10.472	2.618	4.704	0.8154	3.659
9		Trim	2	2.840	1.420	4.985	2.493	2.144	0.7550	3.554
10			4	5.680	1.420	9.603	2.401	3.923	0.6906	3.335
11		Scale	2	2.822	1.411	4.691	2.346	1.869	0.6622	3.274
12			4	5.097	1.274	8.802	2.201	3.706	0.7270	4.377
Row standard										
13	$(1/d)^2$	Raw	2	3.172	1.586	4.657	2.329	1.486	0.4685	2.267
14			4	6.343	1.586	9.315	2.329	2.972	0.4685	2.268
15		Trim	2	2.981	1.491	4.514	2.257	1.534	0.5145	2.563
16			4	5.550	1.388	9.022	2.256	3.472	0.6257	3.240
17		Scale	2	2.676	1.338	4.347	2.174	1.671	0.6243	3.472
18			4	4.449	1.112	8.679	2.170	4.230	0.9507	10.421
19	$\sqrt{1/d}$	Raw	2	3.010	1.505	4.912	2.456	1.902	0.6317	2.883
20			4	6.020	1.505	9.823	2.456	3.803	0.6317	2.883
21		Trim	2	2.902	1.451	4.760	2.380	1.858	0.6402	3.060
22			4	5.525	1.381	9.510	2.380	3.984	0.7211	3.613
23		Scale	2	2.713	1.357	4.565	2.283	1.853	0.6829	3.597
24			4	4.500	1.125	9.109	2.277	4.609	1.0243	10.218

Appendix A. Water savings and innovation patterns

See Tabel A1.

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