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Patterns and controlling factors of residential water use in Los Angeles, California

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Abstract

The current study evaluates residential water use patterns and driving factors across Los Angeles, California. Ten years of monthly residential water data were obtained from the Los Angeles Department of Water and Power. Socio-economic, vegetation characteristics, climate, and water pricing data were utilized to develop a statistical model to determine controlling factors of single-family residential water use. Key drivers were found to be household income, landscape greenness, water pricing, household volume allocation, precipitation and temperature. Results show that low water users are less sensitive to climate variability than high water users, likely because these customers have reduced outdoor water use. In the lower income group, average household size is a predictor for household water consumption, which increases with more residents. Lower water users are also more sensitive to changes in their first level household water allocation (Tier 1). However, low, medium and high water users all respond more to changes in Tier 1 rate than Tier 2 rate and generally reduce consumption if this block rate is increased.

Keywords: EVI; Landscape; Los Angeles; Regression model; Residential water consumption

1. Introduction

Water stress is increasing across the southwestern U.S. (Fawcett *et al.*, 2011) and California is expected to experience increasing drought (Seager *et al.*, 2007; Overpeck & Udall, 2010; Natural Resources Defense Council [NRDC], 2011). A warmer, drier climate will impact water deliveries from the Colorado River Basin (CRB), a system that supplies water to seven western states, including California (Christensen & Lettenmaier, 2007; McCabe & Wolock, 2007; Barnett & Pierce, 2009).

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Urban water consumption is growing at a faster rate than any other use in the CRB, increasing stress on overall water supplies for the region (Reese, 2011). In addition, water management is divided into numerous separate entities, introducing significant challenges in understanding the complex management of urban water budgets in the western U.S. (Pataki *et al.*, 2011). Quantifying and predicting urban water use is a critical step toward improved management of water resources, especially in regions with significant dependency on remote water sources vulnerable to climate change (Jenerette & Larsen, 2006; Los Angeles Department of Water and Power [LADWP], 2010; Pataki *et al.*, 2011).

The LADWP, one of the largest municipal utilities in the country, is implementing policies to reduce residential water demand. The utility is primarily focused on price increases, promotion of indoor water-saving devices and irrigation restrictions (LADWP, 2010). Conservation policies over the last decade have resulted in the lowest water consumption per capita per day among cities over 1 million people in the U.S. (LADWP, 2011). Ongoing conservation strategies in Los Angeles include evaluation of sustainable 'local' supplies to potentially mitigate climate extremes and plan for acute water loss (LADWP, 2012). We suggest that these efforts will be better informed by rigorous evaluation of spatial and temporal water use patterns and determination of the key factors that drive consumption across the City.

Previous work on residential water consumption has related water use to a range of socio-economic, housing, climate, and pricing factors. Researchers typically integrate these variables into regression models and implement them across a range of spatial and temporal scales (Worthington & Hoffman, 2008). The influence of these various factors on water consumption varies significantly across socio-demographic groups, regional climates and types of urban development; however, several common key variables emerge from such studies.

Income is generally shown to be significantly related to residential water consumption, where increasing incomes equates to greater water use (Arbues *et al.*, 2003; Guhathakurta & Gober, 2007; Harlan *et al.*, 2009). This is an important finding for the implementation of conservation policies as targeting higher water users may achieve higher reductions. Another important characteristic is that household size has been shown to be negatively correlated with water use per capita (Domene & Saurí, 2006; Wentz & Gober, 2007; Schleich & Hillebrand, 2009).

Studies have also shown the influence of climate on residential water use. Balling *et al.* (2008) and Balling & Gober, (2007) show that higher temperatures, lower precipitation and drought conditions are positively correlated with annual residential water use. Large lots, higher percentages of pools, irrigated surfaces, and non-native landscaping also increase water consumption in semi-arid climates (Balling & Gober, 2007).

The size of lots, gardens, and buildings, as well as building age are noted to influence residential water use (Domene & Saurí, 2006; Wentz & Gober, 2007; Balling *et al.*, 2008; House-Peters *et al.*, 2010). A common finding across these studies is that dense urban structures are typically associated with lower water demand and lower sensitivity to climate variations (Balling *et al.*, 2008), while larger lots and irrigated gardens increase water demand sensitivity to climate (Balling *et al.*, 2008).

Finally, water pricing has been incorporated into water consumption models to evaluate the impact of water rates on use (price elasticity), which is critical for utilities and policy making (Arbues *et al.*, 2003; Hoffmann *et al.*, 2006; Kenney *et al.*, 2008; Worthington & Hoffman, 2008; Schleich & Hillenbrand, 2009). Previous studies in California, Arizona and Texas found price elasticities ranging from −0.55 to −0.11 (Agthe & Billings, 1980, 1987; Agthe *et al.*, 1986; Nieswiadomy & Molina, 1989; Renwick & Archibald, 1998; Gaudin *et al.*, 2001). These values are low, and different from zero, showing that customers have a low response to price but that price remains a key tool for utilities to influence water demand. Water pricing can be represented as the marginal price or average price and studies show that the choice of this pricing structure and its impact on consumer behavior is still unanswered (Arbues *et al.*, 2003).

The goal of our work is to understand the influence of socio-economic, climate, vegetation greenness and pricing variables on single-family residential (SFR) water consumption in a large, semi-arid metropolis. Los Angeles has been characterized as profligate in its water use, relying heavily on external sources, including the CRB, northern California and the eastern Sierra Nevada. Studying water use patterns in a system dependent on far flung sources will yield important insights for other southwest cities potentially facing water stress and in the process of evaluating water conservation policies. Our work is unique in that we combine a range of variables into a single integrated model, developed with 10 years of residential water consumption data at the census tract level for the entire city of Los Angeles. No previous studies have developed water consumption models at this scale and with the proposed range of controlling factors. Our analysis is being done in direct collaboration with LADWP to help inform the development of future conservation programs and pricing structure.

2. Study area

Los Angeles has 3.8 million inhabitants (U.S. Census Bureau, 2010) and covers 1,300 km^2. Los Angeles has a Mediterranean climate, receiving 381 mm of rainfall per year and having an annual average temperature of 19°C (National Oceanic and Atmospheric Administration [NOAA] National Weather Service, 2012), with significant gradients in temperature and precipitation from the coastal area to inland valleys. Urbanization has significantly altered the region, resulting in extensive non-native species and landscapes (Pouyat *et al.*, 2007).

Los Angeles depends primarily on three water sources: (1) Owens Valley/Mono Lake, (2) Northern California rivers, and (3) the Colorado River. Water delivery within the City boundary is managed by LADWP, a municipally-owned utility that is divided into separate water and power divisions, with revenues generated from the rate-payers. Currently, 52% of the water supply is imported from the Metropolitan Water District (MWD), 36% from the Los Angeles Aqueduct, 11% from local groundwater sources, and less than 1% from recycled water (LADWP, 2010). Approximately 90% of the City's water supply is snowpack dependent. In recent years, LADWP has implemented water conservation measures in response to regional drought, which include a tiered pricing structure and watering restrictions.

3. Water pricing

Currently residential pricing consists of an increasing block rate structure with a lower first tier rate (Tier 1) corresponding to a specified water allotment, and a second higher tier rate (Tier 2) for every additional billing unit (1 Hundred Cubic Feet [HCF] or 2,831.5 liters or 748 gallons) above the previous Tier 1 allocation amount for the billing cycle (LADWP, 2010). The Tier 1 allotment is based on lot size and the temperature zone identified for each ZIP code. Lot size in the LADWP service area is divided into five categories between 0 and 4,047 m^2 (43,560 square feet) and larger. Additional volume in the Tier 1 block is allocated for larger households (>6 persons). For example, in the Pacific Palisades (in a lower temperature zone) the Tier 1 block allocation for the high season ranges from 45,307 L (32 HCF) to 155,743 L (110 HCF) per bimonthly billing period based on residential lot size, compared to Pacoima (in a higher temperature zone) with a Tier 1 allotment varying from 53,802 L (38 HCF) to 184,060 L (130 HCF). The Tier 2 rate consists of low season (November through May) and high season (June through October) rates. Water charges are directly tied to the amount of water consumed and there are no fixed charges. Therefore, if no water is consumed during a billing cycle, the customer pays no charge for water service (LADWP, 2010). In comparison, single-family customers in the City of San Diego pay a flat fee in addition to charges depending on the amount of water used within three Tiers (City of San Diego Public Utilities Department, 2013).

4. Residential water data

Water consumption data was provided by LADWP for January 1, 2000 to December 31, 2010. The initial database contained 480,000 individual SFR customers identified by census tract numbers. Less than 1% of the records (500 to 600 single-family customers) did not match the USPS ZIP code database and were removed. The LADWP reading period is bimonthly (every 60 days) and the agency pro-rates the data to calculate monthly water consumption. However, some reading intervals were >60 days. In these cases, the readings are pro-rated monthly over the given period.

Monthly records were aggregated to the census tract level to protect customer privacy and to correspond to other variables available at the census tract scale. The census tract scale also was appropriate to enable investigation of spatial water consumption trends across the entire City and was noted to be relevant for LADWP water management policies. Only census tracts contained completely within the City were analyzed. The final aggregated list includes 857 census tracts with monthly water data covering a 10-year period. Monthly data was also aggregated by fiscal year (FY) (July 1st–June 30th) and normalized per SFR account/SFR customer for each census tract. The GIS census tract boundary layer utilized comes from the 2000 US Census.

5. Study variables

Variables utilized in our analysis include: (1) Water rates and block allocation, (2) Income and household size, (3) Percent grass cover, (4) Landscape greenness, and (5) Precipitation and temperature. Variables were estimated at the census track level for each of the 10 study years (2000 to 2010) (Table 1). Lot size data was available but was strongly correlated to income ($r = 0.7$; $p < 0.05$) and was not included.

1. *Water rates and block allocation.* Both Tier 1 and Tier 2 block rates (described above) are included in our analysis. Water rates were inflation-adjusted to 2,000 dollars and lagged by one bimonthly period in the model as customers receive their bill every two months. By including the two rates, we can analyze the effects of the block rates on water consumption. We use Tier block price in our regression model as water billing prices are on customer bills. Additionally, since there are no fixed charges, theoretically the two rates should improve customer response to marginal price billing.
2. *Income and household size.* Average household size (average number of persons per household) and median household income were collected from the 2000 and 2010 U.S. Census and American

Table 1. Study neighborhoods with key characteristics (U.S. Census, 2000 and 2010).

Neighborhood	Zip code	Population 2010 (thousands)	Average household size 2010	Number with high school degree or less 2000 (thousands)	Temperature zone (LADWP)	Median household income in 1999-dollars (thousands)	10-yr average single-family water use (m^3/ SFR cust./ year)
Florence (FL)	90003	66.3	4.2	17.8	Medium	29.5	385
Koreatown (KR)	90005	37.7	2.5	43.9	Medium	30.6	514
Leimert Park (LM.P)	90008	32.3	2.3	3.1	Medium	45.9	352
Mid-Wilshire (MD.W)	90019	64.5	2.7	8.5	Medium	58.5	461
Downtown (DW)	90021	4.0	1.6	13.5	Medium	15.0	369
Silver Lake (SL.L)	90039	28.5	2.5	8.9	Medium	54.3	359
Playa Vista (PL.V)	90045	39.5	2.4	0.8	Low	68.6	342
Pacific Palisades (PC.P)	90272	23.0	2.5	1.5	Low	168.0	827
Venice (VN)	90291	28.3	1.95	7.2	Low	67.7	307
Pacoima (PC)	91331	103.7	4.6	31.7	High	49.1	572
Reseda (RS)	91335	74.4	3.2	21.1	High	54.8	515
Sherman Oaks (SH.O)	91423	31.0	2.1	10.8	Medium	69.7	700
North Hollywood (NR.H)	91601	37.2	2.3	27.6	Medium	42.8	506

Community Survey (ACS) at the census tract level (U.S. Census Bureau, 2010). Linear interpolation was applied to estimate average household size and median household income between 2000 and 2010. Median household income was scaled by 1,000 dollars, calculated for each bimonthly period and converted to 2,000-dollars using the All Items Consumer Price Index (CPI-U-RS) (Bureau of Labor Statistics, 2012).

3. *Percent grass cover*. The percentage of grass area for each census tract was estimated using a land cover database derived from high-resolution satellite imagery (McPherson *et al.*, 2011). This original database was created using Quickbird imagery and aerial photography from 2002 to 2005 at very high spatial resolution (<2 m) and identifies four primary landcover types: tree, grass, dry grass/bare soil, and impervious surfaces (includes pervious pavement) (McPherson *et al.*, 2011). The percentage of grass landcover area is the portion of grass surface within each census tract area. Between 2001 and 2006, the developed area in the City increased by 0.18% and impervious surface area increased by 0.41%, (National Land Cover Database [NLCD], 2001, 2006; NOAA Coastal Change Analysis Program [C-CAP], 2001, 2006), therefore we assumed that land cover was generally static in our models for the study period.
4. *Landscape greenness*. Vegetation greenness was estimated using the Enhanced Vegetation Index (EVI) from NASA's Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Product (MOD13Q1). MODIS EVI is a 16-day composite data product with 250-m resolution (Huete *et al.*, 2002) and is a measure of photosynthetic activity or greenness. Values range from 0 to 1 with values closer to 1 indicating more photosynthetic activity. EVI data were averaged spatially for each census tract. Cumulative EVI was then computed as the annual sum of the 16-day EVI values for each census tract, providing an index of the total greenness or productivity for each year (Archibald & Scholes, 2007; Ponce Campos *et al.*, 2013).
5. *Precipitation and temperature*. Daily precipitation data were collected from the Los Angeles Department of Public Works (LADPW) ALERT stations, including 47 gauges with complete precipitation

records for the study period. Daily maximum temperature data were retrieved from National Climatic Data Center (NCDC) stations from 2000 to 2010. Four stations with complete temperature records were used and four additional stations with more than nine years of data were also included. Inverse-distance weighting was used to estimate bimonthly precipitation totals and the average daily maximum temperature values by bimonthly period at the centroid of each census tract.

6. Methods

A descriptive analysis of residential water consumption was undertaken for 12 representative neighborhoods from July 2000 to June 2010. The 12 selected neighborhoods are representative of the City's characteristics and were selected based on population, median household income, average household size, education level and microclimate criteria (Table 1). Census tracts within each neighborhood boundary were identified and median single-family water use and average EVI were estimated for each unit.

We also developed a statistical model to represent residential water consumption as a function of price, climate, socio-economic and landscaping variables (Table 2). We modeled water use bimonthly over a seven-year period prior to the implementation of residential irrigation restrictions (2000–2007). Single-family census tracts are included in the model if the ratio of aggregated single-family lot size over census tract area is greater

Table 2. Dependent and independent variables used in the regression models.

	Variables	Definition	Units	Source
Variables are calculated at the census tract level per bimonthly period for fiscal years 00/01-06/07				
Dependent variable	SFR Water use	Single-family water use per household	HCF/hsld/bimonthly period	LADWP
LADWP pricing structure	Marginal block prices	Tier 1 and Tier 2 rates (lagged by one bimonthly period)	2000-dollars/HCF	LADWP
	First tier usage block	Bimonthly quantity of water allocated for the first tier averaged per household	HCF/hsld/bimonthly period	LADWP
Socio-economic	Average household size	Average number of persons per household	Persons /household	U.S. Census, 2000/2010
	Median household income	Median household income scaled by 1000	Inflation-adjusted 2,000-dollars/hsld	U.S. Census 2000 ACS 2006–2010
Vegetation	Grass area percentage	Percentage of grass landcover area (constant)	%	McPherson *et al.*, 2011 landcover database (2002–2005)
	Cumulative EVI (EVI)	Sum of 16-day EVI values	[0–1]	MODIS Terra (250 m, 16 days)
Climate	Bimonthly total precipitation	Cumulative daily precipitation	mm	LADPW
	Average daily maximum temperature	Bimonthly average of the daily maximum temperatures	°C	NCDC

than 0.5, resulting in a subset of around 160 census tracts for which single-family land use area represents more than half of each census tract. The linear model utilizes a natural logarithm on the dependent variable (SFR water use) and on the Tier 1 and Tier 2 price variables for each census tract, *i*, at the bimonthly period, *t*

$$\begin{aligned}\ln(\text{water use}_{i,t}) = {} & \beta_0 + \beta_1 \text{avg hsld size}_{i,t} + \beta_2 \text{median hsld income}_{i,t} \\ & + \beta_3 \text{cum}\, EVI_{i,t} + \beta_4 \text{percent grass}_i \\ & + \beta_5 \text{tot precip}_{i,t} + \beta_6 \text{avg max temp}_{i,t} \\ & + \beta_7 \text{usage block}_i + \beta_8 \ln(\text{rate } 1_{i,t-1}) + \beta_9 \ln(\text{rate } 2_{i,t-1}) + \varepsilon_{i,t} \\ \varepsilon_{i,t} = {} & a_i + u_{i,t}\end{aligned}$$

The error term ($\varepsilon_{i,t}$) is composed of the idiosyncratic error, u_{it}, and unobserved effects, a_i, specific to each census tract and considered time invariant (Wooldridge, 2009). Several studies previously cited use the Ordinary-Least-Squares (OLS) to estimate parameters in a water demand model (Agthe & Billings, 1980; Hoffmann *et al.*, 2006). However, due to the presence of unobserved effects at the census tract level, the OLS parameter estimates may be biased (Wooldridge, 2009). Thus, a random effects approach is developed to address this issue. This is also the preferred method considering that one independent variable is assumed to remain constant over time and other variables (i.e. income) may experience minimal variations over time. However, factors that have significant variability across the census tracts can be accounted for in a random effects approach. The expression of the error term in two components allows us to consider the unobserved census tract-level effects (i.e. building age and other socio-demographic variables).

After general model development, two additional scenarios were created to allow for more in-depth analysis of the explanatory variables, including price, on distinct groups of water users across the City.

Scenario One disaggregates SFR data into low (below 25th quartile), medium and high (above 75th quartile) water use tracts based on the annual average single-family water use for each census tract for the study period (similar to Kenney *et al.*, (2008)).

Scenario Two disaggregates SFR data into two groups based on the annual average median household income from 2000 to 2007: above the median value (high income) and below the median value (low income).

We also tested the difference of the parameter coefficients between the groups by adding an interaction term for each independent variable in the equation, which is the product of the independent variable and a dummy variable. This allows us to test if the estimated coefficients are significantly different ($p < 0.05$) between the different groups; that is, between low, medium and high water use census tracts, and between low and high household income census tracts.

7. Results

7.1. Trends and patterns

To address recent state-wide drought conditions, voluntary (2007) and mandatory (August 2008 and June 2009) irrigation restrictions of two days per week were enacted across the City. The additional mandatory restrictions in June 2009 included a 15% reduction in the Tier 1 block *allocation* and an increase in Tier 2 *rates* (LADWP, 2010). By FY 09/10, total LADWP water use had decreased to water use levels observed in FY 93/94, despite an additional 1.1 million inhabitants in the City of Los Angeles (LADWP, 2010).

Significant spatial variation in average single-family water use is noted across the City (Figure 1). Los Angeles can be divided roughly into three zones: the northern warmer area (San Fernando Valley), the older denser downtown area and the coastal zone. In general, higher water use occurs across the warmer northern parts of the City (a mix of higher and lower income residents) and along the coastal areas with wealthier inhabitants. In contrast, lower water use occurs in the downtown region. Average single-family water use ranges from 106 m^3/SFR customer/year in the downtown area to 3,440 m^3/SFR customer/year in the coastal neighborhoods. These distinct spatial gradients reflect significant variability in income, land use, density and climate across the City. Wealthier coastal areas tend to have larger lots with more landscaping, while more central and older neighborhoods have smaller lots.

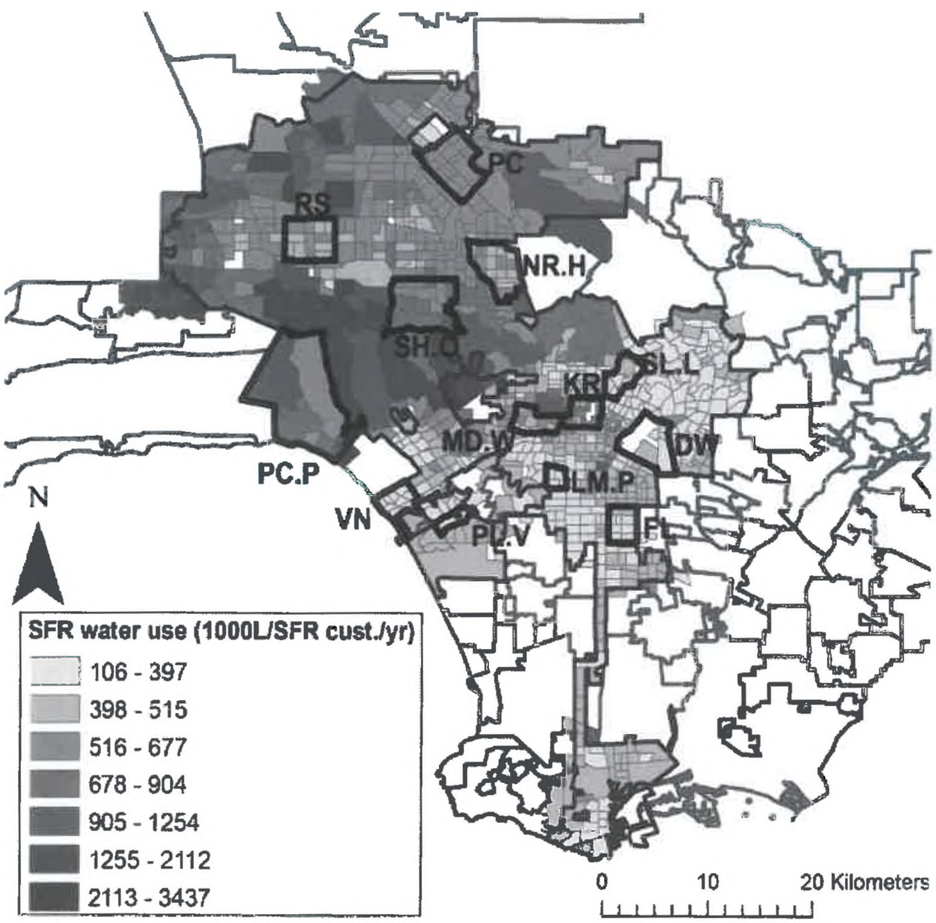

Fig. 1. Ten-year average single-family (SFR) water use per census tract (1,000 L/SFR customer/year) across Los Angeles at the tract level. The selected study neighborhoods are also outlined (black lines) with abbreviations, including Florence (FL), Koreatown (KR), Leimert Park (LM.P), Mid Wilshire (MD.W), Silver Lake (SL.L), Playa Vista (PL.V), Pacific Palisades (PC.P), Venice (VN), Pacoima (PC), Reseda (RS), Sherman Oaks (SH.O), Downtown (DW) and North Hollywood (NR.H).

A temporal analysis of SFR water use in the 12 neighborhoods shows significant variability and distinct seasonal trends in residential consumption (Figure 2). For example, between two coastal communities, annual water use ranges from 307 m^3/SFR/yr in relatively less wealthy Venice to 827 m^3/SFR/yr in more affluent Pacific Palisades (Table 2; Figure 2), reflecting their different socioeconomic and housing characteristics. Denser urban areas show lower annual use (Florence, Leimert Park, Silver Lake, Downtown). They also have lower incomes, higher population density and less green space. Playa Vista may be an exception, however, being a newer area with higher densities and modern construction, showing lower annual water use. In the affluent parts of the warmer northern San Fernando Valley, there is overall higher annual use (Sherman Oaks). Lower income neighborhoods in the warmer parts of the city (North Hollywood for example) also show greater water use than in the denser, more central and older neighborhoods, though less than the more affluent Sherman Oaks. Overall lower income neighborhoods consume relatively less water than their more affluent counterparts.

Neighborhoods with high water use also exhibit higher seasonal fluctuations in consumption due to increased irrigation in summer (Figure 2) with distinct clustering by neighborhood, income and water use (Figure 3). The observed decrease during the winter months is correlated with an increase in

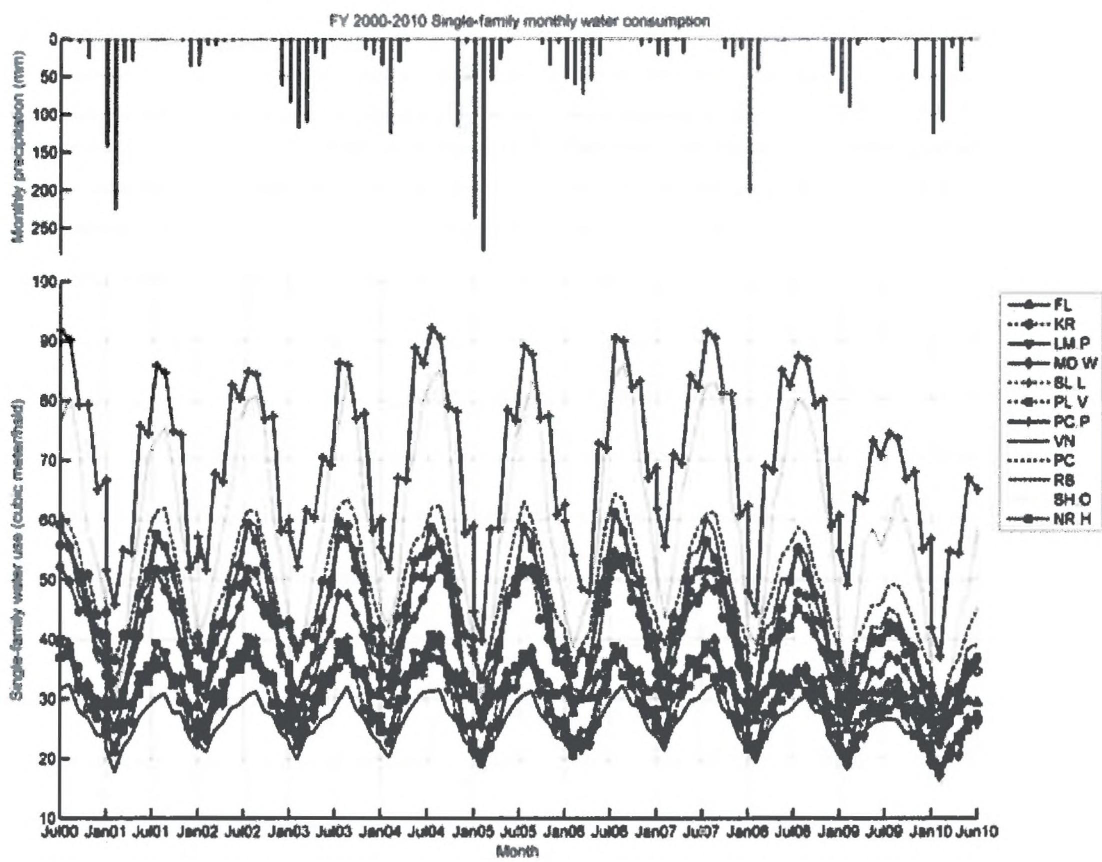

Fig. 2. Monthly median single-family water consumption (cubic meters/single-family customer) for 12 neighborhoods (bottom plot). Monthly precipitation totals (mm) for downtown LA are also shown (inverse bar plot). Study neighborhoods are as defined in Figure 1.

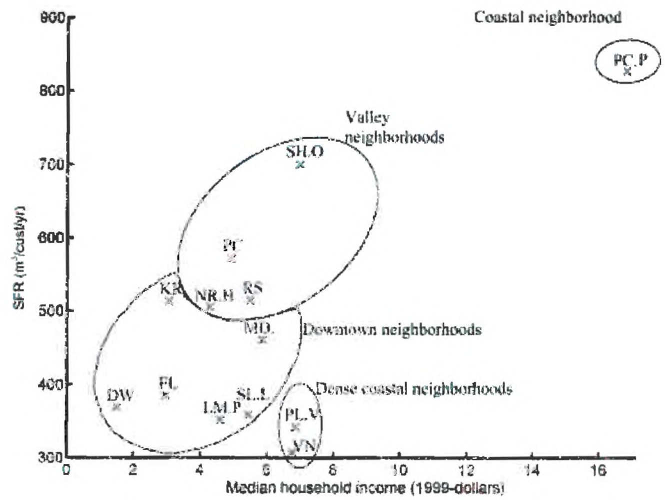

Fig. 3. Coastal, Valley and Downtown neighborhoods identified by SFR water use and income. SFR water use is 10-fiscal year average annual single-family water use (m^3/customer/year) and income is median household income in 1,999-dollars (1999). Study areas are abbreviated as noted in Figure 1.

precipitation (significant at $p < 0.05$) and cooler temperatures. In the lower water use neighborhoods of downtown, the average difference between monthly summer and winter consumption is around 11 m^3/SFR/month compared to around 40 m^3/SFR/month in Pacific Palisades.

A slight decrease in water use is observed in several of the medium-to-high water use neighborhoods in 2007 due to water use restrictions (Figure 2). The implementation of more stringent mandatory restrictions in June 2009 had a much larger impact, resulting in a decrease in all neighborhoods. Even dense, low landscape and lower income neighborhoods (Florence, Leimert Park, Koreatown, etc.) showed a decrease in water consumption. For example, for two neighborhoods with distinct water use levels in two different regions, annual single-family water use decreased by 17% for Pacific Palisades and 11% for Florence between FY 07/08 and FY 09/10.

7.2. Statistical regression model

Model results highlight the influence of each variable on water consumption across the City (Table 3). We describe results for each of the tested variables in the general model (all groups/data) and then highlight results in the model relative to income level (low, high) and water use category (low, medium, high).

7.2.1. Price. Price elasticity coefficients are significant and negative for the first Tier block (−0.188) and second Tier block (−0.07), suggesting that if there were a 10% increase in the first Tier block rate, this would decrease water demand by 2% and by 0.7% for the second Tier. The lower elasticity of Tier 2 pricing indicates that this block price may not be reaching its conservation target. The price elasticity estimates in our work are consistent with previous studies using marginal price, including Arbues *et al.*, (2003) where price elasticity ranged from −1.57 to −0.003. Renwick & Archibald, (1998) also found price elasticity from −0.53 to −0.11 in California. Other similar studies showed similar values, ranging from −0.55 to −0.12 across Arizona and Texas (Agthe & Billings, 1980, 1987; Agthe *et al.*, 1986; Nieswiadomy & Molina, 1989; Gaudin *et al.*, 2001).

The random effects model disaggregated by water use levels shows that elasticity for the first Tier rate for low water use customers (lowest quartile group) is −0.112 and for high water use customers (highest quartile) is −0.251. The coefficient estimates are also statistically significantly different between the three water use groups. This indicates that higher water users are more sensitive to price changes than lower water users. Such results suggest that if there were a 10% increase in the first Tier rate, water demand would decrease by just over 2% for high water users. Results by income category reveal that for Tier 1 rate, the lower income customer group is less responsive to increased water rates than the higher income customer group. Price elasticity for the Tier 1 rate is equal to −0.134 for the lower income group compared to −0.239 for the higher income group (significant at $p < 0.05$) and these coefficient estimates are statistically different. We hypothesize that lower income level customers generally have lower outdoor water use, and hence have less potential or margin for water conservation than customers in the higher income group. It is likely that the lower income-level group has a relatively higher indoor usage with household size being a significant determinant.

All groups (low, medium and high water users) have similar responses to changes in the Tier 2 rate (differences between the estimated coefficients were not statistically different between the three groups). This indicates that if there were an increase in the Tier 2 rate, water use for the three water use groups would vary by a similar amount. However, lower income customers are more sensitive to an increase in the Tier 2 rate than higher income customers, with a price elasticity equal to −0.10 for the lower income group, similar to Tier 1 price elasticity. Higher income customers have a price elasticity of −0.027 in the Tier 2 rate (both coefficients statistically different at $p < 0.05$) (the two coefficients are statistically significantly different between the two groups). This indicates that lower income customers respond to higher water prices more than higher income customers for the Tier 2 rate. This result is similar to price responsiveness by income levels found in the Renwick & Archibald, (1998) study in which they demonstrated that lower income households respond more to an increase in water price.

We note that Tier 2 price elasticity was lower than Tier 1 price elasticity across all tested groups, suggesting that Tier 2 does not trigger additional conservation behavior. In addition, for the medium and high water use groups, and high income group, Tier 1 and Tier 2 price elasticities are statistically significantly different in each group.

7.2.2. Block allocation. Block water allocation is the amount of water allocated per household and charged under the Tier 1 rate. The coefficient for the tract-average household water allocation is positive and significant (0.009), indicating if there were an increase in water quantity allocated in the Tier 1 block of 10 HCF per single-family customer (equivalent to a 30% increase on average over the selected census tracts), it would result in an increase in single-family water consumption of around 9% (i.e. if more water was available in the Tier 1 allocation, consumption would go up). The Tier 1 allocation impacts consumption across the tested water use groups with statistically significant differences between the three groups (for the respective coefficients). There is a greater sensitivity to changes in the Tier 1 water allocation for low water users, with a higher model coefficient (0.017) in this group compared to high water users (coefficient of 0.007). High income customers and low income customers have similar response to changes in the first Tier water allocation (i.e. if the block allocation was increased, water consumption would increase similarly in both groups). The coefficient is positive and significant for low (0.0096) and high (0.0080) income consumers, respectively. The difference between these two coefficients is not statistically significant.

7.2.3. Income and household size. Our general model indicates that income is significantly related to SFR consumption while household size is not (Table 3). A 1,000-dollar increase in median household income would increase single-family water use by about 2% (coefficient of 0.020). The income coefficient is significant and positive for both the low water use (equal to 0.020) and the high income customers group (equal to 0.014). Household size is a significant predictor for low water use (0.07) and lower income-level customers (0.069) ($p < 0.5$). However, household size is not a key predictor for high water users and higher income customers. We note that average household size for single-family household varies over a small range over our study period and this may be influencing our model's sensitivity to this variable.

7.2.4. Greenness. Landscape greenness (EVI) is positively correlated to water use (Table 3) in the general model. Over one bimonthly period, a 0.2 EVI increase (about 25% of the average cumulative EVI across the selected tracts) would be associated with an increase in water use of 2.9% (coefficient of 0.143). The cumulative EVI coefficient estimates range from 0.168, 0.151, and 0.131 for low, medium and high water users groups respectively ($p < 0.05$). However, the three coefficients are not statistically significantly different from each other. This indicates that response to changes in greenness is similar between the three tested water use groups. These results hold true across low and high income groups.

7.2.5. Grass cover. The percentage of grass generally does not have a statistically significant impact on residential water use in the general model (Table 3). However, the low water use customers group did show sensitivity to this variable with a statistically significant coefficient. If there were a 10% increase in grass cover, this would lead to an increase in water use of 3.7% in these lower water use tracts

Table 3. Regression coefficients from random effects model.

Dependent variable ln(SFR water use per household per bimonthly period)						
		By water use level			By income level	
Variables	All	Low	Medium	High	Below median	Above median
ln(First Tier block rate)	− 0.188*	− 0.112*	− 0.212*	− 0.251*	− 0.134*	− 0.239*
ln(Second Tier block rate)	− 0.070*	− 0.080*	− 0.073*	− 0.045*	− 0.103*	− 0.027*
First tier usage block allocation per household	0.009*	0.017*	0.009*	0.007*	0.0096*	0.008*
Average household size	0.003	0.070*	− 0.033	0.023	0.069*	0.018
Median household income	0.020*	0.020*	0.008	0.008	− 0.004	0.014*
Percent grass cover	− 0.416	0.367*	− 0.298	− 0.394	− 0.151	− 0.578
Cumulative EVI	0.143*	0.168*	0.151*	0.131*	0.131*	0.154*
Total precipitation	-5.52×10^{-4}*	-4.98×10^{-4}*	-4.98×10^{-4}*	-7.10×10^{-4}*	-4.58×10^{-4}*	-6.40×10^{-4}*
Average daily maximum temperature	0.029*	0.021*	0.029*	0.030*	0.028*	0.030*
R^2	0.895	0.845	0.909	0.913	0.890	0.904

*Denotes significance at the 5% level.

(coefficient of 0.367 at $p < 0.05$). We hypothesize that lower water users likely have a smaller landscaping area but that a significant portion of that area may be irrigated grass. These customers may reduce grass irrigation to reduce water use, demonstrating higher sensitivity to this variable. The coefficient estimate for the other census tract groups is not statistically significant in our model, indicating that their water consumption is independent of the presence of grass in this model.

7.2.6. Precipitation. There is an inverse and significant relationship between precipitation and water use (Table 3). Each additional 10 mm of precipitation over the bimonthly period would lead to a slight decrease in water use (around 0.6%). This holds true across all tract-level single-family water use groups, with the coefficients ranging from −0.000498 (low water use group) to −0.00071 (high water use group). High water users are also slightly more sensitive to variations in precipitation than low water users; which coincides with the lower water use group having less seasonal fluctuation in water use throughout the year given higher portion of indoor water use due to household size. High water users are also more likely to have large outdoor consumption. The coefficients for high and low water use groups are statistically different. Results hold across income groups (coefficients of −0.000458 and −0.00064 for low and high income groups, respectively and statistically significant), with higher income customers seeming to respond more to changes in precipitation than lower income customers. Higher income customers at the tract level are more likely to have large landscaping outdoor use. These coefficient estimates are also statistically significantly different between the two income groups

7.2.7. Temperature. There is a positive and significant relationship between average daily maximum temperature and water use (coefficient of 0.029) (Table 3). For each degree Celsius increase in the average daily maximum temperature over the bimonthly period, an increase in water use of 2.9% is observed. This holds across all tract-level water use groups, with coefficients from 0.021 to 0.030, and high water users showing slightly more sensitivity to changes in temperature than low water users. The coefficient estimates are also statistically significantly different across the three groups. Both low and high income users show similar and increasing water use with increasing temperature. Model coefficients are similar between the two groups, (0.028 for low income users and 0.030 for high income users significant at $p < 0.05$) with no statistically significant difference between the two groups. This indicates that low and high income groups have similar response to variations in temperature.

8. Conclusions

This study is one of the first to undertake an extensive spatial (1,300 km^2) and temporal (10 years) water consumption analysis in a semi-arid, highly-altered, urban metropolis. Our analysis provides critical information about several key variables that affect residential water consumption in the southwestern U.S. We hope to facilitate the development of models to ultimately predict regional urban water budget, especially indoor and outdoor water consumption, and better target conservation measures through more effective tier pricing. Investigation of the key predictors across different customer groups provides insight on consumer behavior and information for targeted conservation efforts at the neighborhood scale and for different customer groups.

Analysis of spatial variability in single-family water use at the tract level provides key information to create water conservation incentives and determine where in the City these may be effective. Higher water use occurs in the warmer northern parts of the City and the coastal areas where customers generally have larger lots and higher household income. The denser downtown region with smaller lot size and less green space has lower water use. Higher water use tracts exhibit higher seasonal fluctuations, which reveal higher climate sensitivity and higher outdoor use portion in total household water use budget. This is critical to create conservation goals and tools in targeted areas: customers with higher outdoor use have likely more margin to reduce their consumption and would achieve higher reduction volume than lower water use customers in denser areas.

To reduce consumption and influence water demand, utilities have a range of pricing and non-pricing measures. As an example, LADWP successfully implemented price increases, reduction in household water allocation and irrigation restrictions on the time and frequency of landscape watering in response to water shortage conditions. Together these measures significantly reduced water use. Our study brings critical information on the impact of these price and household water allocation at the census tract level by types of customers to achieve conservation.

In general, our results show that consumers are more sensitive (higher elasticity) to changes in the Tier 1 price than the Tier 2 price across the City. We also note that higher water user and higher income census groups are slightly more sensitive to increases in the Tier 1 rate than lower water user and lower income groups. Hence, increasing Tier 1 rates may be an effective tool to achieve conservation in Los Angeles. We do note that lower income groups are more sensitive to Tier 2 rates than higher income groups, so increasing Tier 2 rates may also bring more conservation, but would raise equity concerns as lower income customers respond more to changes in these higher rates (i.e. would reduce use more than higher income consumers). This also raises the question of revising the pricing structure to be more effective by possibly adding a third Tier where increased elasticity might be observed in higher water users. Adding a third Tier may also bring revenues for utilities to create conservation programs and target high landscape water use.

Decreasing household water allocation may also be an effective tool to reduce water consumption, but would impact lower water user customers more than higher water use customers, as demonstrated by a higher coefficient for the low water use group in our model. However, lower water use customers have less margin to reduce consumption and indoor use is likely a larger portion of their water budget. This is supported by the fact that they are less sensitive to climate variations than the higher water user group and that average household size is a key driver in lower water users and lower income tracts.

Our analysis contributes to improved understanding of residential water demand for this large metropolitan area and we advocate that similar methods could be applied to other semi-arid, highly irrigated cities at the census tract level. Results can also be used by LADWP to improve efficient use of water while paying careful attention to equity concerns. While previous phases targeted indoor water consumption, the next phase of conservation will likely need to target outdoor water use through alternative landscape planting and irrigation system efficiency. However, changes in landscaping are costly to residents. The additional revenues derived from a revised tier structuring could help subsidize a systematic shift toward more climate appropriate landscapes and practices.

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Research Paper

Estimation of residential outdoor water use in Los Angeles, California

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HIGHLIGHTS

- Outdoor use is quantified using water billing data methods and remote-sensing model.
- Traditional methods based on billing data underestimate outdoor use in Los Angeles.
- A remote-sensing model is implemented based on vegetation and land cover products.
- The modeled irrigation estimates were validated with previous outdoor use studies.
- Landscaping irrigation represents 54% of single-family water use in the city.

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ABSTRACT

The current study analyzes existing methods for estimating outdoor use and landscape irrigation in highly developed residential areas across Los Angeles. Outdoor use was estimated using three methods: two methods described by the Pacific Institute and a third approach that utilizes remotely sensed vegetation and water billing data. Monthly individual water use records were provided by the Los Angeles Department of Water and Power (LADWP) for 2000–2010. This period includes voluntary and mandatory restrictions due to drought conditions across the state. Records were aggregated to the census tract level to protect customer privacy. The two Pacific Institute methods, which are based on water billing data, generally underestimate outdoor use due to assumptions that the lowest water consumption month represents indoor use, which is likely not the case in Los Angeles. The remote-sensing model developed between single-family water use and the Landsat normalized difference vegetation index (NDVI) surplus performed well in greener areas of the city and indicates that landscape irrigation use represents 54% of total single-family water use. The model also predicts an average decrease in landscaping irrigation of 6% and by 35% during voluntary and mandatory restrictions, respectively. Voluntary conservation and mandatory waste restrictions were less effective for higher income groups in the city, while more stringent pricing and non-pricing mandatory restrictions in FY2010 had similar effects across income groups. Study results contribute to a better understanding of the partitioning of Los Angeles residential water use and can be utilized to evaluate pricing structures and target water conservation efforts.

1. Introduction

Residential water use is the largest urban water use category, with single-family water use noted to represent half of urban water consumption in California (2000) (CDWR, 2005; DeOreo et al., 2011; Gleick et al., 2003). A recent study by DeOreo et al. (2011) notes that residential outdoor use in Southern California is twice as high as in Northern California and represents a significant portion of household water budget (65% of average daily water use in Southern California study sites based on household logged water records and flow trace analysis) (DeOreo et al., 2011). The DeOreo study of single-family water use includes several water agencies across California from Sonoma County Water Agency to San Diego Water Authority including the Los Angeles Department of Water and Power (LADWP). It is important to note that most cities in California's Central Valley do not yet have residential water meters, thus studying residential water use in California is generally restricted to the major coastal metropolitan areas. It is evident that

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outdoor water use has the largest potential for water conservation. Recent work highlights that residential outdoor use in California can be reduced by 25% to 40% with improved management practices and increased use of available irrigation technology (Gleick et al., 2003). The difficulty resides in quantifying and predicting outdoor water use for which current approaches entail significant uncertainties related to heterogeneous land cover characteristics, water consumption metering, climate, and availability of data (Gleick et al., 2003).

A range of methods has been developed to estimate residential outdoor use. Early methods developed by Costello and Jones (1994) and Costello, Matheny, & Clark (2000) focused on landscape coefficients and estimated irrigation requirements based on the landscape characteristics and reference evapotranspiration (ETo). The landscape coefficient (K_L) is the product of three factors including species, density and microclimate conditions based on field observations (Costello and Jones, 1994 and Costello et al., 2000). The landscape method is difficult to apply at regional and longer temporal scales as it requires data for each plant species within heterogeneous urban landscapes. Previous studies have implemented this method at the household level, producing reasonable estimates of landscaping irrigation requirements that also account for effective precipitation and irrigation system efficiency (DeOreo et al., 2011; Domene, Saurí, & Parés, 2005; Haley, Dukes, & Miller, 2007; Salvador, Bautista-Capetillo, & Playán, 2011). The landscape method is particularly challenging to apply to Southern California as the region has high floral biodiversity, perhaps some of the highest in the nation, due to its benign climate (Pincetl, Gillespie, Pataki, Saatchi, & Saphores, 2012; Pincetl et al., 2013). Based on this approach, Al-Kofahi, VanLeeuwen, Samani, & St Hilaire (2011) proposed an approach that integrates different types of residential tree, shrubs and grass to estimate a water budget for homeowners' residential landscape in Albuquerque, New Mexico.

A second category of methods relies on the formulation of urban water balance models. Grimmond et al. (1986, 1996) and Grimmond and Oke (1986) estimated urban water budget coupled with an energy balance approach to evaluate human impacts in urbanized areas. The model relies on the partition of the urban domain into three surfaces: impervious, pervious irrigated and pervious non-irrigated. The developed model can be run from daily to annual time scales but requires climate data, land cover characteristics, surface retention capacities, soil storage capacity, field capacity, water use data (for the imported water supply component), water storage conditions and surface aerodynamic characteristics for evapotranspiration, many of which are difficult to obtain in highly urbanized areas (Grimmond, Oke, & Steyn, 1986; Grimmond and Oke, 1986).

Urban irrigation is also not routinely incorporated in urban hydrologic models including land surface models (LSMs) which are commonly used for longer term climate and ecosystem impact studies. Micro-scale urban water models have been employed to better understand runoff and landscape irrigation processes (Xiao, McPherson, Simpson, & Ustin, 2007). Xiao et al. (2007) developed an urban water model at the residential parcel scale based on physical parameters to evaluate the impact of best management practices on landscaping irrigation. Vahmani and Hogue (2013) developed an irrigation module within the coupled Noah-SLUCM (single layer urban canopy model) to assess residential irrigation and the impact on urban meteorological processes at the block level in Los Angeles.

Several studies have also used total and indoor water use to derive outdoor use estimate as a residual (DeOreo et al., 2011; Endter-Wada, Kurtzman, Keenan, Kjelgren, & Neale, 2008; Grimmond, Souch, & Hubble, 1996; Syme, Shao, Po, & Campbell, 2004). There are different models used to estimate indoor use, including water billing data and direct measurement through household logged water data and flow trace analysis (DeOreo et al., 2011; Mayer and DeOreo, 1999). Total water use is generally obtained from water billing data or logged water records from these same studies. These methods evolved due to the lack of indoor-outdoor metering information. Few places in the U.S. require dual metering, thus determining the apportionment of water use between indoor and outdoor use remains difficult.

The Pacific Institute (Gleick et al., 2003) developed minimum use month and average minimum use methods for regions of California which can be applied using monthly water use billing data. The assumption underlying both aforementioned methods is that indoor use remains consistent throughout the year (non-seasonally dependent). This hypothesis was tested in the Mayer and DeOreo (1999) study which showed there were no statistically significant differences in indoor use between different seasons in the cities selected in warmer and cooler climates (except for Tampa, FL). For the minimum use month method, the month with the minimum water use is identified for each year as indoor use and the difference between the minimum value and each monthly water use value represents outdoor use. The same approach is used for the average minimum use method: the average of the three lowest water consumptions is computed to be equal to indoor use and outdoor use is calculated as the residual. However, the estimation of indoor use using the minimum use month in semi-arid climates generally includes some residential irrigation and overestimates indoor use (Gleick et al., 2003; Mayer and DeOreo, 1999). Several studies have shown that the minimum and average minimum use methods underestimate outdoor use in warmer and more arid climates in cities such as San Diego, CA, Scottsdale, AZ, Phoenix, AZ, Tempe, AZ and Las Virgenes, CA (DeOreo et al., 2011; Gleick et al., 2003; Mayer and DeOreo, 1999). Thus, the advancement of these types of methods needs to be designed with specific consideration of climate zones. Data loggers installed on household water meters provide records used in flow trace analysis in studies at the household level, allowing more accurate estimates of indoor and outdoor use (DeOreo et al., 2011; Mayer and DeOreo, 1999). This approach is limited by the duration of the logging period as annual and outdoor consumption totals are difficult to estimate for data collected over small logging periods. However, logged water use data is often combined with billing records to obtain more accurate total and residential outdoor use estimates (Mayer and DeOreo, 1999).

More recent approaches involve the use of remote-sensing vegetation indices to estimate urban irrigation which is a significant part of the outdoor water budget in many semi-arid cities. The normalized difference vegetation index (NDVI) is a measure of the photosynthesis activity of plants and has been shown to be strongly related to evapotranspiration (Keith, Walker, & Paul, 2002; Li, Lu, Yang, & Cheng, 2012; Szilagyi, 2002). Results from Keith et al. (2002) demonstrate the relationship between maintained high NDVI values and increased water use during moderate and severe drought conditions in domestic and agricultural water use categories. In addition, Szilagyi, Rundquist, Gosselin, & Parlange (1998) found strong correlation between monthly mean NDVI and one month-lagged evaporation in a natural prairie water-limited environment (study area consisted of a natural mixed-grass species). Szilagyi (2002) confirmed the existence of a strong correlation between monthly NDVI and areal evapotranspiration in a prairie domain with areal evapotranspiration being lagged by one month. Kondoh and Higuchi (2001) also found a strong relationship between NDVI and daily evapotranspiration rate during the growing season in a grassland area. Finally, Johnson and Belitz (2012) estimated urban irrigation rate from the relationship between evapotranspiration and NDVI surplus calculated as the difference between irrigated landscaping NDVI and non-irrigated landscaping NDVI values. They also found a strong exponential relationship between water delivery and NDVI surplus ($R^2 = 0.94$) over a 2-year period (Johnson & Belitz, 2012). NDVI can also be used to estimate vegetated surfaces at the parcel level from an integrated remote-sensing and GIS method utilized to model residential landscape water needs (Xie, 2009).

The primary goal of the current study is to quantify outdoor and irrigation water use using several previously-published methods and to investigate the relationship between residential water use and urban vegetation greenness surplus across a semi-arid and highly developed urban metropolis. Our work is one of the first to quantify outdoor and landscaping irrigation use during drought periods with voluntary and mandatory utility restrictions on outdoor watering. We compare two methods from the Pacific Institute (Gleick et al., 2003) that quantify outdoor use using LADWP water billing data and also utilize a remote-sensing approach inspired from Johnson and Belitz (2012) that provides landscaping irrigation estimates. We developed the remote-sensing model based on NDVI, land use and land cover products. The developed model is then used to compare the efficacy of two outdoor watering restrictions periods implemented during 2007–2010 on landscaping irrigation application. Ultimately, the developed model could be used by regional utilities as a predictive tool for landscaping irrigation budgets and to help target conservation efforts across the city.

2. Study area and conservation efforts

The city of Los Angeles has a population of approximately 3.8 million (U.S. Census Bureau, 2010) and an areal extent of around 1300 km^2. The city contains 114 neighborhoods with distinct demographic and socioeconomic characteristics (Los Angeles Times, 2010). The twelve selected neighborhoods are generally representative of the city's characteristics and were selected based on population, median household income, average household size, education level and microclimate criteria (Table 1). In response to the drought conditions, voluntary water restrictions were first implemented in June 2007 (through fiscal year (FY) 2008) to ask the customers to voluntarily reduce their water use by 10% (through rebates for water-saving devices, fixing leaks or taking shorter showers) (LADWP, 2007). In August 2008, mandatory water restrictions were enacted to prohibit waste practices (e.g. no irrigation during rain, fixing leaks) no irrigation between 9 am and 4 pm, and limiting landscape watering time up to 15 min per cycle (up to two cycles per water day) when using sprinklers or similar non-conserving techniques (spray head, bubblers, standard rotors). In June 2009, mandatory water conservation requirements were increased with more stringent water restrictions including a two-day landscaping irrigation per week limit, increased restrictions on the time and frequency of landscaping irrigation for the use of sprinklers (spray head, bubblers, standard rotors and rotary heads) and additional prohibited water-waste usage such as car washing. Price conservation measures were also enacted in June 2009 throughout FY2010 corresponding to a reduction in Tier 1 water allocation by 15% and an increase in Tier 2 rates in order to trigger higher reductions.

3. Data

3.1. Water consumption data

Monthly single-family residential (SFR) water billing and lot size data was provided by LADWP from January 1, 2000 to December 31, 2010. The initial database contained around 480 000 individual residential customers identified by census tract numbers. Less than 1% of the records (500–600 single-family customers) did not match the U.S. Postal Service ZIP code database and were removed. The LADWP reading period is bi-monthly (every 60 days) and the utilities pro-rated the data to calculate monthly water consumption. The 2000–2010 data includes the following restriction periods: 1) voluntary water conservation implemented throughout fiscal year (FY) 2008; 2) additional mandatory water waste provisions implemented in August 2008 to limit irrigation time (a fiscal year is defined as the period from July 1st of the preceding year to June 30th of the current year); and 3) increased mandatory two-day per week outdoor watering restrictions and water rates increase (increase in Tier 2 rate coupled with a 15% decrease in Tier 1 water allotment) implemented in June 2009 for FY2010 (LADWP, 2010).

The current LADWP service area includes customers residing in the city of Los Angeles and on the edge of the city boundary. However, only the census tracts contained within the city boundary were analyzed and the LADWP customer data was matched with the census residential population data in the city of Los Angeles. The final set of monthly individual customer records was aggregated to the census tract level to protect customer privacy. The aggregated list includes 855 census tracts with monthly water data for a ten-year period (from FY2001 to FY2010). The average customer lot size was calculated for each census tract. Monthly water consumption data was normalized per the number of SFR accounts or SFR customers and per average lot size area including built and vegetated areas (as it was not possible to differentiate these data from LADWP records). The GIS census tract boundary layer comes from the 2000 US Census Bureau.

3.2. Land cover data

Irrigated, non-irrigated and impervious areas across the city were selected using a land cover database derived from high resolution satellite imagery (McPherson, Simpson, Xiao, & Wu, 2011). The database was created using Quickbird imagery and aerial photography from 2002 to 2005 at high spatial resolution (<2 m pixel resolution) and identifies four primary land cover types: tree (tree and shrub), grass (green grass and ground cover), dry grass/bare soil (dry grass and bare soil), and impervious surface (includes pervious pavement) (McPherson et al., 2011). Eight golf courses and irrigated urban parks were delineated to represent irrigated areas in the city. Non-irrigated surfaces were identified in the Northern part of the city using the dry grass land cover areas and the non-irrigated fields next to airports. Impervious areas were selected in the downtown neighborhood and at airports runways. We assumed that land cover was generally static over the 10-year study period (from FY2001 to FY2010) for the delineated endmembers in the city.

3.3. Land use data

Land use data was acquired using the NOAA C-CAP 2006 (30 m) classification database. We selected the pixels in the low density development category within each census tract boundary as it primarily includes single-family residential areas. The land cover was assumed to remain static over the 10-year study period. Between 2001 and 2006, developed area in the city increased by 0.18% and impervious surface area increased by 0.41%, (NCLD, 2001, 2006; NOAA C-CAP, 2001, 2006), therefore we assumed that land use was generally static for the study period.

3.4. Vegetation indices

Urban vegetation greenness was estimated using the NASA Landsat Thematic Mapper 5 (Landsat TM 5) satellite that provides remote-sensing products at 30-m resolution every 16 days. This higher resolution data compared to NASA's Terra moderate resolution imaging spectroradiometer (MODIS) 250-m product is more appropriate to extract and map vegetation characteristics in the delineated land cover areas and census tracts. We used spectral

Table 1
Twelve focus neighborhoods and key characteristics from the U.S. Census (2000 or 2010).

Neighborhood	Zip code	Population 2010 (in thousands)	Average household size 2010	Number of people with a high school degree or less 2000 (in thousands)	Temperature zone (LADWP)	Median household income in 1999-dollars (in thousands) (1999)	10-fiscal year average annual single-family water use (m^3/SFR cust./year)
Florence (FL)	90003	66.3	4.2	17.8	Medium	29.5	385
Koreatown (KR)	90005	37.7	2.5	43.9	Medium	30.6	514
Leimert Park (LM.P)	90008	32.3	2.3	3.1	Medium	45.9	352
Mid-Wilshire (MD.W)	90019	64.5	2.7	8.5	Medium	58.5	461
Downtown (DW)	90021	4.0	1.6	13.5	Medium	15.0	369
Silver Lake (SL.L)	90039	28.5	2.5	8.9	Medium	54.3	359
Playa Vista (PL.V)	90045	39.5	2.4	0.8	Low	68.6	342
Pacific Palisades (PC.P)	90272	23.0	2.5	1.5	Low	168.0	827
Venice (VN)	90291	28.3	1.95	7.2	Low	67.7	307
Pacoima (PC)	91331	103.7	4.6	31.7	High	49.1	572
Reseda (RS)	91335	74.4	3.2	21.1	High	54.8	515
Sherman Oaks (SH.O)	91423	31.0	2.1	10.8	Medium	69.7	700
North Hollywood (NR.H)	91601	37.2	2.3	27.6	Medium	42.8	506

band 3 (wavelength is from 0.626 μm to 0.693 μm, red band) and band 4 (wavelength is from 0.776 μm to 0.904 μm, near-infrared band) to calculate NDVI (Rouse, 1974). Landsat images were downloaded over the study period using a cloud cover threshold below 10%, resulting in 111 images for the study period.

4. Methods

A ten-year period – from FY2001 to FY2010 – was used to estimate outdoor water consumption based on the minimum use month, average minimum use month and remote-sensing approaches.

4.1. Descriptive analysis

A descriptive analysis was undertaken for twelve representative neighborhoods using monthly time-series plots for the study period using single-family customer water consumption and NDVI data. The twelve selected neighborhoods are generally representative of the city's characteristics and were selected based on population, density, ethnicity, median household income, average household size, housing tenure, education level, immigration status and microclimate criteria. Census tracts within each neighborhood boundary were identified and median single-family water use and average NDVI were estimated for each tract. Trend analysis in monthly single-family water consumption and NDVI were conducted using a Seasonal Mann–Kendall trend test. Linear trends were estimated using the Sen's slope or Seasonal Kendall slope estimator. The Seasonal Mann–Kendall test accounts for seasonality: the test is derived for each monthly "season" (Hirsch, Slack, & Smith, 1982). The resulting slope is the median of all slopes computed from each pair of observations (Helsel & Hirsch, 2002).

4.2. Outdoor use: Minimum use month and average minimum use month models

Two existing methods described by the Pacific Institute (Gleick et al., 2003) use monthly water-billing data to estimate residential outdoor use as the residual of monthly total water use minus indoor use per single-family customer. The underlying assumptions of the two methods are that indoor use is consistent throughout the year and that the minimum use month is the best estimate of indoor water use.

Minimum use month: A monthly minimum water use is identified for each fiscal year and for each tract and is assumed to represent monthly indoor use.

Average minimum use: The average of the three lowest monthly water use records is calculated and is assumed to represent monthly indoor use.

The monthly outdoor use values were obtained from the minimum and average use methods for each fiscal year and for each tract from the initial set of 855 tracts. Finally, the ratio of outdoor use to total single-family water use was calculated.

4.3. Landscaping irrigation estimates: Remote sensing model

Our approach is based on Johnson and Belitz (2012) that was utilized to estimate the rate of urban irrigation in residential neighborhoods in the San Fernando Valley in Southern California using Landsat NDVI products and water delivery records as input. We build upon this approach to estimate landscaping irrigation patterns over 10 years at the census tract scale across Los Angeles and include differing climate conditions, including "dry" and "wet" years relative to the 30-year average precipitation in Los Angeles. We analyze the impact of the restrictions periods (voluntary and mandatory) on landscaping irrigation. We also account for individual tract-specific effects. We first describe the NDVI surplus calculations at the census tract level and then apply the model to estimate the amount of landscaping irrigation per census tract.

4.3.1. Calculation of NDVI values

To calculate NDVI values by pixel within the city from the Landsat images, the raw digital numbers (DNs) values for bands 3 and 4 were processed using the Landsat ecosystem disturbance adaptive processing system (LEDAPS) developed by Masek et al. (2006). The LEDAPS provides processed Landsat data including atmospherically-corrected surface reflectances for bands 3 and 4. The LEDAPS software was originally developed by Vermote et al. (1997) for the Terra MODIS platform using the atmospheric correction 6S radiative transfer model. Atmospheric correction minimizes the impacts of scattering and absorption by atmospheric gas and particles on measured reflectance. The NDVI values range from −1 to 1, with values close to 1 for healthy plants and around 0 for impervious, non-vegetation surfaces. The NDVI pixel values were averaged spatially in single-family areas for each census tract and for the delineated irrigated, non-irrigated and impervious surfaces.

4.3.2. Calculation of NDVI surplus

Each pixel in a Landsat image may be modeled as a linear mixture of image endmembers (Adams et al., 1995). Each image endmember is composed of a "pure" land cover type that participates in the mixed pixels in the image. Johnson and Belitz (2012) selected two endmembers to represent single-family residential land-use class targeted in this study: irrigated landscaping and impervious surfaces. In addition, this land use class is not likely to include extensive natural native vegetation that has high NDVI values and no landscaping irrigation. Previous studies have shown that Los Angeles urban vegetation, as in many semi-arid cities, is more likely to be non-native and well-watered (Bijoor, McCarthy, Zhang, & Pataki, 2012). In Los Angeles, 12% of urban land cover area is estimated to be irrigated grass and 21% is estimated to be tree canopy cover; the remaining percentage represents mostly impervious and dry grass/bare soil areas (McPherson et al., 2011).

To compute the amount of irrigation, three endmembers are needed that each represents one land cover type: irrigated landscaping, non-irrigated landscaping and impervious areas (Johnson & Belitz, 2012). The endmembers were delineated using a high resolution land cover database developed by McPherson et al. (2011) that classifies land cover types as tree, grass (green grass), dry grass/bare soil and impervious surfaces. Google Earth imagery was an additional resource used to visually check the endmembers. The irrigated landscaping endmember includes eight golf courses and irrigated urban parks identified in the tree/grass land cover type and visually checked on Google Earth. For the non-irrigated endmembers, dry grass surfaces were delineated in the Northern part of the city and in non-irrigated fields next to the Los Angeles international airport. Impervious surfaces were delineated in the Downtown area and using the Los Angeles international airport runways to constitute the impervious endmember. These endmembers were kept the same for all images and are assumed to remain invariant over time. The 30-m NDVI pixel centroids were extracted within each endmember boundary. The resulting NDVI values were averaged for each endmember land cover type (irrigated landscaping, non-irrigated and impervious) and for each Landsat image.

To compute the NDVI values in the targeted single-family land use areas within each census tract, we utilized the NOAA C-CAP 30-m land cover database. The single-family land-use pixels classified in the low intensity development category were selected in each census tract. The 30-m NDVI pixel centroids were extracted from the single-family areas in each census tract and each Landsat image. The resulting NDVI values were spatially averaged for each census tract. Similar to Johnson and Belitz (2012), NDVI in single-family areas is represented as a two-endmember model (Eq. (1)):

$$\mathrm{NDVI}_{\mathrm{tract}}(t) = F_{\mathrm{irr,tract}}(t) \times \mathrm{NDVI}_{\mathrm{irr}}(t) + (1 - F_{\mathrm{irr,tract}}(t)) \times \mathrm{NDVI}_{\mathrm{imp}}(t) \tag{1}$$

where $\mathrm{NDVI}_{\mathrm{tract}}(t)$ is the average NDVI value for single-family areas within each tract and each Landsat image, $F_{\mathrm{irr,tract}}(t)$ is the portion or "fraction of irrigated landscaping" in each single-family tract area and for each image, $\mathrm{NDVI}_{\mathrm{irr}}(t)$ is the irrigated landscaping endmember and $\mathrm{NDVI}_{\mathrm{imp}}(t)$ is the impervious endmember. $F_{\mathrm{irr,tract}}(t)$ is computed from Eq. (1) in single-family areas within each tract and for each image using the averaged NDVI values per endmember and tract.

The NDVI values from irrigated landscaping areas are expected to remain constant over time as they are maintained by residential irrigation. The NDVI values from non-irrigated landscaping areas follow precipitation patterns. The difference in NDVI between the two endmembers called "NDVI surplus" is related to the amount of irrigation and defined as (Johnson & Belitz, 2012) (Eq. (2)):

$$\mathrm{NDVIsurplus}(t) = \mathrm{NDVI}_{\mathrm{irr}}(t) - \mathrm{NDVI}_{\mathrm{nonirr}}(t) \tag{2}$$

where $\mathrm{NDVIsurplus}(t)$ is the NDVI surplus between the irrigated landscaping endmember and the non-irrigated landscaping endmember for each Landsat image.

The last step involves multiplying the NDVI surplus by $F_{\mathrm{irr,tract}}$ representing the portion of irrigated landscaping in single-family areas within each tract and for each image (Eq. (3)):

$$\mathrm{NDVIsurplus}_{\mathrm{tract}}(t) = \mathrm{NDVIsurplus}(t) \times F_{\mathrm{irr,tract}}(t) \tag{3}$$

where $\mathrm{NDVIsurplus}_{\mathrm{tract}}$ is the NDVI surplus calculated in single-family areas for each census tract and each image. A total of 220 Landsat images were possible over the 10 years of the study period. We utilized a final 111 images after quality controlling for cloud cover. The 111 images were then interpolated to monthly values using a piecewise cubic Hermite algorithm. This variable is then used as an input in the relationship with monthly single-family water use normalized per customer and lot size.

4.3.3. Development of the relationship between NDVI surplus and single-family water use

A non-linear mixed effects exponential model was developed to predict the relationship between NDVI surplus in single-family areas and single-family water use (in mm/SFR customer/month) at the census tract level. This method is based on the approach developed by Johnson and Belitz (2012) that includes these two variables. The current study aims to apply the previously-developed model to a larger study domain using the key variables first selected by Johnson and Belitz (2012). Other socio-economic variables influence residential water use and outdoor use. Therefore, we further analyzed the relationship between NDVI surplus and other socio-economic variables (income, ethnicity, household size, household type, housing tenure). The socio-economic variables were collected using the 5-year American community survey at the census tract level (2005–2009).

Single-family water use was lagged by one month as a one-month lag was observed between NDVI and water inputs (Szilagyi et al., 1998). The final model equation is (Eq. (3)):

$$\mathrm{SFRwateruse}_{\mathrm{tract}}(t-1) = b_{\mathrm{tract}} \times \exp(k_{\mathrm{tract}} \times \mathrm{NDVIsurplus}_{\mathrm{tract}}(t) + m \times \mathrm{restriction} \times \mathrm{NDVIsurplus}_{\mathrm{tract}}(t)) \tag{4}$$

where $\mathrm{SFRwateruse}_{\mathrm{tract}}(t-1)$ is monthly single-family water use in mm/household/month lagged by one month, b_{tract} is the constant tract-specific intercept, $\mathrm{NDVIsurplus}_{\mathrm{tract}}$ is monthly NDVI $\mathrm{surplus}_{\mathrm{tract}}$ in single-family areas within each tract, "restriction" is a dummy variable interacting with NDVI surplus for the fiscal years FY2008, FY2009 and FY2010 during which residential irrigation restrictions were implemented. The model dummy variable controls for the overall impact of restrictions on residential irrigation.

The non-linear mixed effects model was selected in order to account for omitted variables specific at the census tract level. Possible tract-level specific variables might include socio-demographic or building characteristics (building age for example). Other models were tested (such as simple linear regression) that produced lower R^2 values. A few outlier tracts (17) were identified and were removed to improve the normality of residuals and reduce uncertainty in the model; these tracts had with very low total water consumption (under 20 mm/hsld/month, lower water use than the other tracts for total water consumption) and under 10 customers per tract. The final model was run for 710 tracts across the city at the monthly time scale over a ten year period (FY2001–FY2010). We also controlled for heteroskedasticity and serial correlation of the residuals. The serial correlation issue was solved by de-trending the monthly water use and NDVI data for each tract: the difference term between the monthly mean and the annual mean per tract was computed and subtracted from the monthly values for each tract.

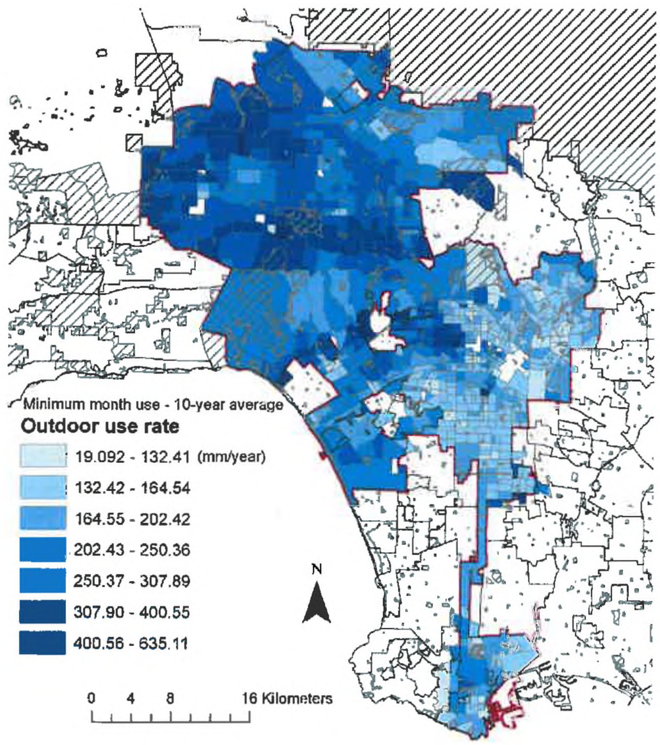

Fig. 1. Average outdoor use rate (in mm/year) over 10 years using the minimum month use method.

The b constant in the exponential model is assumed to represent water used for purposes other than landscaping irrigation, including household indoor use and outdoor usage such as pool and dry-weather runoff (it is the intercept estimated when NDVI surplus is equal to zero). The exponential term contributes to water used for landscaping irrigation in single-family households, which is related to the NDVI surplus variable. This equation form was adjusted from the initial model equation found by Johnson and Belitz (2012). In their study, the water use component excluding landscaping irrigation is a separate constant added to the exponential term. This original model was tested and not selected as it did not represent a good fit over the ten year study period.

5. Results and discussion

The following section presents results from the minimum use month and average minimum use methods (applied on the total set of 855 tracts) and compares our results with previously-published values (including DeOreo et al., 2011 and Mayer and DeOreo, 1999). It also describes the landscaping irrigation results from the developed remote-sensing model, including water use and NDVI surplus analysis (applied on 710 tracts as explained above in the methods section).

5.1. Outdoor use estimates: Minimum month and average minimum month models

The 10-year average outdoor use rate for the minimum use month model has a mean of 213 mm/year (27.3% of total single-family water use) and ranges from 19 to 635 mm/year (Fig. 1, Table 2). The median value for the minimum month method is equal to 199 mm/year and the standard deviation is equal to 71 mm/year. Higher outdoor use values are located in the Northern part of the city and Coastal tract neighborhoods while lower values are observed for census tracts located in the Downtown area.

The average minimum month model provides similar results: the 10-year average outdoor use rate has a mean of 211 mm/year (27% of total single-family water use) and ranges from 18 to 630 mm/year (Table 2). The median value for the average minimum month method is equal to 196 mm/year and the standard deviation is equal to 70 mm/year. For both methods, high outdoor water use values are positively related with high vegetation indices in the northern arid part of the city and in the coastal tract neighborhoods (correlation (r) between average annual outdoor use and NDVI in single-family areas equal to 0.47 significant at $p < 0.05$). The outdoor use values calculated using the minimum use and average minimum use methods in Los Angeles are similar to California Department of Water Resources (CDWR, 2005) estimates (232 mm/year in 2004) but are generally lower than estimates found in previous studies which range from 384 to 980 mm/year (Table 1). DeOreo et al. (2011)'s outdoor use estimate averages 384 mm/year representing 56.8% of total single-family water use in Los Angeles. LADWP estimates that 54% of total single-family water use is for outdoor purposes, combining data from wastewater flow, minimum month and landscape ET requirements. Previous studies support that these methods likely underestimate actual outdoor use and have relatively high uncertainties (DeOreo et al., 2011; Gleick et al., 2003; Mayer and DeOreo, 1999). This uncertainty primarily comes from the fact that many single-family customers still irrigate during winter months. Johnson and Belitz (2012) calculated that landscaping irrigation accounts for 1/3 of total water delivery during winter months in the San Fernando Valley in Southern California.

5.2. Irrigation use: Remote-sensing NDVI model

5.2.1. Descriptive time-series analysis

Monthly time-series of single-family water use and NDVI were first analyzed to identify trends and correlations in the selected study neighborhoods (Figs. 2 and 4). Single-family water use time-series normalized per household and lot size reveals seasonal variability correlated with the precipitation patterns over the 10 years (correlation r between −0.49 and −0.61 significant at $p < 0.05$). A decrease in single-family water use is observed during the winter months followed by an increase during the summer months (Fig. 2). On average, monthly single-family water use ranges from 54.8 mm/hsld/month to 72.9 mm/hsld/month across the selected neighborhoods over 10 years. After the voluntary conservation period, mandatory water waste provisions and more stringent mandatory water restrictions went into place (in June 2007, August 2008 and June 2009 respectively), single-family water use was observed to decrease (from FY2008 to FY2010). The Seasonal Mann–Kendall trend test performed on monthly single-family water use per neighborhood confirms the presence of a downward and statistically significant trend for all selected neighborhoods for FY2008–FY2010 (significant at $p < 0.05$) with average slope equal to a decrease of 5 mm/year (or 7.5% of average single-family water use) over a year for the selected neighborhoods.

Non-irrigated areas identified in Los Angeles follow seasonal precipitation patterns (Fig. 3). Higher NDVI values are observed in the winter months and lower NDVI values in the summer months. NDVI for non-irrigated endmember ranges from 0.130 to 0.523. NDVI for irrigated landscaping endmember remains relatively stable over 10 years with an average NDVI equal to 0.507. Impervious surfaces have smaller NDVI values that are relatively constant over 10 years. The average NDVI value for the impervious endmember is equal to 0.057.

The NDVI surplus time-series reveals a seasonal pattern over 10 years for single-family land use areas in the selected neighborhoods (Fig. 4). High NDVI surplus values are observed during summer months and lower values during winter months and are correlated

Table 2
Comparison of outdoor use estimates from Los Angeles water billing data with estimates of outdoor use including a CDWR estimate of outdoor use, DeOreo et al. (2011), Mayer and DeOreo (1999) and Grimmond et al. (1996). Outdoor use rate: depth of water applied over entire lot size area (mm/year), except for Mayer and DeOreo (1999) study for which outdoor use estimates are over irrigable area. Outdoor use estimates from billing data are averages over 10 years. Salvador et al. (2011) study provides applied irrigation water use in the Zaragoza region in Spain, which has a semi-arid climate with similar annual average precipitation (average precipitation of 337 mm in Zaragoza compared to 396 mm in Los Angeles).

Method	Outdoor use rate (mm/year)
	Outdoor use estimates from billing data
Minimum use (over entire lot size area)	213 (standard deviation = 69.7)
Average minimum use (over entire lot size area)	211 (standard deviation = 68.9)
	Outdoor use estimates for comparison
CDWR (estimate WY 2004)	232
DeOreo et al. (2011) (Los Angeles, 2005–2008 estimates) (over entire lot size area)	384
Mayer and DeOreo (1999) (San Diego, CA) (over irrigable area)	841
Mayer and DeOreo (1999) (Phoenix, AZ) (over irrigable area)	980
Mayer and DeOreo (1999) (Las Virgenes, CA) (over irrigable area)	914
Salvador et al. (2011) (Spain) (over entire lot size area)	1276–1378
Hunt et al. (2001) (Irvine, CA) (over entire lot size area)	1764
Grimmond et al. (1996) (Los Angeles) (over entire lot size area)	482–500

with seasonal precipitation patterns (correlation r between −0.27 and −0.54 significant at $p < 0.05$). High positive NDVI surplus values indicate that residential vegetation maintained by irrigation is greener than non-irrigated vegetation that follows precipitation pattern. Average monthly NDVI surplus ranges from 0.071 to 0.174 across the selected neighborhoods over 10 years. The Seasonal Mann–Kendall trend test performed on monthly NDVI surplus per neighborhood revealed a statistically significant downward trend over FY2008–FY2010 for the neighborhoods (significant at $p < 0.05$) except for two neighborhoods: Silver Lake (SLL) does not have a statistically significant trend and Playa Vista (PLV) has a positive trend. The average slope across the selected neighborhoods is equal to a decrease of 0.0072 (or 3% of average NDVI surplus) over a year.

5.2.2. *Correlation of NDVI surplus with socio-economic variables*

We tested the correlation of NDVI surplus with socio-economic variables to better understand which variables are captured by NDVI surplus. Income is correlated with NDVI surplus with a correlation equal to 0.58 ($p < 0.05$), showing that a greener landscape and higher income are related. The percent Hispanic or Latino origin residents per tract is negatively correlated with NDVI surplus ($r = -0.57$, $p < 0.05$). NDVI surplus has a lower correlation with average household size ($r = 0.35$, $p < 0.05$). This lower correlation may be due to the fact that households with a greener landscape and higher irrigation volume have a larger proportion of total water use being for irrigation compared to water used for indoor purposes. Household composition exhibits a lower correlation with NDVI surplus: the percent of households with one or

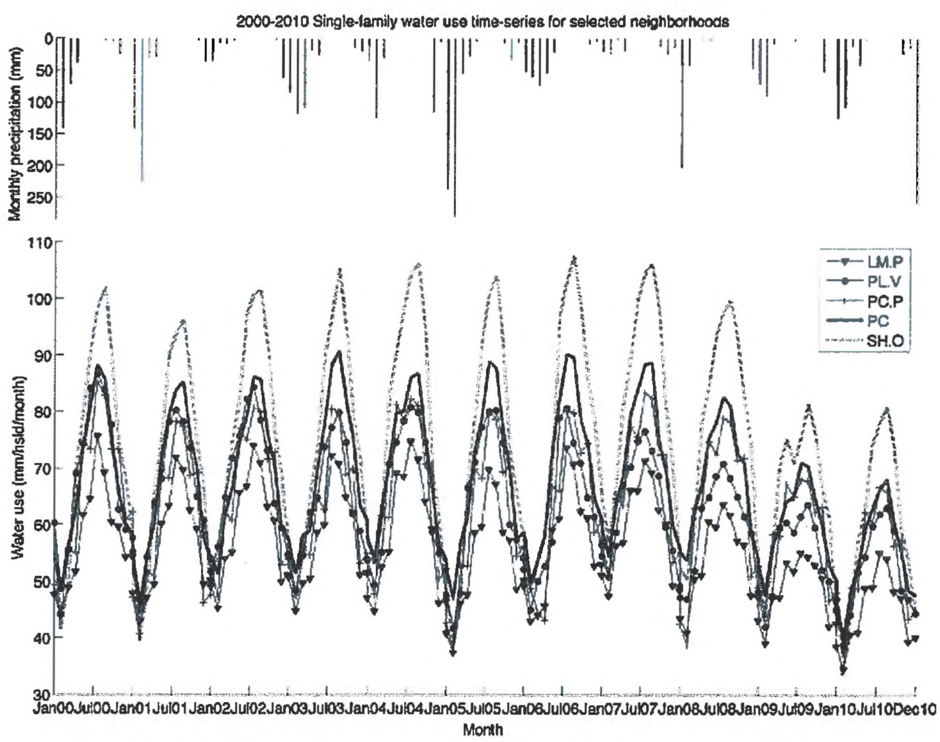

Fig. 2. Time-series plot of median single-family water use in mm per single-family customer per month over FY2001–FY2010 for the selected neighborhoods with precipitation (mm) on the inverse bar plot.

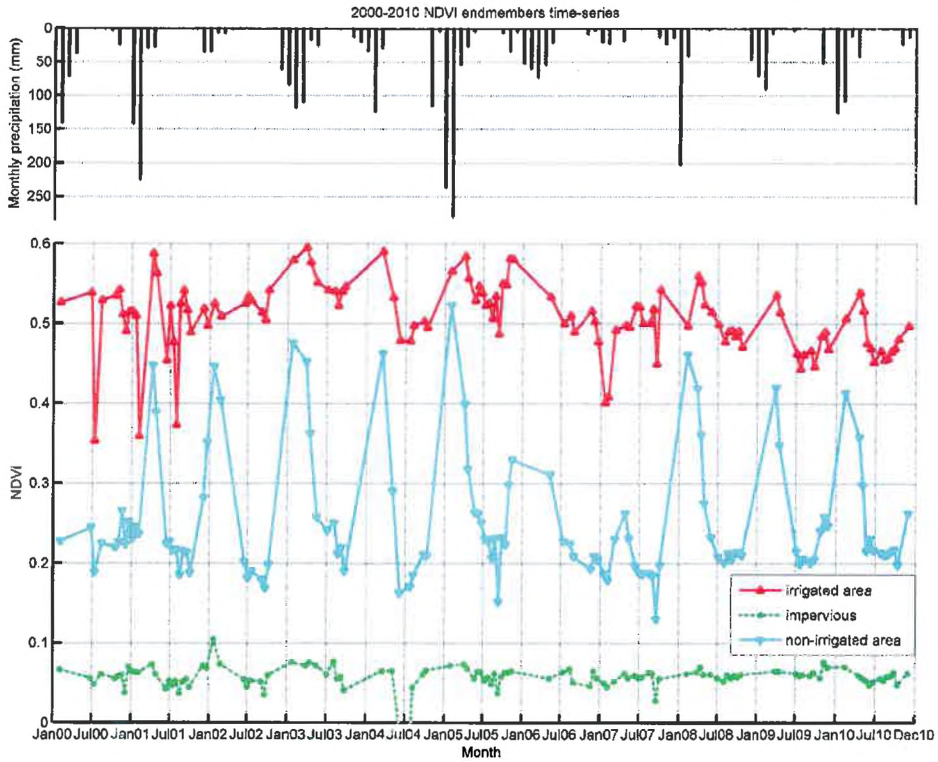

Fig. 3. NDVI time-series for the three endmembers: irrigated landscaping, impervious and non-irrigated landscaping areas from 2000 to 2010 with precipitation (mm) on the inverse bar plot (precipitation data is from the Downtown LA station).

more people under 18 years and NDVI surplus have a correlation of −0.32 ($p < 0.05$). The percent of households with one or more people over 60 years and NDVI surplus have a correlation equal to 0.30 ($p < 0.05$). The percent of owner-occupied housing units is also correlated with NDVI surplus (correlation $r = 0.48$, $p < 0.05$). Therefore, the NDVI surplus value captures income and ethnicity effects that also impact residential water use. It also captures variations in weather conditions as it is built on the difference in NDVI between irrigated and non-irrigated areas over time.

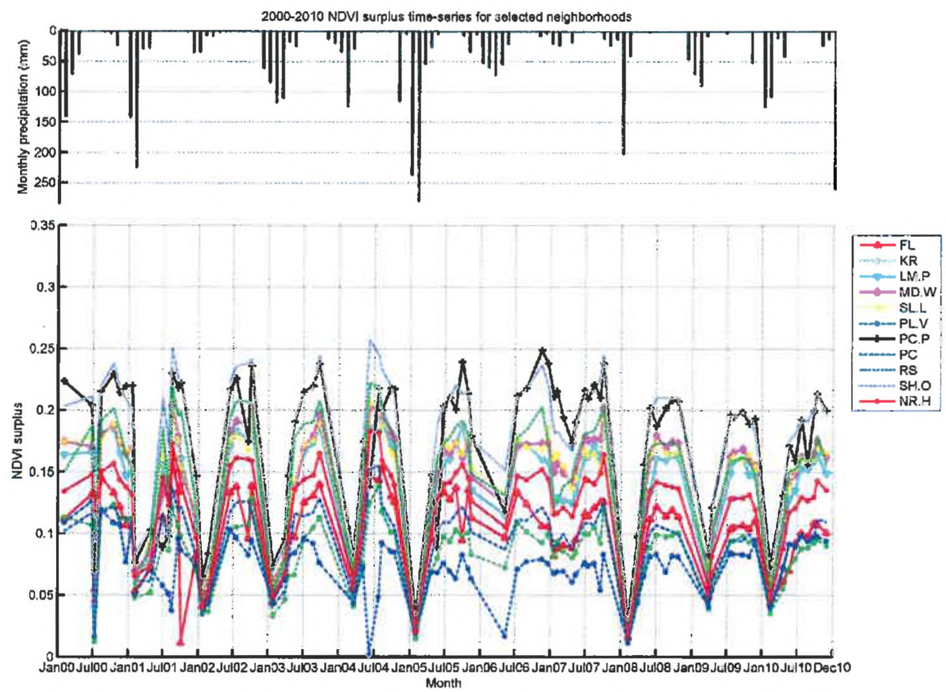

Fig. 4. Time-series plot of average NDVI surplus for the selected neighborhoods from 2000 to 2010 with precipitation (mm) on the inverse bar plot.

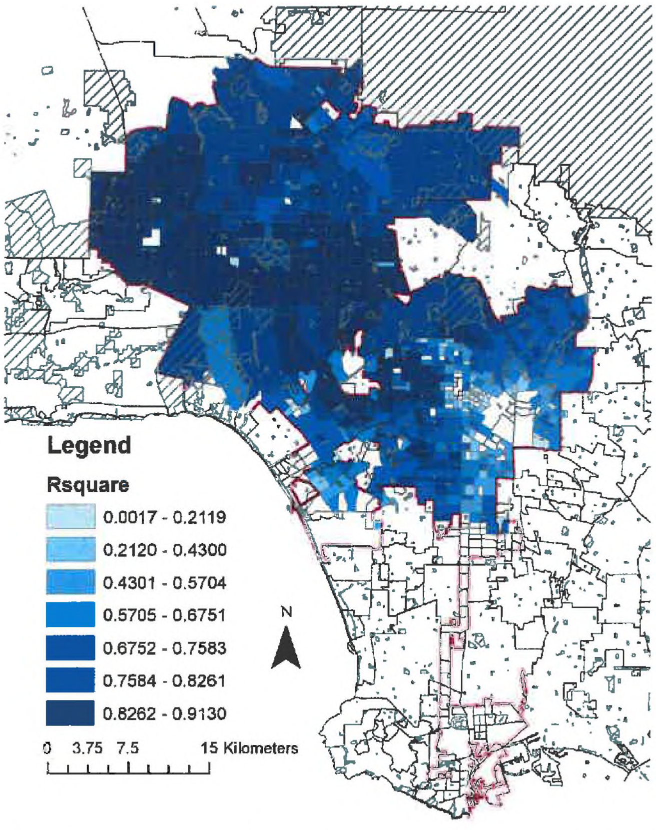

Fig. 5. R^2 results from single-family water vs. NDVI surplus exponential regression at the Census tract level.

5.2.3. *NDVI surplus vs single-family water use*

The non-linear exponential model was first applied to each individual tract in the city over the 10 year period to assess the distribution of the b and k coefficients in Eq. (4). The b coefficient (intercept) follows two distinct distributions: the first normal distribution has a mean of 26.5 mm/hsld/month with standard deviation equal to 6.41 mm/hsld/month and includes 61% of the tracts. For the second group, 39% of the tracts also follow a normal distribution with a mean equal to 41.3 mm/hsld/month and standard deviation equal 15.38 mm/hsld/month. Two non-linear mixed effects models were implemented to reflect these two different coefficient distributions. The final equations for the two models are:

$$\mathrm{SFRwateruse}_{\mathrm{tract}}(t-1) = 25.9 \times \exp(6 \times \mathrm{NDVIsurplus}_{\mathrm{tract}}(t) + 0.050 \times \mathrm{restriction} \times \mathrm{NDVIsurplus}_{\mathrm{tract}}(t)) \quad (5)$$

$$\mathrm{SFRwateruse}_{\mathrm{tract}}(t-1) = 39.1 \times \exp(5.1 \times \mathrm{NDVIsurplus}_{\mathrm{tract}}(t) - 0.110 \times \mathrm{restriction} \times \mathrm{NDVIsurplus}_{\mathrm{tract}}(t)) \quad (6)$$

The mean value for the b intercept is 25.9 mm/hsld/month (with a standard deviation equal to 4.2 mm/hsld/month) for the first group (61% of the tracts) (Eq. (5)) and 39.1 mm/hsld/month (with a standard deviation equal to 16 mm/hsld/month) for the second group (39% of the tracts) (Eq. (6)). The value for the mean k coefficient is 6 with a standard deviation of 1.4 for the first group and mean of 5.1 with a standard deviation of 2.4 for the second group. All the estimated coefficients are statistically significant at $p<0.05$ (Table 3). Note that the estimated coefficient for the interaction variable with NDVI surplus is positive for the first group and negative for the second group, indicating that the 3-year watering restrictions may have different impacts on the tracts. However, this does not reflect the response at the individual tract level. Results from both equations (Eqs. (5) and (6)) are highlighted (Figs. 5 and 6) to analyze the overall performance of the model and landscaping irrigation estimates across the city.

Table 3
Summary of the remote-sensing model coefficients.

Non-linear mixed effects model	Eq. (5)	Eq. (6)
Mean intercept b (mm/hsld/month)	25.9[a]	39.1[a]
Mean coefficient k (mm/hsld/month)	6[a]	5.1[a]
Interaction variable (NDVI surplus and restrictions)	0.05[a]	−0.11[a]
N (tracts)	433	277
Overall R^2	0.721	

[a] Denotes significance at $p<0.05$.

5.2.4. *Performance of the NDVI model*

The R^2 value indicating the performance of the model was calculated for each tract to compare the actual and simulated water use values (Fig. 5). The mean R^2 value is equal to 0.721 and ranges from 0.0017 to 0.913 with a standard deviation equal to 0.169 (Fig. 5). Higher values are observed in the northern arid part of the city as well as in tracts surrounding the Santa Monica Mountains and Griffith Park area (Fig. 5). The correlation between the R^2 values and household income is equal to 0.43 (significant at $p<0.05$), showing a moderate correlation between model R^2 and income patterns. The model R^2 appears to coincide with vegetation greenness patterns: the correlation between R^2 values and average annual NDVI in single-family areas for each tract is equal to 0.58 and significant at $p<0.05$. Hence, the NDVI model performs better in greener landscape areas.

According to the derived model, single-family water use can be divided into two terms: a constant value b (intercept) and the exponential term related to NDVIsurplus, which represents landscaping irrigation. Hence, the b intercept is the volume of water used for purposes other than landscaping irrigation and we assume that it

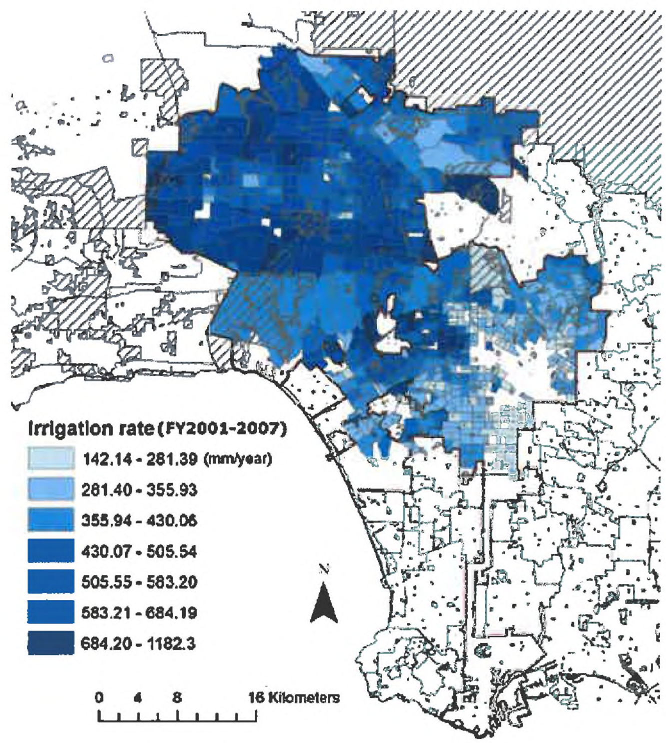

Fig. 6. Average landscaping irrigation rate (in mm/year) for the FY2001–FY2007 period from single-family customers at the Census tract level.

Table 4
Comparison of landscaping irrigation rate (in mm/year) from NDVI model with other irrigation rate and evapotranspiration (ET) estimates including Moering (2011), Johnson and Belitz (2012), Mayer and DeOreo (1999). Net ET requirement estimates for Mayer and DeOreo (1999) study are for turf grass areas. Moering (2011)'s ET estimate is for irrigated park in Los Angeles. Vahmani and Hogue (2013) ET estimate is simulated grass ET. Irrigation estimates from NDVI model are averages over the given period assuming volume of water used for other purposes than irrigation is kept constant. Salvador et al. (2011) study provides irrigation requirements in the Zaragoza region in Spain, which has a semi-arid climate with similar annual average precipitation (average precipitation of 337 mm in Zaragoza compared to 396 mm in Los Angeles). Note: For 57 tracts, the model produced negative values for FY2010 due to low R^2 values (below 0.4) relative to all the other tracts; these values were not accounted for in Table 2.

Method	Irrigation rate (mm/year)
Remote-sensing model	*Irrigation estimates from NDVI model (actual or expected)*
FY2001–FY2007	439 (standard deviation = 132)
FY2008–FY2009 (voluntary conservation and mandatory water waste provisions)	412 (6% decrease) (standard deviation = 140)
FY2010 (mandatory restrictions + pricing measure)	285 (35% decrease) (standard deviation = 98)
	Irrigation estimates for comparison
Moering (2011)	1200
Johnson and Belitz (2012) (1997 estimates)	114–541
Salvador et al. (2011) (Spain)	502–599
Vahmani and Hogue (2013)	759
Mayer and DeOreo (1999) (San Diego, CA)	1118
Mayer and DeOreo (1999) (Phoenix, AZ)	1864
Mayer and DeOreo (1999) (Las Virgenes, CA)	1222

remains constant for the study period. This assumption was also used by Johnson and Belitz (2012) to compute the average amount of water used for purposes other than irrigation in the San Fernando Valley over three years. Previous studies assumed constant indoor use (Mayer and DeOreo, 1999; Endter-Wada et al., 2008; Syme et al., 2004). Mayer and DeOreo (1999) calculated indoor use in two different periods in different cities and showed no significant difference in indoor use. They assumed in their outdoor use analysis that indoor use remained constant throughout the year. We also compared our indoor use estimates with those found in previous studies.

The b value was multiplied by the average lot size per tract to obtain the volume of water for household indoor uses and other consumption not related to the landscape and to compare with other previously-found values. The mean b value is equal to 667 L/hsld/day, which matches relatively well (583 L/hsld/day) with the volume of water used for purposes other than irrigation in Johnson and Belitz (2012). To some extent we can also compare this value to indoor use values found by Mayer and DeOreo (1999) and DeOreo et al. (2011). The resulting value of 667 L/hsld/day is comparable with indoor use of 589 L/hsld/day found in San Diego, CA and 771 L/hsld/day in Las Virgenes, CA (Mayer and DeOreo, 1999). The DeOreo et al. (2011) study showed indoor use for the LADWP area equal to 685 L/hsld/day, which is also relatively close to our estimate.

5.2.5. NDVI model irrigation estimates

Finally, landscaping irrigation is estimated by subtracting the b value from total single-family water use for each individual tract. The landscaping irrigation rate was expressed for FY2001–FY2007, and the expected landscaping irrigation was calculated for FY2008–FY2009 (voluntary water conservation and beginning of mandatory water waste provisions) and FY2010 (mandatory two day-per week irrigation restrictions coupled with water rates increase and decrease in water allotment). As mentioned previously, we assumed that water consumption for purposes other than landscaping irrigation remains constant over the study period and that in this case, water reductions would occur primarily in landscaping irrigation. We acknowledge that other variables may influence indoor and outdoor consumption. The current study focused on the impact of restrictions on landscaping irrigation through the NDVI surplus variable and the interaction term in the model (Eq. (4)) to quantify what would be the expected reduction in irrigation due to restrictions only. We then ran predictions to estimate the expected reduction in irrigation in response to restrictions.

For the FY2001–FY2007 period, the average landscaping irrigation estimate of 439 mm/year is well within the range of values published by Johnson and Belitz (2012) (114–541 mm/year) and comparable to irrigation values from Salvador et al. (2011) (Table 4). Our values are slightly lower than evapotranspiration (ET) estimates found in an irrigated park in Los Angeles or for turf grass areas (from 759 mm/year to 1864 mm/year) (Mayer and DeOreo, 1999; Moering, 2011). The difference between our irrigation estimates and values published from these previous studies can be explained by potential difference in the types of urban landscape plants and also by the fact that we used the entire lot size area instead of the vegetated surface area to calculate the volume of irrigation per area. The average expected landscaping irrigation estimates for the two restrictions periods considered are equal to 412 and 285 mm/year, for FY2008–FY2009 and increased mandatory restrictions in FY2010 respectively. This shows a potential large decrease in landscaping irrigation due to increased mandatory restrictions in FY2010 (35% decrease relative to the FY2001–FY2007 period) compared to 7% decrease due to outdoor watering restrictions in FY2008–FY2009, highlighting the effectiveness of mandatory restrictions (including two-day irrigation per week, water rates increase and decrease in water allotment), rather than voluntary conservation and limited water waste provisions in FY2008–FY2009, in reducing landscaping irrigation.

Across the city, landscaping irrigation during FY2001–FY2007 ranges from 142 to 1182 mm/year per tract with an average of 439 mm/year and a standard deviation of 132 mm/year (Fig. 6). Higher landscaping irrigation is located in the Northern and warmer parts of the city and in the tracts bordering the Santa Monica Mountains while lower values are observed in the Downtown area. This pattern is similar to spatial trends in total water use and greenness level. Landscaping irrigation volume is also strongly correlated with income across the city (correlation (r) of 0.71 significant at $p < 0.05$). Landscaping irrigation is negatively correlated with the percent of residents with Hispanic or Latino origin per tract (r of −0.51, $p < 0.05$). This may be due to a different landscape type or different water use habits. We also noticed that income and the percent of residents with Hispanic or Latino origin per tract are related (r of −0.65, $p < 0.05$). Correlation with the average household size is also negative (r of −0.21, $p < 0.05$). However, landscaping irrigation is related to household composition; being correlated to the percent households with one or more people 60 years and over (r of 0.45, $p < 0.05$). Owner-occupied housing units also irrigate more than renter-occupied housing; with correlation between landscaping irrigation and the percent of owner-occupied housing units equal to 0.57 ($p < 0.05$).

Table 5
Summary of irrigation rate estimates by period.

Irrigation rate	FY2001–FY2007 (mm/year)	FY2008–FY2009 (% change from FY2001–FY2007)	FY2010 (% change from FY2001–FY2007)
Average	439	−6%	−35%
Range	142–1182	−74%–+109%	−92%–+38%
Standard deviation	132	11%	10.5%

Table 6
Expected irrigation change during restriction periods by income group. Below 25th quartile includes tracts with a median household income below the 25th quartile of the tract income, medium level included tracts with a median household income between the 25th and 75th quartile, and above 75th quartile includes tracts with a median household income above the 75th quartile.

	FY2008–FY2009 Percent expected change from FY2001–FY2007			FY2010 Percent expected change from FY2001–FY2007		
Income group	Below 25th quartile	Medium level	Above 75th quartile	Below 25th quartile	Medium level	Above 75th quartile
Average expected change in irrigation (%)	−12%	−6%	−4%	−36%	−35%	−35%
Range	−74%–+17%	−41%–+108%	−32%–+14%	−77%–+21%	−92%–+38%	−77%–−21%
Standard deviation	14%	11%	6%	14%	10.5%	6%

During the FY2008–FY2009 restriction period, the expected percent change in irrigation relative to the FY2001–FY2007 period ranged from −74% to +109% with an average of −6% (and standard deviation equal to 11%) (Table 5). During the increased mandatory restrictions period in FY2010, the expected percent change in landscaping irrigation varied from −92% to +38% with an average of 35% decrease relative to the FY2001–FY2007 period (and standard deviation equal to 10.5%) (Table 5). These results indicate a large spatial variation in landscaping irrigation change per tract over the city. Overall, a higher decrease in irrigation is expected during the FY2010 period. A higher decrease in irrigation is observed in the warmer and northern parts of the city and a lower decrease is observed in the denser downtown areas. We hypothesize that the increase in irrigation observed in some tracts for these two water restrictions periods may be due to uncertainties in the model or restrictions not being efficient in these areas.

Further analysis of the change in landscaping irrigation was undertaken by income group at the census tract level. The irrigation results were disaggregated in three income groups: the first group includes the tracts with a median household income below the 25th quartile, the second group includes tracts with a median household income between the 25th quartile and 75th quartile, and the last group includes tracts with a median household income above the 75th quartile. In FY2008–FY2009, the average expected percent change in landscaping irrigation was higher for the lower income group than for the higher income group, from −12% to −4% respectively (Table 5). Voluntary conservation and mandatory waste water provisions were less effective for the higher income group. In FY2010, stringent mandatory restrictions including water rates increase and two-day irrigation per week had the same effect on the three income groups, around 35% expected decrease in landscaping irrigation (Table 5). The combination of pricing and non-pricing measures may induce water conservation for all income groups.

Table 6

6. Conclusion

The current study evaluates outdoor use and landscaping irrigation methods in Los Angeles using water billing data and remote-sensing products. Two methods described by the Pacific Institute in California and a developed remote-sensing NDVI model are applied at the census tract level using aggregated water use data and high-resolution vegetation, land cover and land use products.

The minimum use month and average minimum use methods result in outdoor use estimates that are below outdoor use values found in other studies including the analysis of data logging measurements in California (DeOreo et al., 2011; Mayer and DeOreo, 1999). We note that the two methods underestimate outdoor use due to the existence of landscaping irrigation during the lowest water consumption months in Los Angeles. Landscaping irrigation results from the NDVI model compare reasonably well with irrigation requirement estimates from other studies (Johnson & Belitz, 2012; Salvador et al., 2011). However, when compared with ET estimates from turf grass and irrigated turf grass parks, our model produces lower landscaping irrigation estimates. This is likely due to the fact that residential landscape in Los Angeles is often composed of trees, turf grass and tree-covered turf grass which are likely to produce variable surface evapotranspiration (Pincetl et al., 2012).

Based on the NDVI model, landscaping irrigation use represents, on average, 54% of total single-family water use. This use would decrease by 6% and 35% on average across the city during voluntary and mandatory water waste provisions (FY2008 and FY2009) and increased mandatory (FY2010) restrictions periods, respectively, assuming all water reductions would occur in landscaping irrigation. Model results show large variability in landscaping irrigation estimates (large standard deviation found in our results) across the city: the standard deviation is equal to one-third of the average estimate during FY2001–FY2007 and it remains consistent over the three periods (FY2001–FY2007, FY2008–FY2009, FY2010). This might be explained by differences in climate zones and in the proportion of trees and turf grass cover in residential landscaping between the tracts. In addition, our results show that income is strongly correlated with landscaping irrigation patterns in the city.

The current work is one of the first to show where and how residential outdoor water is used across a large, semi-arid metropolis. Key results include that outdoor use varies significantly across Los Angeles, with larger values in the northern and warmer parts of the city and lower values in the Downtown areas. We also note that stringent mandatory restrictions are more efficient at reducing residential irrigation than the voluntary program.

We advocate that introducing a new threshold in water pricing and/or water allotments specifically targeting customers with higher landscaping irrigation may be effective. In addition, partitioning indoor and outdoor use is important to more accurately assess landscaping irrigation needs for specific vegetated cover and the potential savings (for both money and water) from reducing over-watering. We advocate that the use of dual-metering data can address this need and is critical to further improve landscape water budgets and models. It would require additional expense to implement dual-metering systems across the LADWP service area and further investigations of the costs and benefits are needed.

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