Quantifying the Multiplier Effect of Southern California's Turf Removal Rebate Program with Time-Series Aerial Imagery

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Research Impact Statement: Study establishes a multiplier effect for Southern California's Turf Removal Rebate Program improving the understanding of the overall water savings of such programs.

ABSTRACT: From 2014 to 2016, water agencies in Southern California provided more than $350 million in rebates to owners who converted their turf to drought-tolerant landscaping. In order to provide a fuller understanding of the water savings of this program, this study establishes that there was a behavioral contagion, or a multiplier effect, from rebate participants in the program. An imagery-based, time-series analysis of 20 Southern California neighborhoods from 2012 to 2018 was performed to detect what parcels converted their lawns without a rebate and how they were spatially correlated with rebate participants. This correlation was then used on almost 55,000 rebate participants to estimate the multiplier benefits for the entire program at 132%. For every 100 rebate participants, the multiplier effect caused an additional 132 parcels to convert to drought-tolerant landscaping. This methodology was compared with a previous study in the Irvine Ranch Water District providing similar results. This study provides the Metropolitan Water Agency of Southern California a better understanding of the water savings per rebate dollar of the Turf Removal Rebate Program as well as providing a robust approach for cities or water agencies to estimate the multiplier effect of their turf rebate programs.

(**KEYWORDS**: drought-tolerant landscaping; GIS; NAIP; multiplier effect; turf replacement.)

INTRODUCTION

In 2011, California began the longest period of drought the state has ever experienced. The period between 2011 and 2014 was the driest in documented California history (Hanak, 2016), with the drought only lifting with heavy rains in January 2017 (Rogers, 2017). In 2014, then-Governor Jerry Brown instituted a voluntary 20% water reduction to California's local water supply agencies. In June 2015, a reduced amount of snowpack in the Sierra Nevada mountains caused the governor to tighten restrictions and impose a mandatory 25% water reduction throughout the state. Hoping to encourage their communities to reduce their water consumption, local water suppliers and agencies developed a series of government policies and rebates aimed at residents and businesses (Nagourney, 2015).

For this study, we looked at the Turf Removal Rebate Program in the Metropolitan Water District of Southern California (MWD). The Environmental Protection Agency estimates that about 30% of water usage is devoted to outdoor use (WaterSense, 2017), and other previous studies place outdoor water savings at 30% following turf replacement (Sovocool, 2005). Because of these study results, the MWD instituted the $350 million Turf Removal Rebate Program for residents to convert their lawns to drought-tolerant landscaping in January 2014 (Knickmeyer, 2016). Because the MWD is the largest water wholesaler in the nation with an estimated 19 million customers, this program promised significant residential water savings for the state (MWD, 2019).

The Turf Removal Rebate Program was active for 23 months until funding ran out. At its height in July 2015, the MWD offered $2 for each square foot of lawn converted and $10 million in rebate applications were processed per week (Knickmeyer, 2016). In total, nearly 65,000 residents participated in Metropolitan's Regional Turf Removal Rebate Program. While the

MWD estimated that the water savings from participating residents would last for 30 years, it was hoped that exposing non-participating residents to attractive, drought-tolerant landscaping would encourage them to convert their landscape without a rebate (MWD, 2013). Known as a behavioral contagion, or a multiplier effect, this tendency for people to consciously or unconsciously repeat the behaviors of those around them (Chartrand, 1999) has been documented in behaviors such as smoking or aggression (Glad, 1976; Wheeler, 1966). Although the multiplier effect was a secondary reason to why the turf replacement program was funded, it remains unknown if and how much the program impacted others.

Aerial and satellite imagery has been shown to be a powerful tool for characterizing vegetation change over time (Volcani, *et al.*, 2005), and was used in a study that focused on California residential landscapes (Chen, 2015). The most successful studies that analyze changes to vegetation use aerial and satellite imagery taken at the same time each year over the period of the study to reduce differences as a result of the vegetation's phenological curve or annual growth cycle (Pasquarella, 2016), also known as a time-series analysis. These studies typically leverage the red and near-infrared bands of light in the Normalized Difference Vegetation Index (NDVI) to detect significant changes to vegetation (Tucker, 1979). Because chlorophyll in healthy plants strongly absorbs red light and the cell structure of plants strongly reflects near infrared light (NIR), NDVI is an especially effective metric to detect changes to vegetation in times of drought.

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

The value of a time-series analysis of multispectral imagery to characterize vegetation is recognized by the U.S. Department of Agriculture's National Agricultural Imagery Program

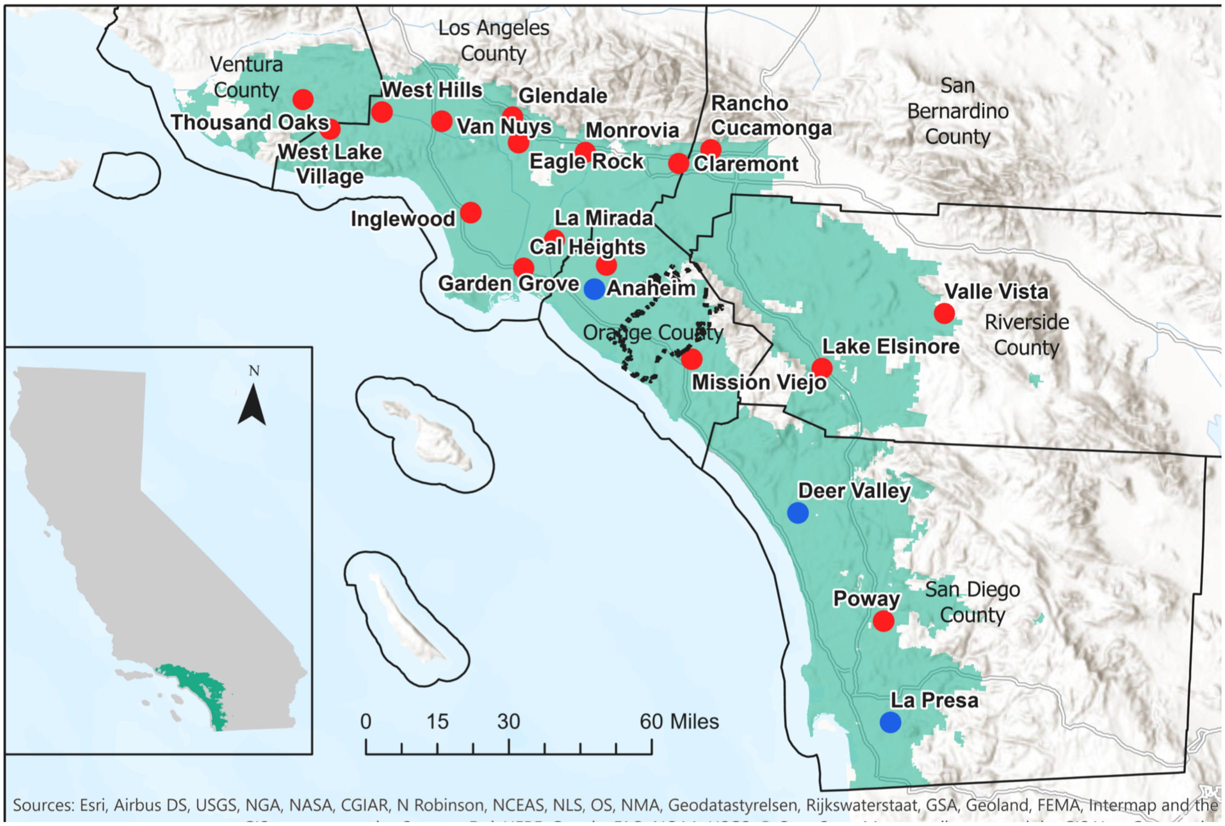

Figure 1. The study area consisted of MWD's 26 member cities and water agencies (green) across all six of Southern California counties (black outline). Twenty study sites were selected containing rebate participants (red dot) and no rebate participants (blue dot) from the 16 largest cities and agencies. Fourteen small neighborhoods were used from the Irvine Ranch Water District (black dashed outline) for a comparison dataset.

(NAIP), which collects nationwide, multispectral imagery every two years during the late summer since 2003 (Grant, 2018). More recently, time-series analysis of NAIP imagery has been used to detect changes to residential turf vigor as a result of decreased irrigation (Quesnel, 2019).

In order to calculate the multiplier effect of Metropolitan's Regional Turf Removal Rebate Program, this study conducted a time-series analysis of multispectral imagery to identify which parcels converted their landscaping without a rebate (non-participant) and analyzed their spatial relationship to nearby rebate participants. From this, a multiplier effect is estimated for each of the six counties in Metropolitan's service area and for the rebate program as a whole, improving the understanding of the overall benefits of this and future turf replacement programs.

STUDY AREA

The study area consisted of MWD's entire 13,000 km^2 service area, which provides water to an estimated 19 million customers (MWD, 2019). Within this area, 20 small study sites were geographically dispersed across the 16 largest member cities and water agencies of MWD (Table 1) (Figure 1). Additionally, twelve sites from the Irvine Ranch Water District's (IRWD) internal study were used for a comparison dataset. The 20 study sites contained an average of 360 parcels in a contiguous neighborhood. Three of the 20 neighborhoods were chosen because they did not contain any rebate participants and were used to estimate the base rate, or the number of non-participants without any participant influence.

DATA

Participants

MWD provided 64,513 participant records, which included addresses, dates of turf conversion, and total turf replaced (MWD, 2018). These parcels were geocoded, providing a latitude and longitude via the Bing Maps geocoder available at www.gpsvisualizer.com/geocoder. These records were spatially joined to a parcel database containing a polygon of their location, and 54,901 participants (85%) were successfully joined to a geometry. The remaining 15% were removed because they 1) did not geocode because of incomplete or corrupted addresses; 2) did not correspond to a parcel polygon; 3) were not within the six Metropolitan water district county study regions; or 4) had multiple rebates for that parcel (only one was used).

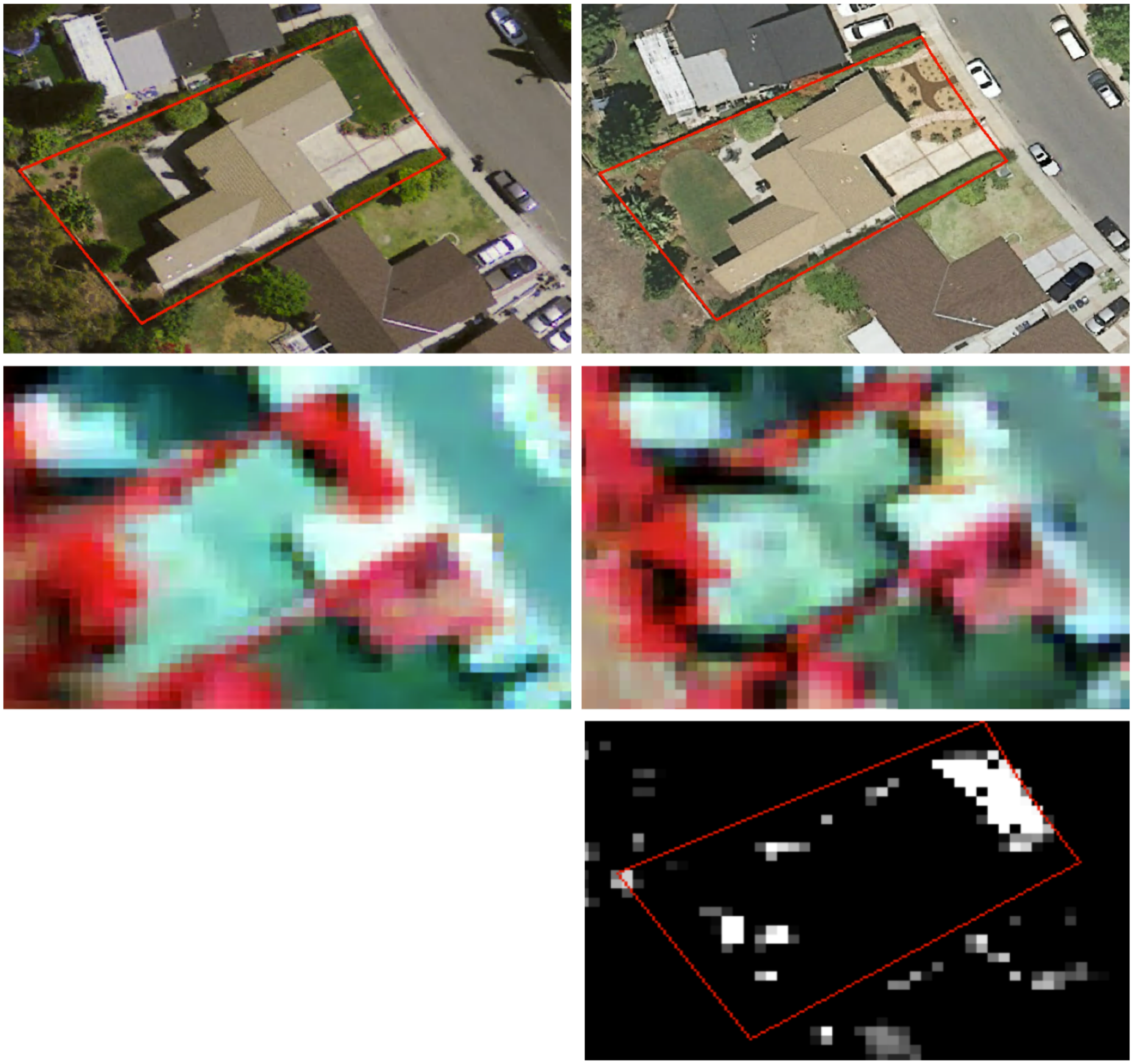

Figure 2. Time-series analysis of imagery was used to detect conversion to drought-tolerant landscaping. NAIP imagery (middle left and middle right) is shown in false color with red indicating healthy vegetation. NAIP imagery was converted to NDVI and differenced (bottom right) with white areas showing a significant decrease in NDVI. While high-resolution imagery from 2012 (top left) and 2018 (top right) easily shows changes to landscaping, it was not used due to cost and inconsistent coverage across the study area and period.

NAIP Imagery

National Agricultural Imagery Program (NAIP) imagery for Southern California was purchased from the U.S. Dept of Agriculture's Aerial Photography Field Office for 2012 and

2018 (APFO, 2012). NAIP imagery is collected at 'leaf on' periods in the late summers containing red, blue, green and near-infrared wavelengths, allowing for the discrimination between artificial lawns and natural green turf. The 2012 imagery is 1 square meter (m^2) spatial resolution and 0.6 m^2 for 2018 (Figure 2).

Alternate Dataset

For comparison with this study's results, an alternate, internal dataset was provided by the IRWD containing the locations of non-participants identified in their study area (IRWD, 2016). Data was generated by driving through 14 neighborhoods in 2016, giving some consideration to the drive path likely taken by residents, administering a survey, and/or looking for drought-tolerate landscaping. Lawn conversion between 2011 and 2016 was confirmed using historic imagery on Google Earth. From these neighborhoods, 300 non-participants were identified.

METHODOLOGY

Identifying Non-Participants

Imagery from 2012 and 2018 NAIP was analyzed for significant, permanent changes to landscaping. The 2018 imagery was resampled, or spatially aggregated, from 0.6 m^2 spatial resolution to 1 m^2 resolution to match the 2012 imagery. NDVI was calculated for each set of images over the study sites and differenced. Areas of significant vegetation change were highlighted in white and followed by manual visual analysis to confirm turf conversion (Figure 2). Brown lawns or cars parked on lawns were not considered permanent changes and not identified as a landscape conversion. A total of 784 non-participant parcels were identified in the 20 study sites between the 2012–2018 images.

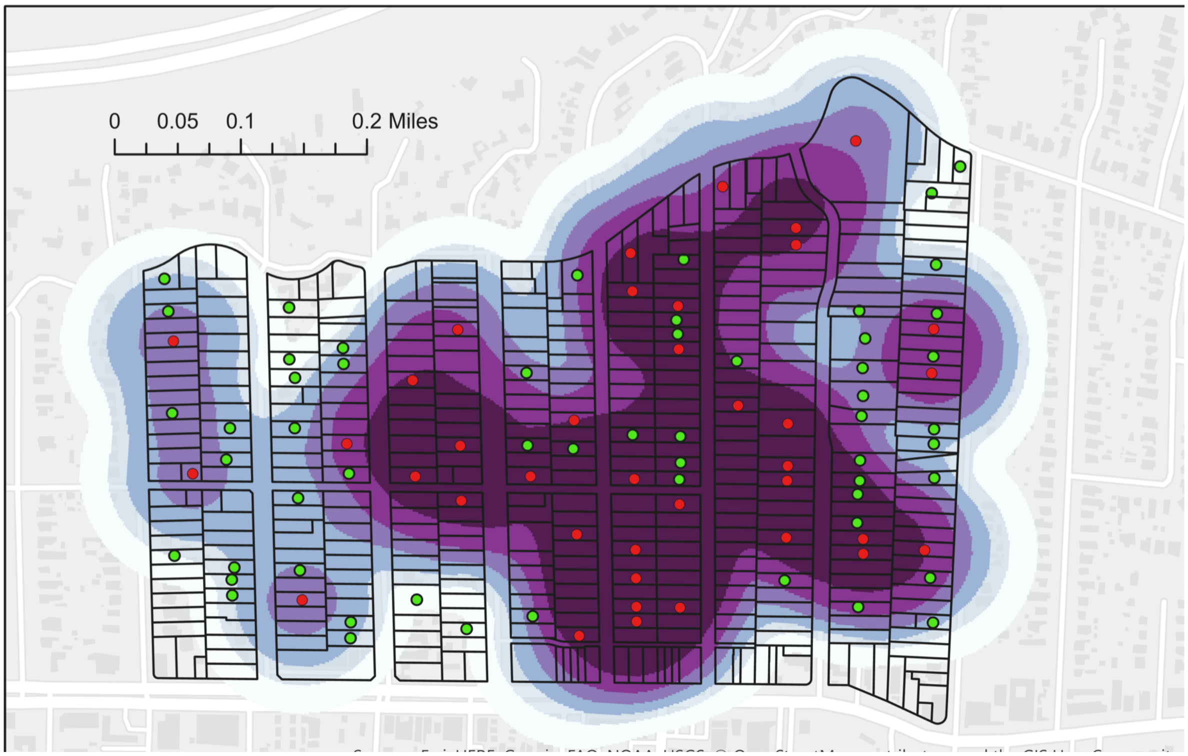

Figure 3. The Eagle Rock study site had a high concentration of participants (red dots) and non-participants (green dots). The participants were used to generate a six-class kernel density which was assigned to each of the non-participants.

Density Analysis of Rebate Participants

Seventeen study sites were used to calculate the density of participants per km^2 using the kernel density method (Esri, 2019a). This kernel density calculates the density of participants in a localized region. The spatial resolution of analysis was a 2-square-meter pixel and the search radius was 133 meters calculated from Silverman's Rule-of-Thumb bandwidth estimation formula, which is resistant to spatial outliers (Esri, 2019a). The output is a continuous surface of 2-square-meter pixels that contains the density of surrounding participants. All pixels below the

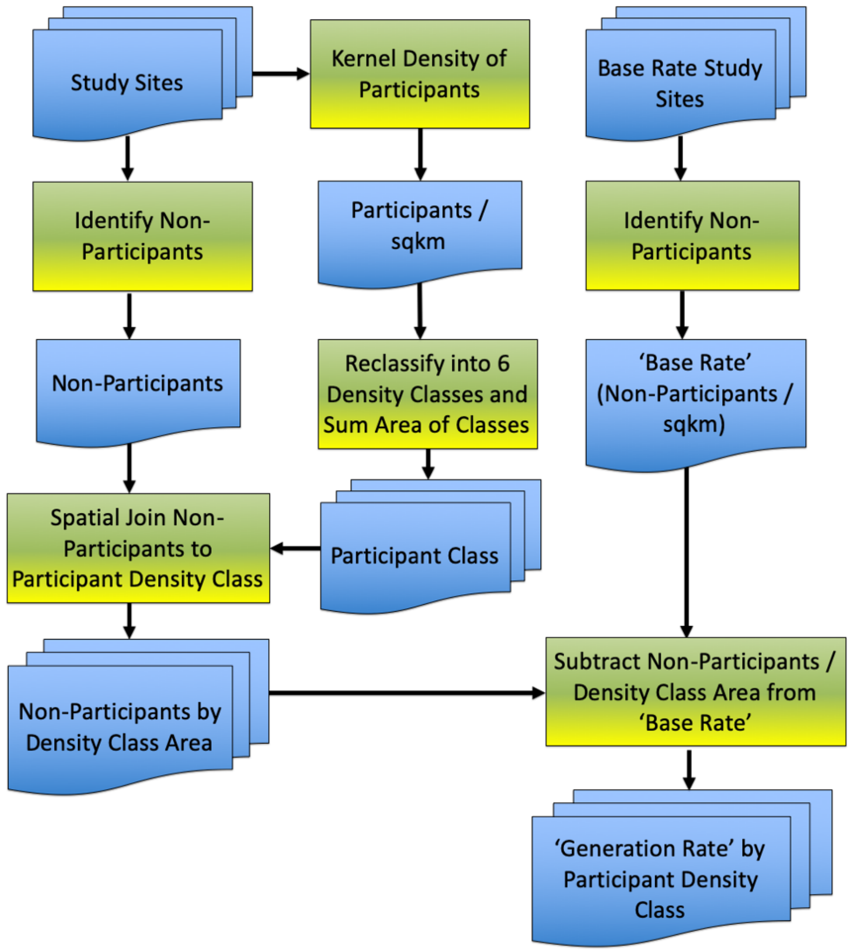

Figure 4. The 'Generation Rate', or the rate at which non-participants are correlated with rebate participant density, is calculated through a kernel density approach.

base rate of 2.01 (see below section) were removed from the analysis and the remaining pixels were reclassified into six groups (Figure 3) using natural breaks classification (Jenks) (Esri, 2019b). The Jenks classification method groups similar values while maximizing the differences between classes.

Calculation of Base Rate

Because there is a natural phenomenon of Southern Californians converting to drought-tolerant landscaping regardless of proximity of participants, this study evaluated three areas

(Deer Valley, Garden Grove, and La Presa) which were similar to the 17 other study areas but had no rebate participants. While these areas did have rebate participants, they did receive regional turf rebate marketing. The total number of non-participants per km^2 was calculated at 2.01 non-participants/km^2. In other words, regardless of if there are rebate participants nearby or not, it can be assumed that there is a base rate of landscape conversion at 2.01 converted parcels/km^2.

Calculation of Non-Participant Generation Rate

For each of the 17 study sites, the area from the six participant density classes was summed along with how many non-participants are in those classes (Table 2). That provided the number of non-participants that tend to be generated as a function of what rebate participant

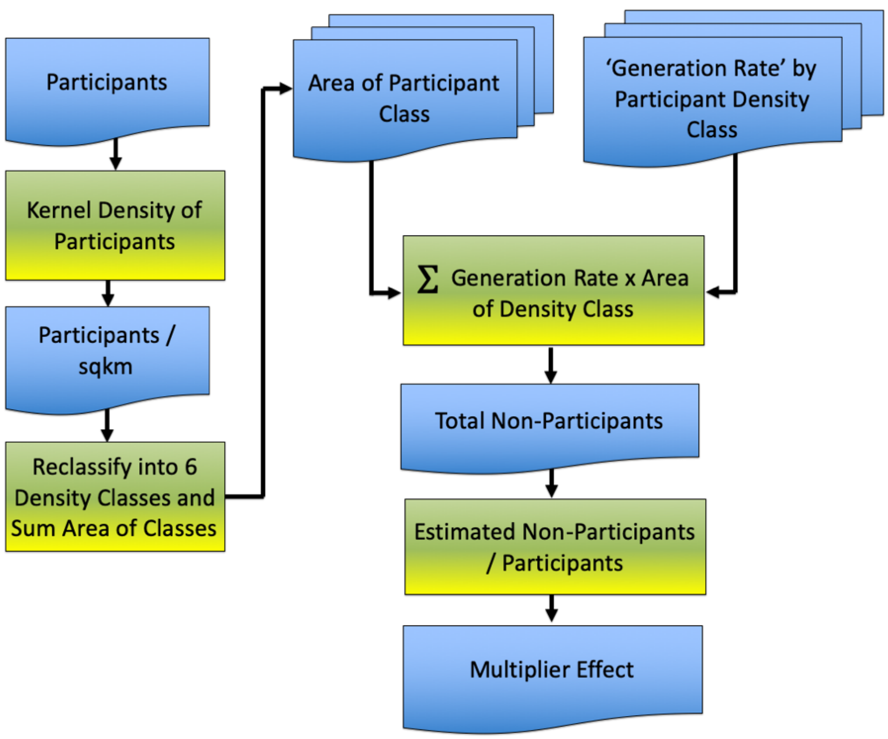

Figure 5. For any group of participants, a multiplier effect can be estimated using a kernel density and the 'Generation Rate' established in this study.

density class they are in, called the 'Generation Rate'. For example, in the Eagle Rock study area

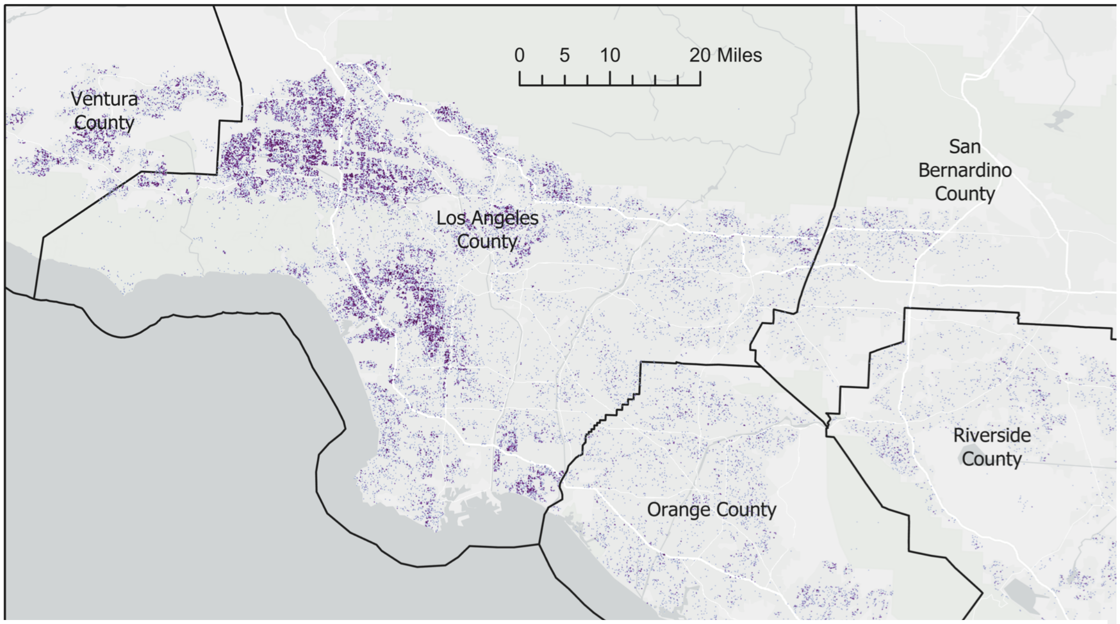

Figure 6. A kernel density from rebate participants was used to estimate the total number of non-participants per county. Los Angeles produced several areas of high-participant density (shown in dark purple).

(Figure 3), 12 non-participants were identified in the highest participant density class which was 0.13 km^2 (Table 3) for an average of 91 participants per km^2. Combining the seventeen study areas, a Generation Rate for each density class was estimated (Table 2).

$$Generation\ Rate = \frac{Non\_Participants}{Area} - Base\ Rate$$

With the relationship of non-participants to area of participant density class, or 'Generation Rate', established, the number of non-participants can be estimated for any group of participants in a set area after running a kernel density on those participants:

$$Estimated\ Non\_Participants = Area\ of\ Participant\ Density\ Class * Generation\ Rate \quad (3)$$

Finally, the multiplier effect is the ratio of estimated non-participants to participants, which was estimated for all of Southern California as well as by the six counties in the study area (Table 4):

$$Multiplier\ Effect = \frac{Estimated\ Non\_Participants}{Participants} \quad (4)$$

RESULTS

This study estimates that between 2012 and 2018, 72,386 parcels transitioned from natural turf to some type of drought-tolerant landscaping due to their proximity to parcels participating in the Regional Turf Removal Rebate Program. With 54,901 rebate participants used for this study, the total multiplier effect is calculated at 132%. In other words, for every 100 rebate participants, an additional 132 parcels converted their turf because of the program.

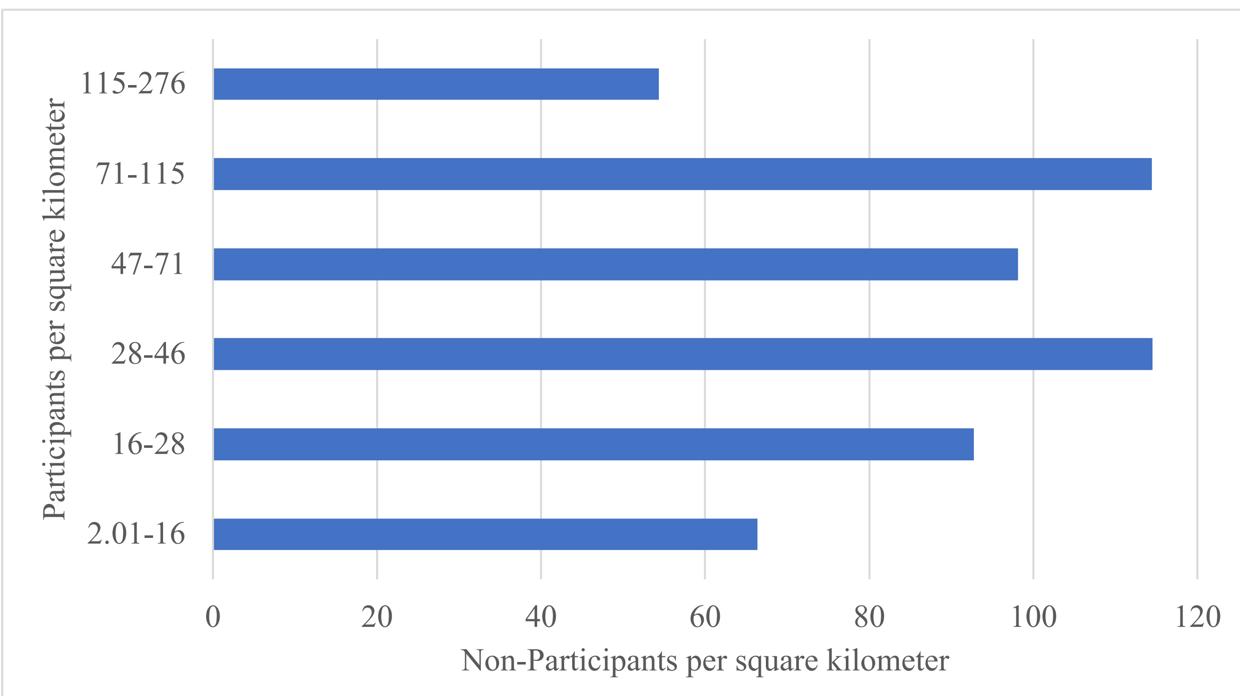

Figure 7. Generation Rate by Density Class. The highest rate of non-participant generation is in the medium density classes. In the lowest class, there is no social contagion and in the higher classes, there is likely a saturation effect

Generation Rate by Density Class

Non-participants tend to be in areas with at least some participants and they appear more often in areas of higher density classes, indicating a social contagion or multiplier effect of the rebate program (Figure 7). Non-participants appear less frequently in areas with low participant density, likely because there is no peer effect, or the demographic of the neighborhood doesn't typically support drought-tolerant landscaping. Additionally, non-participants do not typically appear in the highest category of density participants because of a saturation effect. In other words, the highest class of participant density requires most, if not all parcels in the immediate neighborhood to have participated in the rebate program. Thus, there are few remaining parcels in that localized area to become non-participants.

Multiplier Effect by County

Because this approach estimates non-participants as a function of participant density classes, counties with a high proportion of their rebate participants in higher density classes (such as Los Angeles County) had a higher number of non-participants per km^2 in any of the density classes. However, achieving higher density classes required a significant number of participants. The result was that this produced a lower multiplier effect, or non-participant per participant. Counties with moderate- to low-densities of participants counties generated more non-participants per participant (Figure 8) (Table 4).

Comparison to IRWD Dataset

Because there are no public datasets on parcels that converted their landscape without a rebate, or previous public studies on the multiplier effect of such rebate programs, this project

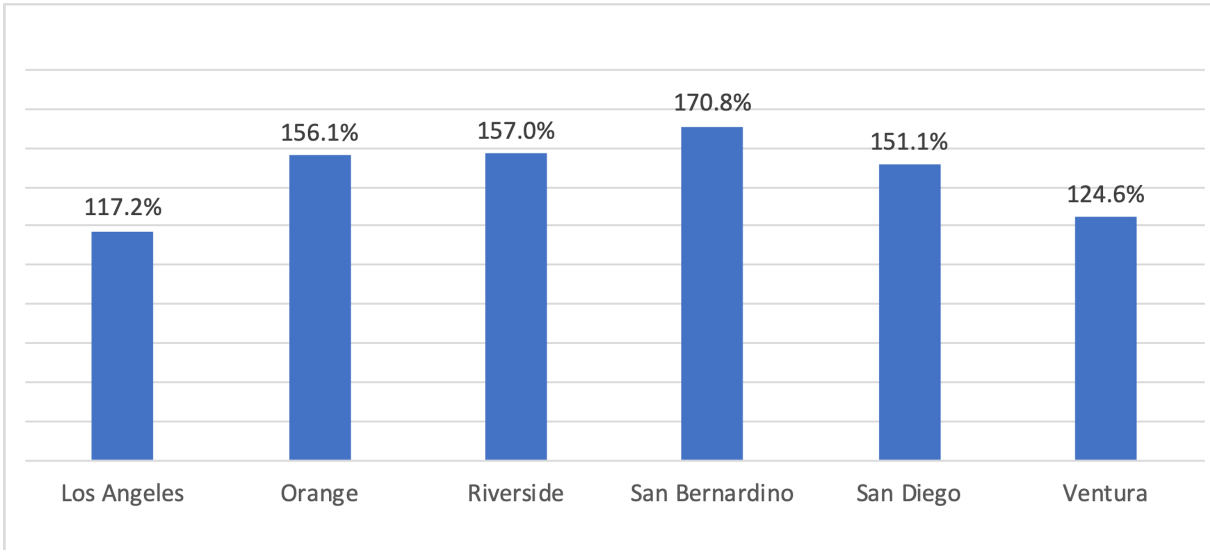

Figure 8. San Bernardino County had a moderate number of rebate participants dispersed at low and medium densities across the county. This resulted in a higher multiplier effect because there was no saturation in high density areas.

obtained an internal study conducted by the Irvine Ranch Water District for comparison. From the number of rebate participants (114) in their 14 study neighborhoods and the number of non-participants (300) identified by driving by and conducting surveys, the IRWD study found a multiplier effect of 263%. Unlike this study that leverages a kernel density approach, IRWD's methodology was to divide the number of participants by non-participants in their 14 study neighborhoods.

An advantage of the approach described in this manuscript is that a multiplier effect can be estimated for any group of rebate participants. To compare with the IRWD results, this study used the same 114 participants in the IRWD study areas and performed a kernel density as discussed in the methodology section (Figure 5). Areas of the different participant density classes were summed and then multiplied by the Generation Rate established in this study to estimate a total number of non-participants at 200 (Table 5). With 114 participants in the relatively dense study neighborhoods in IRWD's study, this results in a multiplier effect of 175%.

DISCUSSION

Estimating a single multiplier effect across all of MWD's service area is challenging due to the various densities of participants and socio-demographic characteristics. Even within the 17 study areas, individual multiplier effects ranged from 43% (Ingelwood) to 673% (Lake Elsinore) (Table 6). That said, this study's approach of using a kernel density with a localized search radius is consistent with other behavioral contagion studies which point to the importance of density of influences, as well as the degradation of those influences over distance (Glad, 1976; Wheeler, 1966). Additionally, the establishment of a base rate of 2.01 non-participants per km^2. is a conservative, but important result for this study.

By leveraging a kernel density approach, this study provides a multiplier effect that gives weight to clusters of participants and uses distance to degrade and resist the effects of spatial outliers. The multiplier effect has shown that the middle density classes have a higher generation rate of non-participants, but the effect is saturated at the highest class. An unexpected result of achieving high density classes is that it is not necessarily beneficial for water districts, because the high number of participants condensed in one area would have less parcels to convert to drought-tolerant landscaping. In terms of a small neighborhood, there will be the greatest multiplier effect if the participants in that neighborhood are moderately dispersed, as opposed to all grouped in a small area, not affecting the rest of the neighborhood.

Differences with IRWD Dataset

While there are likely several reasons why the IRWD multiplier effect (263%) was higher than this study's estimation (175%), the most important reason is the analytic approach. The

IRWD study counted the number of participants and identified non-participants in a neighborhood to get the multiplier effect. So, if a participant is on one side of a neighborhood and a non-participant is on the other, it is still included as influencing that non-participant as much as a next-door neighbor. By contrast, this study creates a localized density surface of participants, which weighs nearby clusters of participants with greater influence, with that effect rapidly diminishing over distance. Because 32% of all MWD rebate participants are at least 133 m away from another participant, and therefore do not affect each other according to Silverman's Rule-of-Thumb bandwidth estimation formula (Esri, 2014a), the method provided here is significantly more robust when expanding to all of Southern California.

If this study utilized the same methodology as IRWD (summing the non-participants and participants identified in the IRWD study areas), the multiplier effect would be 245%, or very close to IRWD’s rate of 263% (Table 6). In other words, these studies have a remarkably close ratio of participants to non-participants. Initially, there was concern that aerial imagery would miss smaller landscape conversions, but the estimates from this study closely match those from on-the-ground surveys and inspections. In that respect, this close comparison provides a good argument that aerial surveys such as this one can produce nearly the same results as on-the-ground surveys and be upscaled more easily.

Additionally, there are differences in the respective study areas which likely produced a higher multiplier effect for the IRWD study. IRWD study areas are neighborhoods as small as 150 parcels, which are mostly single-family homes with significant landscaping. By contrast, this study’s average study site was a neighborhood of 360 parcels, covering larger sections of neighborhoods that often contained some parks or parcels that had no landscaping that could be converted. Because of their small study sites, the individual multiplier effect in the IRWD study areas ranged from 60% to 2000% across their 14 study sites, while this study had a tighter range from 45% to 673% (Table 6).

CONCLUSION

This study provides a methodology and first estimate of the overall multiplier effect of Metropolitan's Regional Turf Removal Rebate Program, showing that the value of the program is greater than just the water savings from participants. For water agencies, this study provides evidence that further implementation of such programs may be best served by focusing rebate eligibility to areas that currently have low participants, which would maximize the multiplier effect. More broadly, future work could include identifying common traits among study sites that had high numbers of non-participants. These may be geographic, social or demographic. Once identified, advertising for the rebate or additional rebate dollars could be focused in those areas that will likely see the best multiplier effect and therefore the greatest water savings per rebate dollar.

Estimating a single multiplier effect across a socially and geographically diverse area similar to MWD’s service area is extremely challenging. There remains, however, a critical need for the nation’s largest water wholesaler, and indeed all agencies concerned with water conservation, to fully understand the conservation effects of turf rebate programs. As MWD’s Board of Directors calculate the water savings per rebate dollar in support of California’s water conservation efforts, a full understanding of this program’s effectiveness is critical.

ACKNOWLEDGEMENTS

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article represent those of the author and do not necessarily reflect the views or policies of the Metropolitan Water District of Southern California or the Irvine Ranch Water District.

TABLES

Table 1. Member Cities and Water Agencies in the Metropolitan Water District of Southern California by area.

Member City and Water Agency	Area (sqkm)	Study Locations
San Diego County Water Authority	9,695	La Presa, Poway, Deer Valley
MWD of Orange County	4,040	Mission Viejo, Garden Grove
Eastern MWD	3,740	Valle Vista
Western MWD	3,480	Lake Elsinore
Los Angeles	3,122	West Hills, Van Nuys, Eagle Rock
Calleguas MWD	2,494	Thousand Oaks
Inland Empire Utilities Agency	1,606	Rancho Cucamonga
Central Basin MWD	1,179	La Mirada
West Basin MWD	1,095	Inglewood
Upper San Gabriel Valley MWD	967	Monrovia
Three Valleys MWD	912	Claremont
Las Virgenes MWD	829	West Lake Village
Long Beach	342	Cal Heights
Anaheim	338	Anaheim
Glendale	205	Glendale
Santa Ana	181	
Pasadena	151	
Fullerton	148	
Foothill MWD	142	
Torrance	138	
Burbank	116	
Santa Monica	55	
Compton	54	
Beverly Hills	34	
San Marino	25	
San Fernando	16	

Table 2. Generation Rate. For the six density classes, the estimation of how many non-participants are generated per km^2, minus the base rate is calculated.

Classes	Total Area (sqkm)	Non-Participants	Generation Rate (Non-Participants / sqkm-base rate)
2.01-16	1.46	97	66
16-28	0.93	85	93
28-46	1.30	148	115
47-71	1.15	119	98
71-115	0.97	113	114
115-276	0.67	38	54

Table 3. Eagle Rock Study Site Calculations

Class	Density	pixels (2sqm)	area (sqkm)	Non - Participants	Non-Participants / sqkm	Non-Participants / sqkm - Base Rate
2	2.01-16	19,669	0.08	4	50.8	48.8
3	16-28	12,835	0.05	4	77.9	75.9
4	28-46	23,002	0.09	15	163.0	161.0
5	47-71	20,152	0.08	10	124.1	122.1
6	71-115	20,085	0.08	9	112.0	110.0
7	115-276	32,975	0.13	12	91.0	89.0

Table 4. Estimations of Multiplier Effect by County

County	Non-Participants	Participants	Multiplier Effect
Los Angeles	35,657	30,424	117.2%
Orange	8,727	5,591	156.1%
Riverside	7,001	4,458	157.0%
San Bernardino	1,882	1,102	170.8%
San Diego	14,354	9,502	151.1%
Ventura	4,765	3,824	124.6%

Table 5. IRWD Study Location Calculation of Non-Participants

Classes	Density	pixels (2sqm)	area (sqkm)	Non-Part / sqkm-base rate	Non-Participants Created
2	2.01-16	818,660	1.64	66.4	109
3	16-28	100,802	0.20	92.7	19
4	28-46	129,556	0.26	114.5	30
5	47-71	110,124	0.22	98.2	22
6	71-115	71,757	0.14	114.5	16
7	115-276	41,589	0.08	54.3	5
			2.54		200

Table 6. Individual Study Sites Calculations

Study Site	Non-Participants Identified	Parcels	Participants	Estimated Non-Participants	Multiplier Effect	Multiplier Effect (IRWD Methodology)
Santa Ana	23	504	10	13.4	134%	230%
Cal Heights	54	520	29	49.0	169%	186%
Claremont	70	393	37	59.2	160%	189%
Deer Valley	0	540				
Eagle Rock	56	423	40	53.0	132%	140%
Garden Grove	2	339				
Glendale	30	295	12	24.6	205%	250%
Ingelwood	31	329	30	12.8	43%	103%
La Miranda	20	405	6	13.6	226%	333%
La Presa	3	306				
Lake Elsinore	65	328	5	33.7	673%	1300%
Mission Vejio	27	378	16	21.2	133%	169%
Monrovia	36	332	14	20.5	146%	257%
Poway	87	310	18	71.2	395%	483%
Rancho Cucamonga	45	232	11	26.2	238%	409%
Thousand Oaks	69	336	26	64.1	247%	265%
Valle Vista	37	293	2	9.9	494%	1850%
Van Nuys	46	318	18	39.4	219%	256%
West Hills	43	276	26	30.2	116%	165%
West Lake	40	324	16	10.8	68%	250%
	784	7181	316	552.6	175%	248%

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