Title
A Probabilistic Framework to Evaluate Spatiotemporal Patterns of Participation in the Irvine Ranch Water District Turf Rebate Outdoor Water Conservation Program

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Publication Date
2019

UNIVERSITY OF CALIFORNIA,
IRVINE

A Probabilistic Framework to Evaluate Spatiotemporal Patterns of Participation in the Irvine Ranch Water District Turf Rebate Outdoor Water Conservation Program

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil and Environmental Engineering

by

Kimberly Angel Duong

Dissertation Committee:
Professor Emeritus Stanley B. Grant, Chair
Associate Professor Russell Detwiler
Professor David L. Feldman

2019

DEDICATION

To

my loved ones
and
my younger self

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ACKNOWLEDGMENTS

I would like to express the deepest appreciation to my committee chair, Professor Stanley Grant at University of California, Irvine and Virginia Tech, who has the attitude and the substance of a genius: he continually and convincingly conveyed a spirit of adventure in regard to research and scholarship, and an excitement in regard to teaching. Without his guidance and persistent help this dissertation would not have been possible.

I was fortunate to receive financial support from the U.S. National Science Foundation Partnerships for International Research and Education UCI Water-PIRE (OISE-1243543); the Newkirk Center for Science and Society Graduate Student Fellowship at the University of California, Irvine; and UC Office of the President Multi-campus Research Program Initiative (MRPI-17-455083).

I would like to thank my committee members, Professor David Feldman and Professor Russell Detwiler, who provided useful feedback on my work and demonstrated that an interdisciplinary approach to water resources management enriches the discussion and research. I also thank co-author Professor Jean-Daniel Saphores, with whom I wrote a literature review about obstacles to wastewater reuse. Thank you to my co-authors and collaborators: Professor Meg Rippy at Virginia Tech, who taught me a great deal about statistical analysis; Professor Jasper Vrugt at University of California, Irvine for his detailed feedback and valuable contributions to our manuscripts; Professor Gregory Pierce at University of California, Los Angeles, who provided useful feedback and context for the water resources regulatory framework in southern California. I also thank Professor Michael McBride at University of California, Irvine, for showing me a theoretical economics perspective.

I thank the Irvine Ranch Water District (IRWD) for their willingness to partner on this research. Without their collaboration and data, this work would not be possible. In particular, I want to thank Amy McNulty and Enrique Zanetti for their time and effort spent on our collaborative research. I learned a great deal from them about the nuances of the IRWD datasets and their service area. I am also grateful to them for introducing me to others at IRWD and water managers across southern California.

I also thank my many fellow peers over the years that helped me learn day-to-day skills and gave me their time and feedback. I learned something valuable from each of them. I thank my parents and family for their endless patience, sympathy, and support. Finally, I thank my partner Lucas Leung for his unwavering support and encouragement from the very beginning of my PhD and every day since then.

Without the people mentioned above, I would not be where I am today and this dissertation would not be possible. Thank you so much to everyone who has given me their time and support during the course of my PhD. I am so grateful and will forever remember the life lessons that I've learned in these past six years.

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ABSTRACT OF THE DISSERTATION

A Probabilistic Framework to Evaluate Spatiotemporal Patterns of Participation in the Irvine Ranch Water District Turf Rebate Outdoor Water Conservation Program

By

Kimberly Angel Duong

Doctor of Philosophy in Civil and Environmental Engineering

University of California, Irvine, 2019

Professor Stanley B. Grant, Chair

Despite major advances in water efficiency, urban water resources are increasingly strained due to population growth and severe droughts. In arid regions, water managers often promote water conservation rebate programs: the most common is known as a "turf rebate" program – offering participants a fixed rebate amount per unit area (e.g., $2 per square foot) in exchange for replacing turf grass with drought-tolerant landscaping. In southern California where outdoor watering can comprise more than half of residential water use, hundreds of millions of dollars worth of turf rebates were distributed during the 2011-2016 drought.

In my thesis, I focus on single-family residence (SFR) participation in a turf rebate program in the Irvine Ranch Water District (IRWD) in southern California. Spatial analyses at the village (i.e. neighborhood) level and at the parcel level reveal that drivers of participation are tied heavily to aspects of the built environment, whether it's home age (at the village level) or outdoor area (at the parcel level). From these results we propose a probabilistic framework for estimating, and potentially optimizing, the water savings achieved by cash-for-grass programs, taking into account constraints of outdoor area imposed by the built environment, climate, demographic drivers of conservation behavior, and financial incentives.

I also explore temporal patterns of participation and find that a universal temporal pattern captures the majority of the monthly participation probability across all villages (i.e. neighborhoods) in the IRWD service area. This temporal pattern is highly correlated with Google search rates for the phrase “turf rebate”, which serves as a proxy for mass media coverage on the California drought and the turf rebate programs that became more heavily advertised as a result. In conjunction with California Governor Jerry Brown’s 2014 emergency drought proclamations, IRWD conducted water conservation and education programs. These local and state actions led to very high SFR participation in the IRWD turf rebate program.

Together, these built environment, demographic, and mass media coverage variables help explain water savings potential and spatiotemporal patterns of participation in IRWD’s turf rebate program.

INTRODUCTION

The world of water resources is often characterized in terms of supply, demand, or the gap in between. For arid regions that regularly experience drought, numerous strategies have been developed and implemented in attempts to close this gap. Demand reduction commonly manifests as conservation marketing campaigns, educational programs, fines, rebates/incentives, and watering restrictions. From 2011 to 2016, California experienced the most severe drought in the southwest U.S. over the past 1200 years (Griffin & Anchukaitis, 2014), which spurred policy interventions at multiple policy and regulatory scales. Governor Jerry Brown issued statewide emergency proclamations, including unprecedented mandatory urban water conservation and a bevy of legislation, programs, and funding that trickled down to the 400+ urban water agencies across the state (Mitchell et al., 2017).

Outdoor watering is typically first to be restricted in times of drought and, in many arid regions, can account for 50% or more of the total domestic water usage (Cameron et al., 2012; Mini, 2013). Private gardens alone can comprise 22-36% of total urban area (Gaston, Warren, Thompson, & Smith, 2005; Mathieu, Freeman, & Aryal, 2007). But outdoor water conservation comes at a price: between 2014 and 2016, the Metropolitan Water District of Southern California (MWD) spent a record $450 million on water conservation rebate programs - reportedly the “largest single investmtabent in water conservation incentives in the nation’s history” (Metropolitan Water District of Southern California, 2016). Other water agencies across California also doled out millions of dollars for similar water conservation rebates (California Department of Water Resources, 2015; Matt Stevens, 2015).

In light of the prevalence and considerable funds spent on outdoor water conservation during times of drought, my dissertation focuses on the success of one such program implemented by the Irvine Ranch Water District (IRWD) in Southern California. Specifically, my research evaluates their "turf rebate program" (also referred to as "turf removal" or "cash-for-grass" programs), which provided a financial incentive (i.e., rebate) for the conversion of turf grass (also known as lawns) to drought-tolerant landscapes, e.g., with artificial turf or plants with low water demand (Hilaire et al., 2008; Sedlak, 2014; Sovocool, Morgan, & Bennett, 2006). Numerous social barriers – such as neighborhood norms and upfront costs – may limit participation in these programs (Silvy & Lesikar, 2005). Furthermore, residential yards are adaptive coupled human-natural systems, characterized by numerous feedbacks that can affect human and ecosystem health, in addition to water supplies (Cook, Hall, & Larson, 2012; Hale et al., 2015; House-Peters & Chang, 2011). In my thesis I set out to address a key knowledge gap: namely, how policy interventions can overcome social barriers to program participation while avoiding unintended consequences (Hale et al., 2015; Sokolow, Godwin, & Cole, 2016).

Through a research partnership that I formed with the Water Use Efficiency Department at the Irvine Ranch Water District (IRWD), I explore the spatial and temporal patterns of participation in their residential turf rebate program. The IRWD service area is divided into 77 villages, each with a unique development history, architectural theme, demographic composition, and clearly defined edges (Forsyth, 2002). As of October 29, 2018, the IRWD service area has a spatial extent of approximately 470 km^2 and includes six cities (Tustin, Orange, Lake Forest, Costa Mesa, Newport Beach, and Irvine) as well as unincorporated land (Irvine Ranch Water District). Because single-family residences (SFRs) in all villages are eligible to participate in the turf rebate program, the IRWD turf replacement program is a natural experiment in how the built environment, local demographic and political factors influence patterns of outdoor water conservation.

IRWD benefited from the partnership because they had an abundance of data but very little opportunity or time to explore and evaluate the effectiveness of their past programs. Our findings provide feedback for IRWD to consider more efficient program implementation in the future and their input as program managers and water managers provides valuable context for the data analysis and discussion. Because of IRWD's progressive leadership in this region, these results may inform greater water management policy reform for the broader southern California region, potentially impacting millions of people.

In each chapter of this dissertation, I go into more depth on a particular aspect of the IRWD turf rebate program:

Chapter 1 explores the spatial and temporal patterns of participation among SFRs in the IRWD turf rebate program. We first outline a probabilistic framework that includes "participation probability" which is the probability that a SFR will participate in the turf rebate program. The participation probability varies from village-to-village (spatially) and month-to-month (temporally), but we assume in any given village in any given month it is constant (stationary) and not influenced by neighbors (statistically independent). Results show that 96% of the spatial and temporal variability in participation probability boiled down to a few explanatory variables, namely the home age of an SFR (accounting for spatial variability) and the Google Trends search rates for the term "turf rebate" (accounting for temporal variability). At most, the remaining 4% of the variability in our dataset could be explained by social diffusion – a phenomenon whereby participation in a new technology can be attributed to the influence of one's surrounding neighbors or people in the same social networks (Graziano & Gillingham, 2014; Jackson & Yariv, 2005; Pincetl et al., 2019). This analysis draws a connection between temporal patterns of IRWD turf rebate program participation and Google Trends, which we believe serves as a proxy for mass media coverage of the California drought (Quesnel & Ajami, 2017), triggered by California Governor Jerry Brown's unprecedented emergency drought proclamations in 2014 and sustained by local water conservation campaigns and education programs that provided an outlet for residents to participate in water conservation.

Chapter 2 describes spatial patterns of participation in the IRWD turf rebate program at the parcel level. Using built environment, demographic, and political GIS data from the county tax assessor office (via IRWD), U.S. Census Bureau American Community Survey, and Orange County Registrar of Voters, we evaluate the predictive power of 11 explanatory variables (outdoor area, owner occupancy, average household size, median household income, median house value, and six voting preferences across several political parties). 46,915 SFR parcels in the IRWD service area have a full complement of these 11 explanatory variables and were therefore included in our study. Out of these 46,915 SFR parcels, 1366 participated in the IRWD turf rebate program (participation probability of 2.9%). This analysis employs the use of a machine learning algorithm called CART (classification and regression trees) in which a forest of decision trees is generated from the participation status and the explanatory variables of the SFR participants and an equal number of randomly chosen non-participants. Of the 33 decision trees generated, 23 of them (about 70%) split the dataset according to whether a SFR parcel is owner-occupied or not (first node) followed by whether the parcel's outdoor area is greater than 164 m^2 or not (second node, **Figure 2.4a**). Participation probability is three times higher if a SFR is owner occupied compared to when it is not owner occupied. Among owner occupied SFRs, the participation probability is nearly 4% when the outdoor area is greater than 164 m^2, whereas the participation probability is less than 2% if the outdoor area is less than 164 m^2. Participation probability also increases monotonically with median outdoor area and the participation probability for owner occupied SFRs with outdoor area < 400 m^2 is strongly correlated (R^2=0.91) with median outdoor area. The lawn area replaced also increases with outdoor area, whether the SFR is owner occupied or not. On average, 10 to 15 % of a resident's outdoor area is replaced with drought tolerant landscaping. The distribution of outdoor areas across IRWD's service area are well described by a single log-normal distribution with a median parcel area of 300 m^2. Using a simple water savings model, we explore a thought experiment seeking to produce more equitable participation, whereby we simulate a fixed cash rebate, holding average participation probability constant and removing the influence of outdoor area on participation probability. The result is surprising: reduced participation from SFRs with large outdoor area is balanced by the increase in many more SFR participants with small outdoor areas, due to the log-normal distribution of outdoor areas being positively skewed. Based on this result, it appears possible to achieve goals of equitable participation and water savings using alternative rebate structures.

Chapter 3 outlines a theoretical framework to evaluate the distribution of turf patch sizes in the IRWD service area. Using a high-resolution aerial imagery land use classification dataset, I describe a theoretical framework and construct an empirical turf patch distribution that illustrates the wide range of SFR turf patch sizes and their implications for water savings under the existing IRWD turf rebate program. One key result is that less than one percent of the potential water savings is captured by participation in the turf rebate program thus far. Moreover, even if all the SFR turf patches that fall within IRWD's eligibility range (250 to 1500 ft^2) were converted to drought tolerant landscaping, the resultant water savings captures only about two-thirds of the total potential water savings. This results motivates a discussion on the potential water savings under several scenarios in which the rebate program structure changes, e.g., when the minimum and/or maximum turf area limits are different or when the rebate itself is modified.

I conclude my thesis with Chapter 4, which outlines the summary, conclusions, and potential ideas for future study that build on the work in the first three chapters.

Appendix A is a reproduction of “Obstacles to Wastewater Reuse: an overview”, which is a literature review that I wrote with co-author Professor Jean-Daniel Saphores (Duong & Saphores, 2015). Recycled wastewater is uncommon in most places and even where it is used, its potential is typically underutilized. In conjunction with reducing wasteful outdoor water use, like lawns, we can also improve water efficiency and reduce urban water demand by using recycled water for landscape irrigation and other non-potable uses. This is the trend observed in California already: outdoor landscaping legislation and water efficiency legislation in California are further restricting the amount of turf grass (California Department of Water Resources), as well as imposing water budgets on local water agencies starting in 2020-2021 (2018). As more wastewater treatment plants expand their non-potable reuse operations ("Mayor Garcetti: Los Angeles Will Recycle 100% of City’s Wastewater by 2035," 2019), recycled water is an ever-growing component of the urban water supply portfolio.

Appendix B contains the supplementary information for Chapter 1, a series of figures including a set of seven figures that compare the observed and predicted participation probability for each of the 42 villages included in the analysis.

Appendix C contains the supplementary information for Chapter 2, providing figures and more detailed explanation of the methods used and the implementation of the water savings model, the results of which are described in Chapter 2.

Appendix D contains supplementary figures for Chapter 3, providing more details on the methodology of the ten different land use classifications generated by Quantum Spatial (QSI) for the IRWD land use classification dataset.

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CHAPTER 1

Multi-Scale Drivers of Outdoor Water Conservation

Abstract

Outdoor watering of lawns accounts for about half of single-family residential potable water demand in the arid southwest United States. Consequently, many water utilities in the region offer customers a cash rebate to replace their lawn with drought tolerant landscaping. Here we examine patterns of lawn replacement that took place under the auspices of a "cash-for-grass" rebate program offered by the Irvine Ranch Water District (IRWD) during the worst drought on record in Southern California. We analyzed 1559 lawn rebate applications received by IRWD between October 2010 and March 2017, distributed across 77 villages in the utility's service area. From these data we calculated participation probabilities, defined as the likelihood that a resident in a particular village will apply to the rebate program in a particular month. Household participation in the program is associated with only two variables (96% variance explained), an internal variable reflecting the built environment (average home age) and an external variable reflecting mass media coverage of emergency proclamations issued by the Governor of California (Google search rates in California for the phrase "turf rebate"). Across all villages, the participation probabilities are highest when statewide emergency proclamations coincide with multiple carrot-and-stick water conservation programs offered by the local water utility. Thus, multi-scale policy interventions can be an effective tool for motivating long-term (structural) reductions in outdoor water use.

1.1 Introduction

Climate change and population growth threaten the balance of water supply and demand in many urban regions around the world (Feldman, 2017; Stanley B Grant et al., 2013; Stanley B. Grant et al., 2012; MacDonald, 2010; Padowski & Gorelick, 2014; Sedlak, 2014). A dramatic case in point is the urban water stress brought on by the California Drought of 2011 to 2016, the most severe drought in the southwest United States over the past 1200 years (Griffin & Anchukaitis, 2014). In January 2014, California's Governor Jerry Brown issued the first of a series of emergency proclamations to address the statewide drought, and California's roughly 400 urban water agencies responded with an array of short- and long-term water conservation programs (Mitchell et al., 2017). Because irrigation of lawns accounts for roughly half of residential water demand in a typical California home (DeOreo et al., 2011; Hanak & Davis, 2006), many water agencies employed multiple strategies to bring about reductions in outdoor water use (Mitchell et al., 2017). In general, utilities can encourage conservation through one or more of the following strategies (Wichman, Taylor, & Von Haefen, 2016): (1) direct positive financial incentives such as rebates; (2) direct negative financial incentives such as fines; (3) indirect financial incentives such as tiered pricing, (4) public education campaigns; and (5) sanctions, bans, or norming. In this study we focus on an example of the first approach; namely, a "cash-for-grass" lawn replacement rebate program.

Cash-for-grass programs are a popular approach for incentivizing lawn replacement. In these programs, water agencies offer customers a rebate for replacing irrigated grass in their yards with drought tolerant landscaping (Hilaire et al., 2008; Sedlak, 2014; Sovocool, Morgan, & Bennett, 2006). Even with cash incentives, however, social barriers—such as the preference for lawns, requirements for an initial outlay of cash, and neighborhood norms and covenants—can limit participation (Silvy & Lesikar, 2005). Residential yards are adaptive coupled human-natural systems, characterized by feedbacks between legacy effects, urban design practice, multi-scale human drivers, yard ecology, and ecosystem services and disservices (Cook, Hall, & Larson, 2012; Hale et al., 2015; House-Peters & Chang, 2011). In this context, a key knowledge gap is which policy interventions are likely to overcome social barriers to lawn replacement, while avoid unintended consequences such as negative equity impacts and adverse human and ecosystem health outcomes (Hale et al., 2015; House-Peters & Chang, 2011; Sokolow, Godwin, & Cole, 2016).

To address this knowledge gap, we set out to evaluate the impact of policy interventions, demographics, and the built-environment on residential uptake of a lawn rebate program implemented by the Irvine Ranch Water District (IRWD) in Orange County, California. IRWD's program, which began in late 2010, pays residential customers a fixed unit rebate (i.e., fixed dollars per square foot) to replace lawns with drought-tolerant outdoor landscaping. IRWD's unit rebate changed over time as follows: (1) \$1.50 per square foot from 1 October 2010 through 1 June 2014; and (2) \$2 per square foot thereafter, except for a roughly three-week period (May 1-19, 2015) when the rebate was temporarily increased to \$3 per square foot. Over the period of our study (from October 2010 through March 2017), a total of 1559 single-family residences (SFRs), or 2.6% of the 60,000 SFRs in IRWD's service area, participated in the program, about double the participation rate reported for the neighboring City of Los Angeles (1.5%) (Jessup & DeShazo, 2016). Over the study period, IRWD's program replaced approximately 13 hectares of lawn area with drought tolerant landscaping for an annual water savings of between 130 and 222 megaliters (ML), assuming an average reduction in water use of between 1002 and 1711 L/m^2/year (Tull, Schmitt, & Atwater, 2016). IRWD's service area is divided into 77 villages, each of which has its own architectural theme, development history, demographic composition, and clearly defined edges (Forsyth, 2002). Because SFRs in all 77 villages were eligible to participate, IRWD's rebate program is a natural experiment in how policy interventions, local demographic and economic factors, and the built environment influence patterns of outdoor water conservation. To facilitate apple-to-apple comparisons of water conservation across villages and with time, we introduce a new metric (participation probability) for the likelihood a resident will change their water use behavior.

1.2 Probabilistic Framework for Water Conservation Behavior

Here we describe a probabilistic framework that treats a SFR's decision to apply (or not apply) for a lawn replacement rebate as a Bernoulli trial; i.e., the probability (or "participation probability") that a SFR from a particular village will apply to the program in a particular month is constant (stationary) and not influenced by the application status of neighbors (statistically independent). Within those constraints, the participation probability can vary from month-to-month and from village-to-village. Our assumption that the participation probability is statistical independent is contrary to some studies showing that visible conservation behavior can diffuse through residential communities by "spatial neighbor effects"; e.g., see Graziano & Gillingham (2014). Thus, this assumption should be regarded as a null hypothesis, subject to evaluation and possible rejection. Also note that SFRs who replaced their yards under the auspices of IRWD's rebate program may inspire other SFRs to do the same pro-bono; i.e., without participating in IRWD's rebate program. Because we only have information on SFRs that applied to the rebate program (see later), these pro-bono lawn replacements are not captured in our estimates of the participation probability.

To translate the above concepts into a mathematical framework, we let the indices i and j represent, respectively, a particular village in IRWD's service area (the i-th village) and a particular month of the study (the j-th month). For any particular choice of the indices (i,j) there will be $n_{i,j}$ SFRs who have not yet replaced their lawn and who are therefore eligible to participate in the rebate program. We refer to the decision of these $n_{i,j}$ eligible customers to apply (or not apply) to the rebate program as "trials", and let the random variable X_k represent the outcome of k trials. For a single trial ($k=1$), the random variable realizations $X_1=1$ or $X_1=0$ correspond to the decision of a single SFR to apply or not, with corresponding probabilities $p_{i,j}$ or $1-p_{i,j}$, respectively. The probability $p_{i,j}$ is the participation probability we referred to above, and therefore $p_{i,j}$ is assumed to be stationary (for any choice of the indices i,j) and statistically independent from trial to trial. Given these preliminaries, the probability that exactly $X_{k=n_{i,j}}=x$ eligible SFRs from the i-th village will apply on the j-th month is given by the Binomial distribution (Ang & Tang, 2007):

$$\Pr\left(X_{k=n_{i,j}}=x;p_{i,j}\right)=\begin{pmatrix} n_{i,j} \\ x \end{pmatrix} p_{i,j}^{x}\left(1-p_{i,j}\right)^{n_{i,j}-x} \tag{1}$$

From the Binomial distribution we can also estimate the mean number of rebate applications in the i-th village on the j-th month ($\mu_{i,j}$) from the product of the participation probability and number of trials in that village and month, where $E[\cdot]$ is the expectation operator:

$$\mu_{i,j}=E\left[X_{n_{i,j}};p_{i,j}\right]=p_{i,j}\times n_{i,j} \tag{2}$$

The number of trials $n_{i,j}$ is equal to the number of SFRs in the i-th village ($n_{\mathrm{SFR},i}$) minus the number of SFRs in the i-th village that have already applied for a rebate by the j-th month (and hence are no longer eligible to participate in the lawn replacement program):

$$n_{i,j} = n_{\mathrm{SFR},i} - \sum_{k=1}^{j-1} p_{i,k} \times n_{i,k} \tag{3}$$

The total number of applications received from the i-th village by the j-th month follows from summing the mean number of applications from the i-th village up to the j-th month and substituting equation (2):

$$N_{i,j} = \sum_{k=1}^{j} \mu_{i,k} = \sum_{k=1}^{j} p_{i,k} \times n_{i,k} \tag{4}$$

Letting the variable $N_{i,j-1}$ represent the number of applicants received from the i-th village by the $(j-1)$-th month, the variable $n_{i,k}$ can be rewritten as follows: $n_{i,k} = n_{\mathrm{SFR},i} - N_{i,k-1}$. Substituting this last result into equation (4) we arrive at our final result for the cumulative number of applicants received from the i-th village by the j-th month:

$$N_{i,j} = n_{\mathrm{SFR},i} \sum_{k=1}^{j} p_{i,k} - \sum_{k=1}^{j} p_{i,k} \times N_{i,k-1} \tag{5}$$

The first term on the right hand side of equation (5) represents the cumulative number of SFR applications that would be predicted if SFRs are not removed from the pool of eligible applicants after they apply for a rebate. The second term is a correction to account for the fact that, generally speaking, SFRs that have previously applied for a rebate will not apply for a rebate again.

1.3 Experimental Methods

1.3.1 Rebate Application Data

Customers applying to IRWD's lawn rebate program were included in our analysis provided they: (1) filed their application within the study period (October 2010 to March 2017); (2) replaced their lawn with drought tolerant landscaping and subsequently received a rebate check from IRWD; and (3) were an SFR customer, defined as a residential detached dwelling that holds an individual IRWD account and uses potable water for outdoor irrigation. Because lawn rebates were typically processed within 6 months of the initial application, we evaluated the status of rebate applications as of November 2017, eight months after our study period ended.

1.3.2 Maximum Likelihood Estimation of Participation Probabilities

Participation probabilities were calculated from the rebate application data described above as follows. Within our Binomial framework, the maximum likelihood estimator (MLE) of the participation probability is the fraction of trials that yield rebate applications (Ang & Tang, 2007); these MLE values are designated with a caret character. Different participation probabilities were estimated from IRWD's rebate data, depending on the question of interest (see Table 1). Specifically, participation probabilities (units of probability month^{-1}) were estimated for the: (1) i-th village on an average month ($\hat{p}_i$); (2) i-th village on the j-th month ($\hat{p}_{i,j}$); (3) service area ("SA") on an average month ($\hat{p}_{\mathrm{SA}}$); and (4) service area on the j-th month ($\hat{p}_{\mathrm{SA},j}$).

1.3.3 Multiple Linear Regression (MLR)

Village-specific estimates of the participation probability $\hat{p}_i$ were regressed against built-environment and demographic variables using multiple linear regression (MLR). MLR studies were conducted with glmulti in R software (R Core Team). Variables were first (base-10) log-transformed to improve normality and allow for the expression of regression formulas in power-law form (see later). Variance inflation factor (VIF) was used to evaluate multicollinearity of candidate predictor variables; predictor variables were included in the MLR analysis provided the following inequality was satisfied: VIF < 5. Candidate MLR models were ranked by Bayesian Information Criterion (BIC) and then evaluated based on two additional criteria: (1) the significance of model terms ($p<0.01$); (2) leave-one-out-cross-validation Root Mean Squared Error (RMSE). The model with the lowest BIC was selected as the top model, except when the top two or three models differed by less than 2 BIC units. In such cases, a top model was selected from the top two or three models based on the significance of terms (preference given to the model for which all terms are significant, $p<0.01$). If all terms were significant the model with the lowest RMSE was selected as the top model. The relative importance of each explanatory variable (i.e., the proportionate contribution made to the variance explained) was estimated using the averaging over ordering method. The fraction of data variance explained by each model was estimated from the coefficient of determination.

1.3.4 Built Environment and Demographics

Average built-environment and demographic explanatory variables included in the MLR were estimated for each village from the following GIS shapefiles (provided by IRWD, updated 2015 or later): (i) customer account data; (ii) parcel-scale tax assessor information; and (iii) village boundaries. These data were filtered by SFRs and then averaged over village boundaries. For data at the parcel scale (lot size, home age, building area, and owner occupancy) SFR filtering was accomplished using the Spatial Join tool within ArcMap (Esri, ArcGIS version 10.5, Redlands, California).

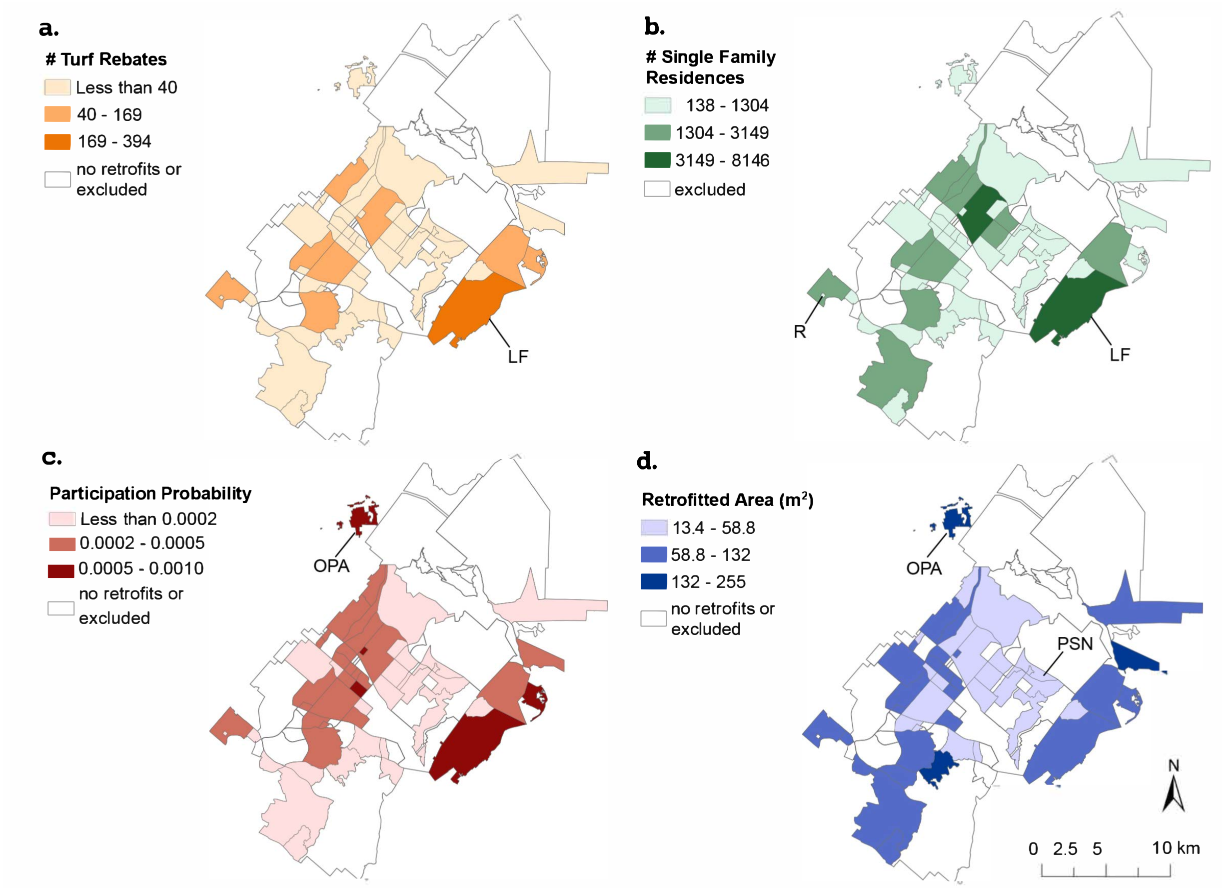

Figure 1.1. Village-specific patterns of SFR participation in IRWD's cash-for-grass lawn rebate program

Maps show for each village the: (**a**) number of rebates issued to SFRs over the study period; (**b**) number of SFRs based on customer account data; (**c**) per-month village-specific participation probability ($\hat{p}_i$); and (**d**) average lawn area retrofitted per rebate. Villages with fewer than 100 SFRs were excluded. Abbreviations denote Lake Forest (LF), Riviera (R), Orange Park Acres (OPA), and Portola Springs North (PSN).

1.3.5 Empirical Orthogonal Function (EOF) Analysis.

EOF analysis was performed to identify the dominant village-to-village and month-to-month patterns associated with the participation probabilities $\hat{p}_{i,j}$. EOF is a spatiotemporal form of principal component analysis (PCA), in which dominant spatial and temporal patterns are represented by PCA coefficients and scores, respectively (e.g., see Jeong et al., 2005). PCA was performed (Matlab, Mathworks, MA) on mean-centered values of $\hat{p}_{i,j}$ from the 15 villages that account for 80% of lawn rebates. A resampling-based stopping rule (Peres-Neto, Jackson, & Somers, 2005) was used to identify PCA modes that explained more variance in program participation than expected by chance (5% threshold).

1.4 Results

1.4.1 Village-Specific Patterns of Rebate Participation

To minimize small sample size bias when analyzing village-specific patterns, we excluded 25 villages that had fewer than 100 SFRs (only two rebates were issued to these 25 villages over the study period). The number of rebates issued in the remaining 52 villages ranged from zero rebates in six villages to 394 rebates in Lake Forest ("LF" in **Figure 1.1a**). The distribution of rebates is positively skewed (skewness coefficient $\theta = 0.93$, **Figure B.1**), with 80% of rebates (1246 out of 1557) coming from approximately 30% of villages (15 out of 52).

Some of the village-to-village variation in rebates may reflect differences in the number of SFRs across villages (**Figure 1.1b**). To remove population size effects, we calculated the average probability that a randomly selected SFR in the *i*-th village will apply to IRWD's rebate program in any given month, or village-specific participation probability $\hat{p}_i$. Values of village-specific participation probability ranged from 0% per month in six villages to 0.1% per month in Orange Park Acres ("OPA" in **Figure 1.1c**). The high participation rate observed in OPA may reflect the fact that IRWD conducted extensive outreach to residents of this village, to help them transition from an inclining block rate structure to IRWD's budget based rate structure in July

2015. Averaged over the service area, the average participation probability is $p_{\mathrm{SA}} = 0.033\%$ per month. The average lawn area replaced per rebate varied from 13.4 m^2 per rebate in Portola Springs North ("PSN") to 255 m^2 per rebate in OPA (**Figure 1.1d**).

Multiple Linear Regression (MLR) studies were conducted to identify built-environment and demographic attributes that might explain the village-to-village variation in village-specific probabilities $\hat{p}_i$. Of the five candidate explanatory variables investigated (see Table 2), average lot area ($\mathrm{lot}_{\mathrm{area}}$) was excluded due to its covariance with average outdoor lot area ($\mathrm{lot}_{\mathrm{outdoor\ area}}$) (VIF >5, see Methods). In addition, 10 villages were excluded because they lacked a full complement of candidate explanatory variables. For the remaining 42 villages, the top MLR model (Model 1 in Table 2) captures 74.2% of the variance in log-transformed $\hat{p}_i$ values ($r^2 = 0.74$). This model, which includes log-transformed mean home age in a village ($h_{a,i}$, units of years) as the sole explanatory variable, is represented in power-law form as follows:

$$\hat{p}_i = 10^{-4.60 \pm 0.09} h_{a,i}^{\ 0.76 \pm 0.07} \tag{6}$$

Participation probability is positively correlated with home age $h_{\mathrm{a},i}$ in all top three MLR models (Table 2). The top second and third models also include positive correlations with average outdoor area (Models 2 and 3) and owner occupancy (Model 3), and a negative correlation with average lot value (Models 2 and 3). Consistent with previous studies (Atwater, Schmitt, & Atwater; Chang, Bonnette, Stoker, Crow-Miller, & Wentz, 2017; Fielding, Russell, Spinks, & Mankad, 2012), all three top MLR models point to features of the built environment (home age, outdoor area, and lot value) as key determinants of water conservation behavior.

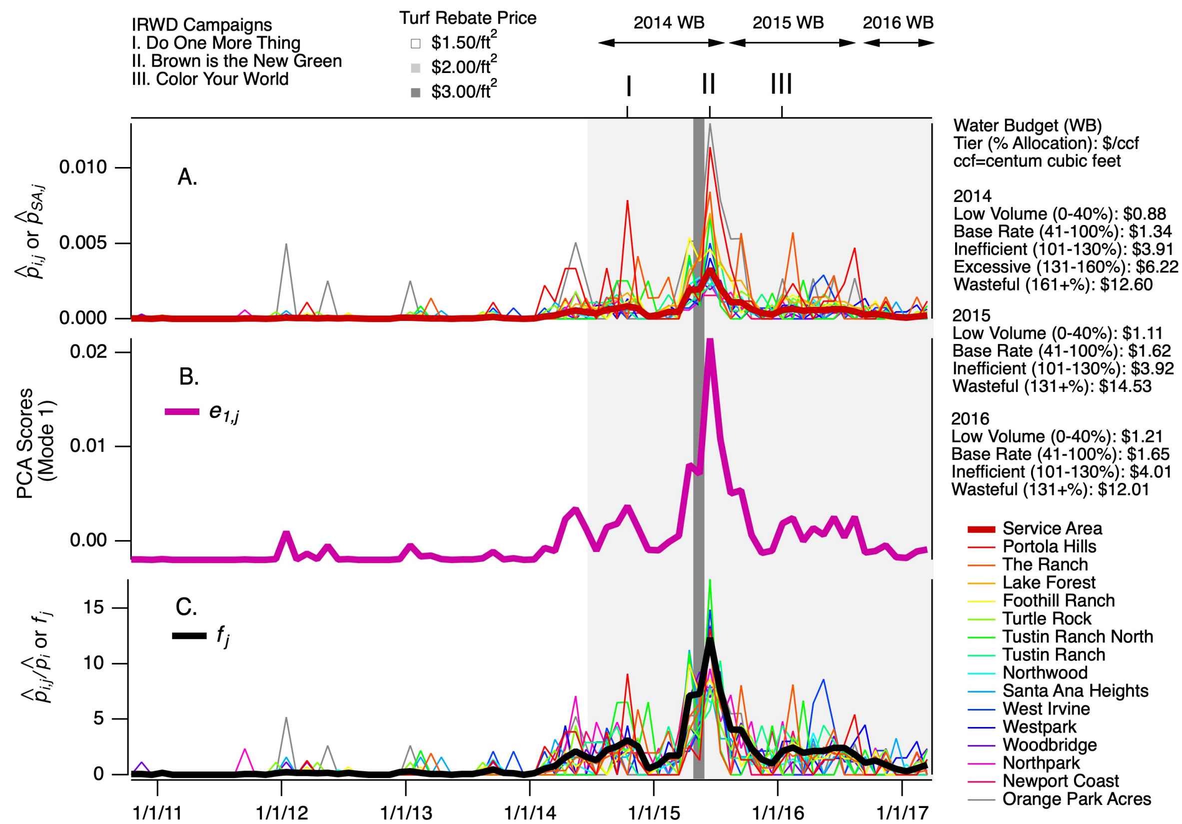

Figure 1.2. Dynamics of SFR participation in IRWD's lawn rebate program.

(**a**) Participation probability in the *i*-th village on the *j*-th month for the 15 villages that account for 80% of rebates (colored curves). Thick red curve represents the monthly participation probability for the service area as a whole. (**b**) The single temporal pattern ($e_{1,j}$) identified by empirical orthogonal function (EOF) analysis. (**c**) Same data as in (**a**) but scaled by the village-specific participation probability. The thick black curve is the universal temporal pattern f_j calculated from equation (3). Background shading indicates the unit rebate IRWD paid for lawn replacement. Labels I, II, and III indicate the timing of ad campaigns. IRWD annual water budgets and tiered pricing structures for fiscal years 2014, 2015, and 2016 are also indicated, as described in the main text.

1.4.2 Rebate Dynamics

To receive a rebate, SFRs completed an online application, passed a pre-retrofit inspection to confirm eligibility, and passed a post-retrofit inspection to certify that grass was replaced with drought tolerant landscaping. Because we know the date successful rebate applications were first lodged, we can gauge interest in the rebate program over time by calculating the participation probability for the *i*-th village on the *j*-th month ($\hat{p}_{i,j}$). The probability $\hat{p}_{i,j}$ is similar to $\hat{p}_i$ except the latter is calculated from applications received from the *i*-th village over the entire 78-month study period, whereas the former is calculated from applications received from the *i*-th village only in the *j*-th month. We also averaged $\hat{p}_{i,j}$ over all 52 villages included in the study, to obtain a monthly participation probability for the service area as a whole ($\hat{p}_{\mathrm{SA},j}$) (see definitions in Table 1.1).

If the monthly participation probability does not vary month-to-month the following equality should hold: $\hat{p}_{i,j} = \hat{p}_i$. Instead, we found that the participation probability in the *i*-th village $\hat{p}_{i,j}$, and in the service area as a whole $\hat{p}_{\mathrm{SA},j}$, exhibits substantial month-to-month variability (**Figure 1.2a**). An EOF analysis of these data (see Methods) reveals that a single dominant mode (denoted here as "Mode 1") explains 71% of the variance in $\hat{p}_{i,j}$. Thus, $\hat{p}_{i,j}$ can be approximated by equation (7), where $e_{1,i}$ and $e_{1,j}$ represent the spatial (village-to-village) and temporal (month-to-month) Mode 1 patterns, respectively (a plot of the temporal pattern $e_{1,j}$ is presented in **Figure 1.2b**):

$$\hat{p}_{i,j} \approx e_{1,i} \times e_{1,j} \tag{7}$$

The temporal pattern $e_{1,j}$ is strongly correlated with $\hat{p}_{\mathrm{SA},j}$ (Pearson's correlation coefficient $r = 0.97$): $e_{1,j} \approx 6.3\hat{p}_{\mathrm{SA},j}$ (**Figure 1.3a**). Likewise, the spatial pattern $e_{1,i}$ is strongly correlated with $\hat{p}_i$ ($r = 0.98$): $e_{1,i} \approx 591\hat{p}_i$ (**Figure 1.3b**). Substituting these correlations into equation (7) and rearranging terms, we arrive at equation (8) where f_j (unitless) is a universal temporal pattern that captures how public interest in the rebate program changes over time across all villages:

$$f_j \equiv 3723 \times \hat{p}_{\mathrm{SA},j} \approx \frac{\hat{p}_{i,j}}{\hat{p}_i} \tag{8}$$

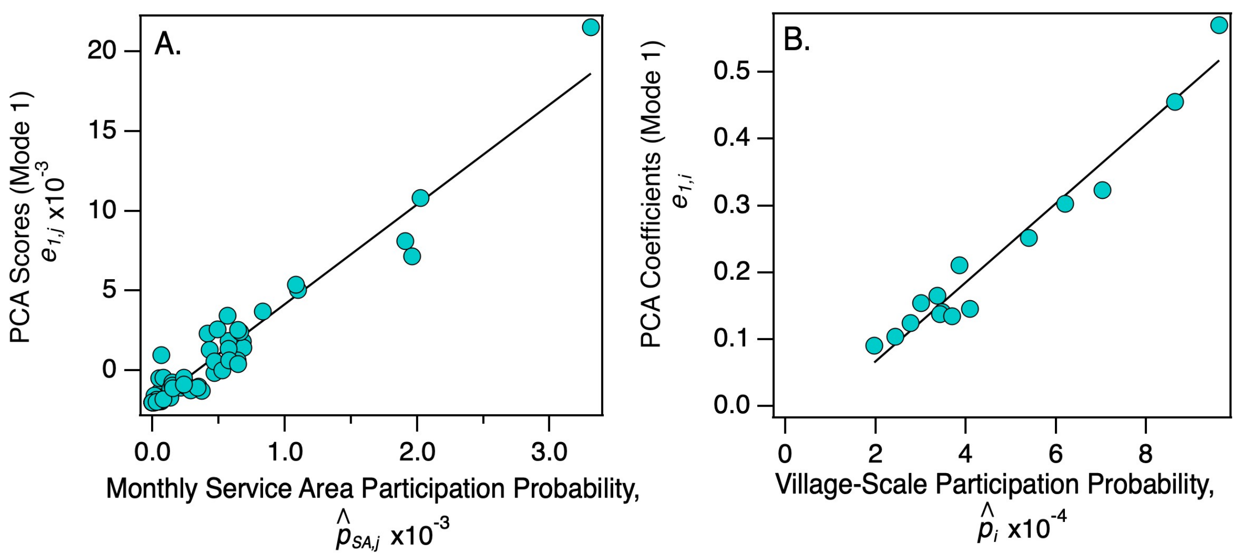

Figure 1.3. EOF Mode 1 spatial and temporal patterns are correlated with two key participation probabilities.

(a) The temporal pattern $e_{1,j}$ is correlated with $\hat{p}_{\mathrm{SA},j}$ (coefficient of determination, $r^2 = 0.94$). (b) The spatial pattern $e_{1,i}$ is correlated with $\hat{p}_i$ ($r^2 = 0.96$).

Equation (8) has two important implications. First, $\hat{p}_{i,j}$ should collapse to a single universal temporal pattern (i.e., f_j) when normalized by $\hat{p}_i$. As predicted, when the $\hat{p}_{i,j}$ values for the top 15 villages (accounting for 80% of rebates; see colored curves in **Figure 1.2a**) are normalized by $\hat{p}_i$, the ratio $\hat{p}_{i,j}/\hat{p}_i$ collapses to f_j (colored curves in **Figure 1.2c**). Second, equation (3) can be rearranged to yield a simple formula for the participation probability in the *i*-th village on the *j*-th month:

$$\hat{p}_{i,j} \approx \hat{p}_i f_j \tag{9}$$

From our earlier analysis we know that $\hat{p}_i$ is strongly correlated with average home age in a village (equation (6)). In the next section we show that f_j is strongly correlated with mass media coverage of drought-related topics.

1.4.3 Mass Media Coverage of Water Scarcity

What causes interest in IRWD's rebate program (as represented by f_j) to rise and fall synchronously across all villages? One possible explanation is that the unit rebate offered by IRWD changed over time (see shading in **Figure 1.2**). The first adjustment (from \$1.50 to \$2.00 per square foot, white to light grey shading) is not coincident with an increase in rebate applications; instead, interest in the program declines modestly (**Figures 1.2b and 1.2c**). On the other hand, the brief (roughly three week) unit rebate increase to \$3.00 per square foot (in May 2015, dark grey shading) may have contributed to the all-time peak rebate application rate one month later. While changes in the unit rebate may have influenced application rates in this one case, on the whole the dynamics apparent in **Figure 1.2** cannot be ascribed to changes in the unit rebate alone.

In a recent study of urban water conservation behavior, Quesnel and Ajami, 2017 reported that SFRs in the San Francisco Bay area “decreased water use at the fastest rate following heavy drought-related news media coverage.” To evaluate if mass media coverage might also drive interest in the rebate program, we evaluated the correlation between f_j and mass media coverage of (and public interest in) drought-related topics in California. As a proxy for mass media coverage, we generated from the online tool Google Trends monthly search rates in California for several phrases including “drought tolerant landscaping,” “mandatory water restrictions,” “turf removal,” and “turf rebate” (see (Quesnel & Ajami, 2017) for a discussion of the relationship between Google search rates for, and mass media coverage of, drought-related topics in California). The monthly search rates generated by *Google Trends* are represented as a percentage of the largest monthly search rate over the period of interest (in our case, from October 2010 to March 2017).

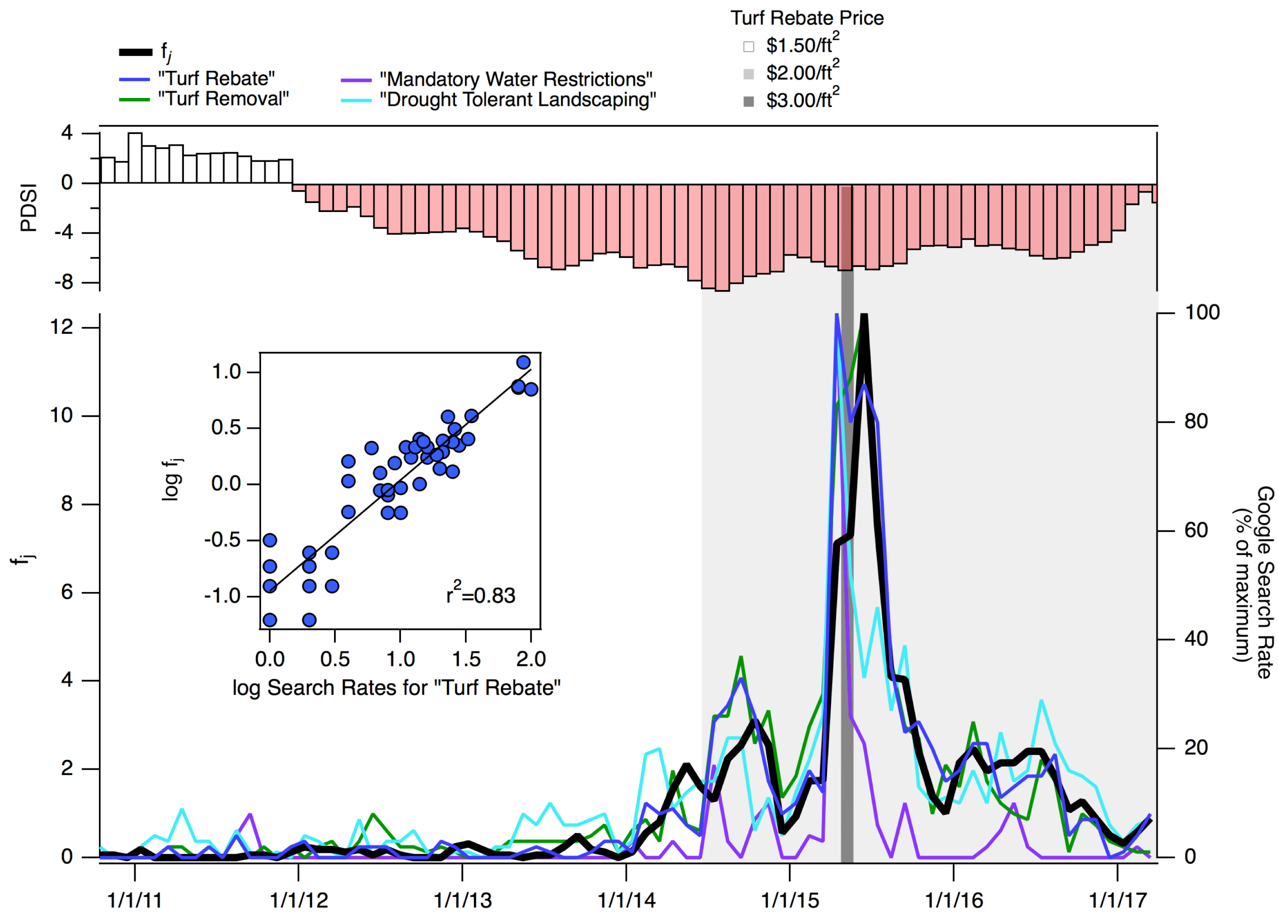

Figure 1.4. Google search rates for drought related topics are correlated with participation in IRWD's lawn rebate program.

Comparison of the Palmer Drought Severity Index for Southern California (PDSI, positive and negative values indicate wet and dry conditions, respectively) (upper plot) with the universal temporal pattern (f_j , black curve) and normalized monthly Google search rates in California for the four phrases indicated (colored curves) (lower plot). Inset shows values of f_j plotted against normalized Google search rates for the phrase "turf rebate", plotted on a log-log basis. The line corresponds to equation (10).

Google search rates for the four phrases above, which were downloaded from *Google Trends* on 11 June 2018, are presented in the lower panel of **Figure 1.4**. Search rates for all four phrases are relatively low (<10%) during the first two years following the onset of drought conditions, as indicated by negative values of the monthly Palmer Drought Severity Index for Southern California (PDSI) (upper panel in **Figure 1.4**). Search rates for "drought tolerant landscaping," "turf removal," and "turf rebate" begin to increase after January 2014, coincident with Governor Brown's first State of Emergency proclamation urging California residents in urban areas to voluntarily curb water use by 20%. Search rates for all four phrases peak in April 2015, coincident with the Governor's second State of Emergency proclamation (issued on April 1, 2015) mandating an unprecedented average statewide 25% reduction in urban potable water consumption. While all four search rates peak in April 2015, they taper off at different rates. "Mandatory water restrictions" tapers off most quickly followed by "drought tolerant landscaping," then "turf rebate" and "turf removal."

The universal temporal pattern f_j is most highly correlated with search rates for the phrase "turf rebate" ($r=0.91$), followed by "drought tolerant landscaping" ($r=0.79$), "turf removal" ($r=0.76$), and "mandatory water restrictions" ($r=0.43$). The relationship between log-transformed f_j and log-transformed search rates for "turf rebate" (denoted here by the variable g_j, units of percent maximum search rate) can be represented in power-law form as follows (see inset in **Figure 1.4**, coefficient of determination, $r^2=0.83$):

$$f_j=10^a g_j^b,\ a=-0.95\pm0.073,\ b=0.99\pm0.07 \tag{10}$$

The linear relationship between f_j and g_j implied by equation (10) imply that rebate applications increased in direct proportion to Google search rates for the phrase "turf rebate". As noted earlier, month-to-month variations in g_j are associated with mass media coverage of Governor Brown's emergency proclamations.

1.4.4 Model for the Evolution of Water Conservation Behavior

The results presented above suggest that the participation probability $\hat{p}_{i,j}$ can be factored into the product of a universal temporal pattern f_j and a village-specific pattern $\hat{p}_i$ (equation (9)). Furthermore, the universal pattern increases linearly with the monthly Google search rates in California for the phrase "turf rebate" g_j (equation (10)), while the village-specific pattern depends on the average home age in a village $h_{a,i}$ (equation (6)). Combining these results we obtain the following simple formula for the participation probability:

$$\hat{p}_{i,j} \approx 10^{-5.55} h_{a,i}^{\ \ 0.76} \times g_j \qquad (11)$$

Substituting this last result into equation (5), we can estimate the cumulative number of rebate applications $N_{i,j}$ received from the *i*-th village by the *j*-th month from only two pieces of information: an internal variable reflecting the built environment (average home age, $h_{a,i}$) and an external variable reflecting public awareness of lawn replacement as a means of addressing the water shortfall in California (Google search rates for "turf rebate", g_j). Remarkably, equation (5) captures 96% ($r^2 = 0.96$) of the variance in observed rebate applications over the 78-month period of our study and across the 42 villages included in the MLR (**Figures B.2 – B.9**). The predictive power of the model is illustrated in **Figure 1.5**, where we compare maps of observed and predicted cumulative rebate applications from the 42 villages at four points in time.

1.5 Policy and Research Implications

1.5.1 Interventions at Multiple Scales

Our results document the dramatic impact that the Governor's statewide emergency proclamations had on mass media coverage of the California drought, and participation in IRWD's rebate program. Google search rates for drought-related topics increased after both proclamations; furthermore, the magnitude of the response reflects the proclamation's urgency. The Governor's first proclamation (January 2014, setting voluntary water conservation targets across California) coincided with a modest increase in normalized Google search rates. The usage across California) coincided with peak search rates for all four phrases investigated (**Figure 1.4**).

As noted earlier, Quesnel and Ajami (2017) found that Google search rates of drought related topics are a proxy for mass media coverage of the California drought, and are strongly correlated with voluntary water conservation in the San Francisco Bay area. While a similar process may be occurring here, several caveats should be noted. First, some of the voluntary water conservation activities captured in Quesnel and Ajami's study are non-structural (e.g., temporary reductions in outdoor watering) and thereby subject to reversion or "drought rebound" after the imminent threat of drought recedes (Beal, Makki, & Stewart, 2014) (Gonzales & Ajami, 2017). By contrast, drought rebound is less likely to occur for structural changes (such as lawn replacement) given the significant investment of time and money entailed. Second, while non-structural conservation may exhibit drought rebound, one potential benefit is that the same residents can curtail water consumption again when the next drought occurs. By contrast, structural conservation can lead to "demand hardening" in which efforts to induce water conservation become progressively more difficult over time (Lund, 1995). As applied to the lawn rebate program, demand hardening might occur if residents more inclined to replace their yards sign up initially, leaving behind a population of residents less willing or able to participate. One implication is that the dramatic increase in participation probability (as represented by the universal pattern f_j) we observed after the Governor's second emergency proclamation may not be reproducible going forward.

IRWD also played a critical role in promoting outdoor water conservation, most obviously by offering the rebate program, but also through its multiple ancillary water conservation and education programs. IRWD (with additional funding from the water wholesaler, the Metropolitan Water District) actively marketed the lawn rebate program as part of several ad campaigns, including "Do One More Thing", "Brown is the New Green", and "Color Your World" (designated I, II, and III, respectively, in **Figure 1.2**). Following the Governor's emergency proclamations, IRWD also increased the unit rebate paid for lawn replacement (from \$1.50 to \$2.00, and briefly to \$3.00 per square foot, see **Figure 1.2**) and adjusted its tiered water pricing to incentivize conservation by: (1) decreasing the water budget assigned to each home through a decrease in the water allocations for outdoor plants; (2) increasing the billing rate within each tier commensurate with the cost of water; and (3) adjusting the boundaries between tiers (as a percentage of a resident's water budget, see water budgets (WB) for 2014, 2015, and 2016, **Figure 1.2**). These (local) "carrot and stick" programs reinforced the Governor's (statewide) emergency proclamations, and enabled the dramatic surge in rebate applications that followed. On the other hand, if the Governor had not issued the two emergency proclamations, a counterfactual simulation with our probability model reveals that IRWD would have received 1431 (95%) fewer rebate applications, equal to a lost water savings of approximately 123 to 211 ML per year or roughly 1.2% to 2% of IRWD's potable water demand reduction target. This counterfactual scenario was simulated by setting the normalized Google Trends search rate for the phrase "turf rebate" in equation (11) equal to the average value observed prior to the Governor's first proclamation. Thus, it was the multi-scale and coordinated nature of policies and programs implemented during the California drought that convinced so many residents to replace their lawns with drought tolerant landscaping.

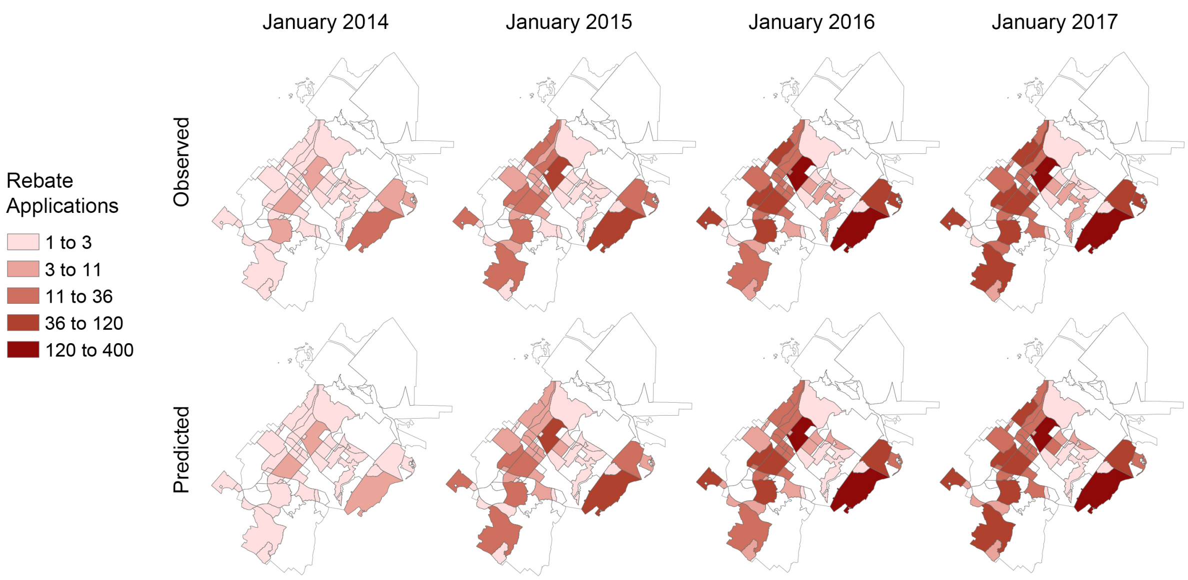

Figure 1.5. A comparison of observed and predicted rebate applications received from each village by the four dates indicated.

Rebate applications are predicted from equations (5) and (11) based on only two pieces of information: (1) the average home age in a village and (2) the normalized monthly Google search rate for the phrase "turf rebate."

1.5.2 Social Diffusion

In his classic model of social diffusion, Bass (Bass, 1969) postulated that new behaviors (or products or innovations) spread through a community through the combined action of "innovators" who adopt the behavior spontaneously, and "imitators" who adopt the behavior under the influence of those who have already adopted. Various forms of social diffusion have been observed in many human and economic systems (Jackson & Yariv, 2005). For example, (Graziano & Gillingham, 2014) found that the adoption of rooftop solar photovoltaic (PV) systems spread through residential neighborhoods in Connecticut in a "wave-like centrifugal pattern" qualitatively consistent with social diffusion of neighborhood scale conservation behavior. In contrast, we explained 96% of the variance in IRWD's rebate applications by adopting the null hypothesis that a SFR's decision to apply for rebate is statistically independent of whether or not neighbors have done the same. While this does not prove that social diffusion is not occurring (i.e., we cannot assume that the participation probabilities are statistically independent based on this result alone), from a practical perspective it implies that the inclusion of social diffusion in our probabilistic framework would have improved the variance captured by no more than 4%.

As noted by Graziano and Gillingham (2014), several features of the PV rebate program in Connecticut—which have no analogs in IRWD's rebate program—may have facilitated diffusion, including the designation of 'Solarize' towns that "choose a preferred installer, receive a group buy that lowers the price with more installations and receive an intensive grassroots campaign with information sessions and local advertising". Unlike rooftop PV installation, replacing grass with drought tolerant landscaping also requires a complex set of household-specific decisions about landscape design, plant selection, irrigation systems, and tolerance for ongoing maintenance requirements (Cook et al., 2012).

1.5.3 Built Environment

Our results also indicate that the average home age in a village is a strong predictor of the probability a resident will apply for a rebate in any given month (equation (6)). We can think of at least three possible explanations, operating alone or in combination, for this result. The first is homophily, a social phenomenon in which similar people tend to live in close proximity (McCrea, 2009). For example, the residents of owner occupied older homes with larger yards (see Table 1.2) may, as a group, have more disposable income for undertaking major landscape investments. The second is physical constraints imposed by the built environment. For example, many newer homes in the IRWD service area are built with drought tolerant landscaping, making them ineligible to participate in IRWD's lawn rebate program. Furthermore, older homes with larger yards are more expensive to irrigate under the water budget and tiered pricing structure used by IRWD. The third is interactions between the built environment and economic incentives intrinsic to IRWD's rebate program. For example, higher program participation by older homes (with larger yards, see above) may reflect the larger cash rebate checks received under IRWD's fixed unit rebate payment structure (either \$1.50, \$2, or \$3 per square foot, depending on the time frame). If SFRs respond to the total rebate payout (instead of unit rebate), households with smaller yards might be more inclined to participate if the unit rebate increased with decreasing lawn area. To the extent that yard size scales with household income, such an approach might also address equity concerns, by minimizing payments to customers who are likely to replace their lawns without a subsidy and maximizing payments to customers who are likely to replace their lawn only with financial assistance. The inequitable phenomenon of higher-income households more commonly taking advantage of environmental rebate programs is well documented, due to the lump sum nature of investments, considerable cash flow required, and long payback periods (DeShazo, Sheldon, & Carson, 2017). Unpacking how these various local demographic and built-environment attributes influence village-scale participation in lawn rebate programs, perhaps in concert with the rate structure of the rebate program itself, is an exciting topic for future study.

Table 1.1. Definitions and formulae for key variables.

Symbol	Calculation*, †, ‡	Description
$\hat{p}_i$	$\dfrac{\text{\# rebates from village } i \text{ over study period}}{(78 \text{ months}) \times (\text{\# SFRs in village } i)}$	Probability an eligible SFR in village i applied to the rebate program in any month
$\hat{p}_{i,j}$	$\dfrac{\text{\# rebates from village } i \text{ on month } j}{\text{\# eligible SFRs in village } i \text{ on month } j}$	In the j-th month, the fraction of SFR in village i that applied to the rebate program
p_{SA}	$\dfrac{\text{\# rebates from service area over study period}}{(78 \text{ months}) \times (\text{\# SFRs in service area})}$	The fraction of SFR in the service area that applied to the rebate program in any month
$p_{\mathrm{SA},j}$	$\dfrac{\text{\# rebates in service area on month } j}{\text{\# eligible SFRs in service area on month } j}$	In the j-th month, the fraction of SFR in the service area that applied to the rebate program
$n_{\mathrm{SFR},i}$	# SFR households in village i	Number of SFR households in village i
$N_{i,j}$	$\sum_{k=1}^{j} \left(\begin{array}{l} \text{\# rebates received from} \\ \text{village } i \text{ on month } k \end{array} \right)$	Cumulative number of rebate applications received from the i-th village by the j-th month

* "month j" is the j-th consecutive month since the start of the study period on 1 October 2010 (for example 1 October 2011 corresponds to $j=12$)

† "eligible SFRs" are SFRs that appear in IRWD's customer account records and have not already applied to the rebate program

‡ "service area" includes the 52 villages included in the analysis of village-specific patterns (see main text).

Table 1.2. Multiple linear regression models for the log-transformed participation probability ($\log_{10} \hat{p}_i$).

Candidate Explanatory Variables			
Variables	Description	Units	Source
$\mathrm{lot}_{\mathrm{value}}$	Mean value of SFR lots	2015 USD	IRWD Parcel data
$\mathrm{lot}_{\mathrm{area}}$	Mean area of SFR lots	square feet	IRWD Parcel data
$\mathrm{lot}_{\mathrm{outdoor\ area}}$	Mean SFR lot area minus mean building area	square feet	IRWD Parcel data
$\mathrm{occup}_{\mathrm{owner}}$	Fraction of owner occupied SFR	--	IRWD Parcel data
$\mathrm{home}_{\mathrm{age}}$	Mean age of SFR homes (relative to 2017)	years	IRWD Parcel data

Top Three MLR Models§						
	Model 1 (top model)		**Model 2**		**Model 3**	
Model Information						
Num. of Observations	42		42		42	
F-statistic¶	119*** (df=40)		48.57*** (df=38)		37.57*** (df=37)	
Model Terms	Coeff. (SE)	VE# (%)	Coeff. (SE)	VE# (%)	Coeff. (SE)	VE# (%)
Intercept	-4.60 (0.09)**	---	-3.67 (1.05)*	---	-3.28 (1.08)*	---
$\log_{10}(\mathrm{home}_{\mathrm{age}})$	0.76 (0.07)**	---	0.48 (0.12)**	41.9	0.43 (0.12)*	36.4
$\log_{10}(\mathrm{occup}_{\mathrm{owner}})$	---	---	---	---	0.75 (0.57)	10.9
$\log_{10}(\mathrm{lot}_{\mathrm{value}})$	---	---	-0.50 (0.20)	19.4	-0.52 (0.20)	17.8
$\log_{10}(\mathrm{lot}_{\mathrm{outdoor\ area}})$	---	---	0.67 (0.26)	18.0	0.63 (0.26)	15.1
Model performance metrics						
Adjusted R^2	74.2%		77.7%		78.1%	
RMSE	0.189		0.188		0.187	
BIC	7.708		6.925		8.737	
BIC Weight	0.224		0.331		0.134	

§ Significance codes: '**' p<0.001, '*' p<0.01
¶ df=degrees of freedom
# VE=variance explained

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CHAPTER 2

Parcel Scale Analysis of Participation in IRWD Turf Rebate Program

Abstract

Outdoor watering of lawns accounts for about half of single-family residential potable water demand in the arid southwest United States. Consequently, many water utilities in the region offer customers cash rebates to replace lawns with drought tolerant landscaping. Here we present a parcel-scale analysis of water savings achieved by a "cash-for-grass" program offered to 60,000 homes in Southern California. The probability a resident will participate in the program, and the lawn area they replace with drought tolerant landscaping, both increase with a home's outdoor area. The participation probability also depends on a home's owner occupancy status. From these results we derive and test a simple mathematical model for predicting the total water savings achieved by a cash-for-grass program, taking into account the number-distribution of parcel outdoor areas across a utility's service area, climate, cultural drivers of landscape choices, conservation behavior, equity concerns, and financial incentives.

2.1 Introduction

Climate change and population growth threaten the balance of water supply and demand in many urban regions around the world (Feldman, 2017; Stanley B Grant et al., 2013; Stanley B. Grant et al., 2012; MacDonald, 2010; Padowski & Gorelick, 2014; Sedlak, 2014). A dramatic case in point is the urban water stress brought on by the California Drought of 2011 to 2016, the most severe drought in the southwest United States over the past 1200 years (Griffin & Anchukaitis, 2014). In January 2014, California's Governor Jerry Brown issued the first of a series of emergency proclamations to address the statewide drought, and California's roughly 400 urban water agencies responded with an array of short- and long-term water conservation programs (Mitchell et al., 2017). Because irrigation of lawns accounts for roughly half of residential water demand in a typical California home (DeOreo et al., 2011; Hanak & Davis, 2006), many water agencies employed multiple strategies to bring about reductions in outdoor water use (Mitchell et al., 2017). In general, utilities can encourage conservation through one or more of the following strategies (Wichman, Taylor, & Von Haefen, 2016): (1) direct positive financial incentives such as rebates; (2) direct negative financial incentives such as fines; (3) indirect financial incentives such as tiered pricing, (4) public education campaigns; and (5) sanctions, bans, or norming. In this study we focus on an example of the first approach; namely, a "cash-for-grass" lawn replacement rebate program.

Cash-for-grass programs are a popular approach for incentivizing lawn replacement. In these programs, water agencies offer customers a rebate for replacing irrigated grass in their yards with drought tolerant landscaping (Hilaire et al., 2008; Sedlak, 2014; K. A. Sovocool, Morgan, & Bennett, 2006). Even with cash incentives, however, social barriers—such as the preference for lawns, requirements for an initial outlay of cash, and neighborhood norms and covenants—are known to limit participation (Silvy & Lesikar, 2005). Pincetl et al. 2019 analyzed the $350 million cash-for-grass program implemented by the Metropolitan Water District (MWD) in Southern California and found that, for the approximately 4% of program participants enrolled in their study, lawns were replaced with diverse land-cover types, and they found some support for a "neighborhood adoption" effect; i.e., when one resident participates in the program their neighbors are more likely to follow suit pro bono. These authors also noted a critical need for research looking at the factors that determine a resident's participation in cash-for-grass programs, including "building density, lot sizes, and other characteristics" (Pincetl et al., 2019).

To address this knowledge gap, this study undertook a parcel scale analysis of a cash-for-grass program implemented by the Irvine Ranch Water District (IRWD) in Orange County, California. IRWD's rebate program, which began in late 2010, pays residential customers a fixed unit rebate (i.e., fixed dollars per square foot) to replace lawns with drought-tolerant outdoor landscaping. The unit rebate paid by IRWD changed over time, from $1.50 per square foot (1 October 2010 through 1 June 2014) to $2 per square foot (1 June 2014 to present), except for a roughly three-week period (May 1-19, 2015) when the rebate was temporarily increased to $3 per square foot. Over the period of our study (from October 2010 through March 2017), a total of 1559 single-family residential (SFR) parcels, or 2.6% of the approximately 60,000 SFR parcels in IRWD's service area, participated in the program, about double the participation rate reported for a similar program offered in the nearby City of Los Angeles (1.5%) (Jessup & DeShazo, 2016). The program replaced approximately 130,000 m^2 of lawn area with drought tolerant landscaping, for an annual water savings of between 130 and 222 megaliters (ML), assuming a conservative unit reduction in water use of between 1002 and 1711 L/m^2/year (Matlock, Whipple, & Shaw, 2019; Tull, Schmitt, & Atwater, 2016). IRWD's service area is divided into 77 villages, each of which has its own architectural theme reflecting the region's master-planned heritage and development history, demographic composition, and clearly defined edges (Forsyth, 2002). Because SFRs in all 77 villages were eligible to participate, IRWD's rebate program is a natural experiment in how financial incentives, local demographic and economic factors, political orientation and the built environment collectively influence outdoor water conservation.

2.2 Data

2.2.1 IRWD Turf Rebate Program Data

The IRWD Water Efficiency Department provided a spreadsheet outlining the application details of SFR participants in the IRWD turf rebate program, including the (1) turf area replaced (m^2) for each participant, (2) application received date for the SFR participant (MM/DD/YY), and (3) SPID, or Service Point Identification Number, which serves as the unique identifier for each individual IRWD customer account.

IRWD also provided a GIS file which links the SPID with the corresponding unique identifier for the parcel where the SFR resides, i.e., the Parcel APN (assessor's parcel number). This allowed us to match the SFR participants of the turf rebate program with the built environment data at the parcel scale.

2.2.2 IRWD Parcel Data

The IRWD Water Efficiency Department provided a GIS parcel shapefile with built environment data attributed to each of the parcels in their service area. The raw data within the GIS parcel shapefile is publicly available through the county tax assessor's office, but the shapefile itself was obtained from IRWD. The data used in our study include: (1) outdoor area [m^2] (calculated as the difference between the lot area and the building area) and (2) owner occupancy (described as Yes or No). The parcel shapefile data was curated using the following definition queries: (1) include only parcels that are SFRs; (2) exclude parcels for which key variables were missing data, e.g., when the lot area was displayed as 0.

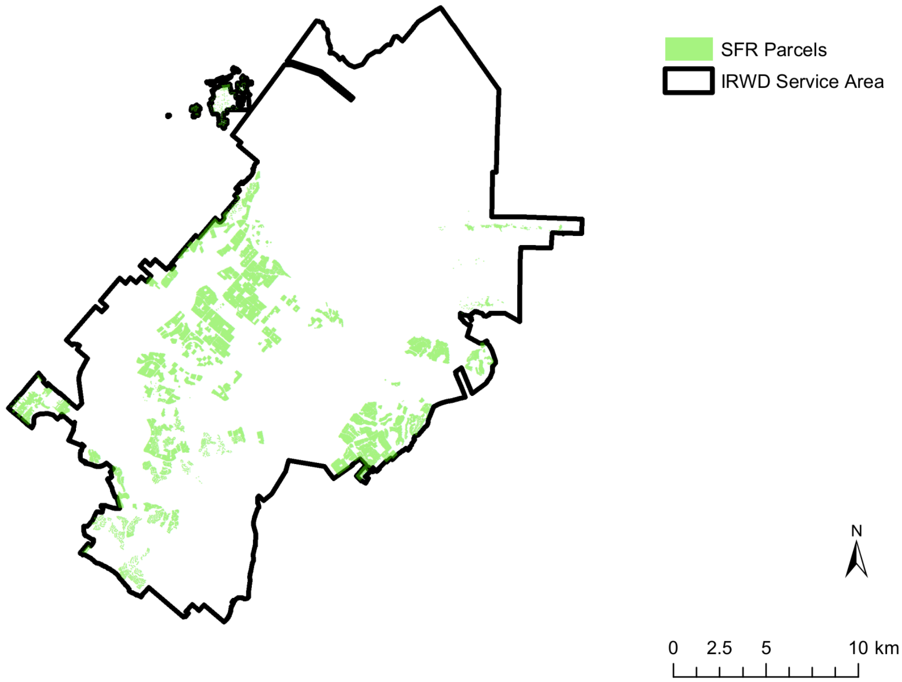

Figure 2.1. Individual SFR parcels within the IRWD service area

Approximately 60,000 individual SFR parcels are displayed as points (lime green). Regions with no SFR parcels are typically zoned as non-residential land for commercial purposes, parks, or wildlife. Regions of the map that appear to be solid green are densely populated with thousands of individual parcels.

2.2.3 Orange County Voting Data for 2016 Presidential Election

We obtained data from the Orange County Registrar of Voters, which retains archives of voting data for the elections in Orange County (Orange County Registrar of Voters, 2016). Specifically, we used archive data for the 2016 General Election, which encompasses voting measures at the local, county, state, and federal level for Orange County voters, aggregated geographically by 2016 voting precincts (see **Figure 2.2**). Within this dataset, we focused on the votes corresponding to the 2016 Presidential election.

The data used in our study include: (1) the number of registered voters, (2) number of ballots cast, and (3) the number of ballots cast for each of the following Presidential and Vice Presidential candidates and their political parties, respectively:

- Hillary Clinton & Tim Kaine (Democratic Party),
- Donald J. Trump & Michael R. Pence (Republican Party),
- Jill Stein & Ajamu Baraka (Green Party),
- Gary Johnson & Bill Weld (Libertarian Party),
- and a group of candidates with independent political party affiliation (Bernard “Bernie” Sanders; Laurence Kotlikoff; Mike Maturen; Evan McMullin; and Jerry White) whose votes we combined to create a variable representing the collective votes for candidates with “independent” party affiliation.

For each precinct in IRWD’s service area, we calculated the fraction of registered voters who cast ballots/voted in the 2016 General Election (by dividing the number of ballots cast in a precinct by the total number of registered voters in that precinct). Similarly, we calculated the fraction of ballots cast for each of the candidates listed above (by dividing the number of ballots cast for that particular candidate in a precinct by the total number of ballots cast in that precinct for the 2016 Presidential Election). For the “independent” category, we divided the number of ballots cast for the 5 independent candidates in a precinct by the total number of ballots cast in that precinct for the 2016 Presidential Election. We curated the dataset to exclude precincts where there were fewer than 100 registered voters due to lack of data in those precincts.

We then have the following variables used for our analysis: (1) Fraction of registered voters who cast ballots/voted in the 2016 General Election, (2) Fraction of 2016 Presidential Election ballots cast for Hillary Clinton & Tim Kaine (Democratic Party), (3) Fraction of 2016 Presidential Election ballots cast for Donald J. Trump & Michael R. Pence (Republican Party), (4) Fraction of 2016 Presidential Election ballots cast for Jill Stein & Ajamu Baraka (Green Party), (5) Fraction of 2016 Presidential Election ballots cast for Gary Johnson & Bill Weld (Libertarian Party), (6) Fraction of 2016 Presidential Election ballots cast for candidates with independent political party affiliation (Bernard "Bernie" Sanders; Laurence Kotlikoff; Mike Maturen; Evan McMullin; and Jerry White).

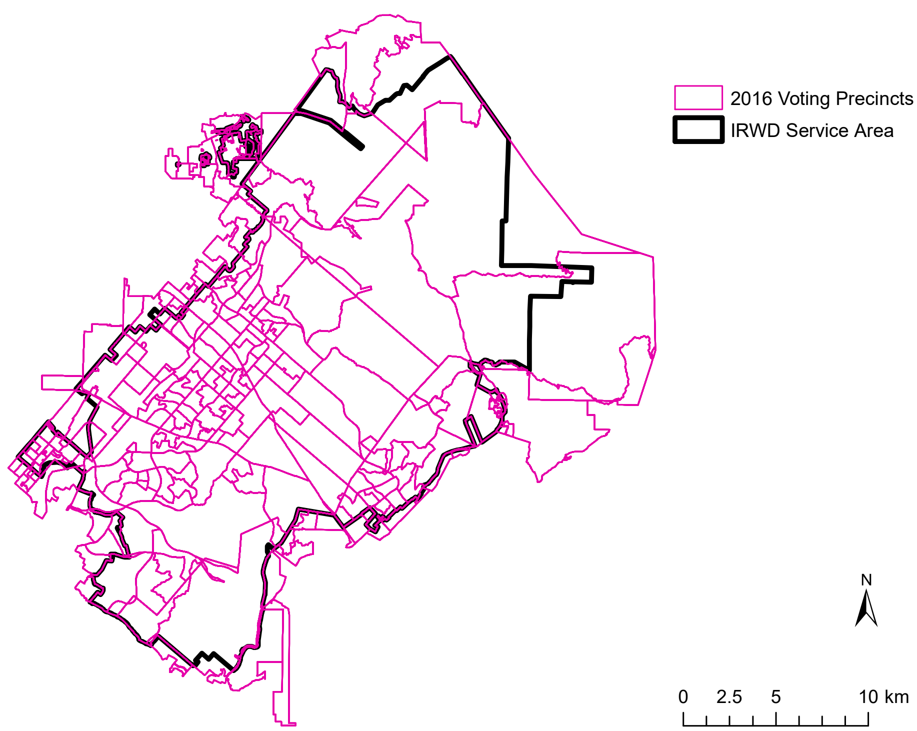

Figure 2.2. Voting precincts for the 2016 General Election in Orange County

Boundaries of the 2016 General Election voting precincts are shown (solid magenta pink lines) where they intersect with the IRWD service area. SFR parcels that fall within a particular voting precinct are designated with the corresponding voting data for that precinct.

2.2.4 American Community Survey (ACS) 2013-2017 (5-Year Estimates)

Through Social Explorer (United States Census Bureau American Community Survey), an online demographic research tool, we acquired data tables for the American Community Survey (ACS) 2013-2017 (5-Year Estimates), querying specifically for the Orange County region. This source data is at the census block group level, the smallest resolution geographic unit that contains Census Bureau data (United States Census Bureau).

The data collected for our study are: (1) Average Household Size (i.e., the number of people occupying a housing unit), (2) Median Household Income (2017 USD), and (3) Median House Value (2017 USD).

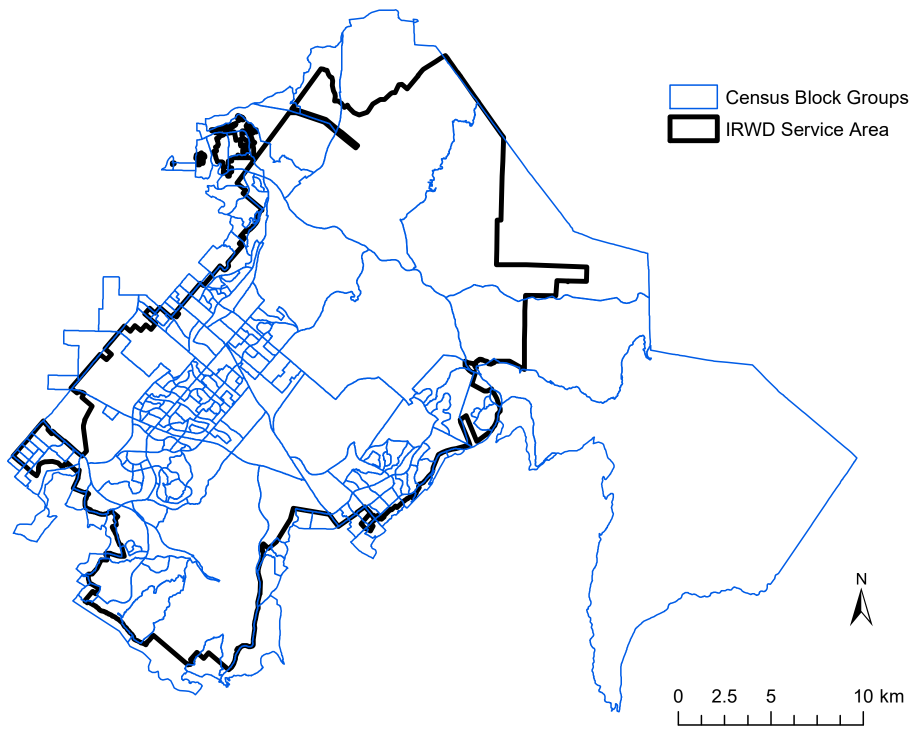

Figure 2.3. U.S. Census Bureau block group boundaries

Boundaries of the U.S. Census Bureau block groups are shown (solid blue line) where they intersect with the IRWD service area (solid black line). SFR parcels that fall within a particular block group are designated with the corresponding census data for that block group.

2.3 Methods

2.3.1 Definitions of SFR Parcel and Rebate Participation

For the purposes of this study, an SFR parcel is defined as a parcel with a residential detached dwelling and an IRWD water meter account with associated service point ID (SPID). SFR parcels were classified as rebate "participants" provided: (1) a rebate application was filed by the resident within our study period (1 October 2010 to 31 March 2017); (2) the resident passed an onsite inspection by IRWD personnel (to verify that lawn was replaced with drought tolerant landscaping as promised); and (3) the resident received a rebate check from IRWD following the inspection. Because rebates were typically processed within 6 months of the resident's initial application, we evaluated application status as of November 2017, eight months after the study window closed. SFR parcels were classified as rebate "non-participants" if they failed one or more of the above criteria. Regardless of participation status, SFR parcels lacking a full complement of explanatory variables (see below) were not enrolled in our study.

2.3.2 Explanatory variables

For each SFR parcel in IRWD's service area we compiled information from IRWD's customer account data, county tax assessor information, census data, and voting records. IRWD customer account data, which was referenced by SPID, included the information needed to classify SFR parcels as participants or non-participants (see last section). Tax assessor information (referenced by Assessor Parcel Number (APN)) included outdoor area (which was calculated as the difference between the parcel's lot area and building area) and owner occupancy. American Community Survey 2013-2017 Five-year Estimates Census Data (United States Census Bureau American Community Survey), included average household size, median household income, and median house value. These data were attributed to all SFR parcels in a single census block group. Precinct-scale voting records for the 2016 General Election were obtained from the Orange County Registrar of Voters (Orange County Registrar of Voters, 2016). This information included the fraction of registered voters who voted in the 2016 General Election, and the fraction of the latter who cast ballots for: (i) Hillary Clinton and Tim Kaine (Democratic Party), (ii) Donald J. Trump and Michael R. Pence (Republican Party), (iii) Jill

Stein and Ajamu Baraka (Green Party), (iv) Gary Johnson and Bill Weld (Libertarian Party), and (v) candidates with "independent" political party (Bernard "Bernie" Sanders, Laurence Kotlikoff, Mike Maturen, Evan McMullin, or Jerry White). The attribution of census and voting records to SFR parcels was accomplished using the Spatial Join tool within ArcMap (Esri, ArcGIS version 10.5, Redlands, California). A map illustrating the granularity of these various datasets is included in Supplemental Information (see **Figure C.1** in Appendix C).

2.3.3 Classification and Regression Trees (CART)

We used the machine learning algorithm CART (R-PART in R Software) to identify explanatory variables that can discriminate between participants and non-participants at the parcel scale. Decision trees were generated from the explanatory variables of all rebate participants and an equal number of randomly chosen non-participants. Separate trees were generated for 33 different realizations of the randomly chosen non-participants to yield a "forest" of decision trees from which dominant explanatory variables could be identified.

2.3.4 Participation Probability and 95% Confidence Intervals

The participation probability $\hat{p}$ was estimated as the proportion of residents who participated in the rebate program in any sample of n SFR parcels, $\hat{p}=\frac{1}{n}\sum_{i=1}^{n}X_i$ where X_i is the random variable for participation ($X_i=1$) or non-participation ($X_i=0$) and the index i represents a particular SFR parcel. The corresponding 95% confidence interval is $\hat{p}\pm\left|k_{0.05/2}\right|\sqrt{\hat{p}\left(1-\hat{p}\right)/n}$ where $k_{0.05/2}=-\Phi^{-1}\left(1-0.05/2\right)=1.96$ and Φ is the standard Normal distribution (Ang & Tang, 2007).

2.4 Results and Discussion

2.4.1 Study Statistics

Of the 60,000 SFR parcels in IRWD's service area, 46,915 had a full complement of the 11 explanatory variables (outdoor area, owner occupancy, average household size, median household income, median house value, and six voting preferences) and were therefore enrolled in our study. Of these 46915 SFR parcels, 1366 participated in IRWD's lawn rebate program for an overall participation probability of 2.9% ($\hat{p}=0.029\pm0.002$).

2.4.2 Classification and Regression Trees (CART)

To determine which, if any, of the 11 explanatory variables can discriminate between rebate participants and non-participants, we generated a forest of decision trees using the machine-learning algorithm CART. A forest of 33 decision trees was generated from the participation status and explanatory variables of 1366 SFR participants together with an equal number of randomly chosen non-participants. Of these 33 trees, 23 (or about 70%) split the dataset according to whether a SFR parcel is owner-occupied or not (first node) followed by whether the parcel's outdoor area is greater than 164 m^2 or not (second node, **Figure 2.4a**) (higher order nodes were variable across trees and not shown). The same two variables appear in reverse order in the top two nodes of three additional trees (**Figure C.3b**). Owner occupancy appears in the six remaining trees, but outdoor area is replaced with either the average number of occupants in a household (> 2.6, **Figures C.3c** and **C.3e**) or fraction of voters for Trump in the 2016 General Election (>37%, **Figure C.3d**). Across the 33 trees, the misclassification rates ranged from 39 to 42%. Interestingly, demographic and voting data did not appear prominently in the results of the CART analysis.

Consistent with the CART results and across all enrolled SFR parcels (N=46,915), the participation probability is three times higher if a SFR is owner occupied ($\hat{p}=0.033\pm0.002$)

compared to when it is not owner occupied ($\hat{p}=0.011\pm0.002$) (**Figure 2.4b**). When owner occupied SFRs are further divided according to their outdoor area, the participation probability is nearly 4% if the outdoor area is greater than 164 m^2 ($\hat{p}=0.037\pm0.002$) compared to less than 2% if the outdoor area is smaller than this threshold ($\hat{p}=0.015\pm0.003$) (**Figure 2.4b**). Thus, participation in the rebate program is highest for SFRs that are owner occupied and have outdoor areas >164 m^2.

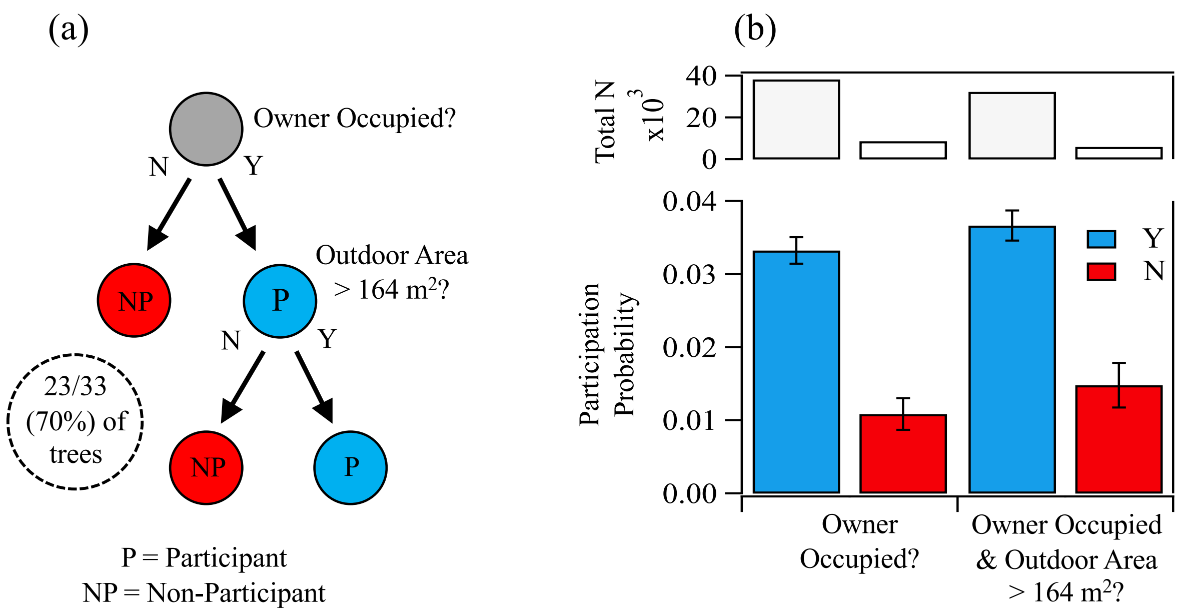

Figure 2.4. Results of CART tree analysis for participation probability

(**a**) CART reveals that a resident's decision to participate in the rebate program depends strongly on whether their home is owner occupied (top node) and whether its outdoor area exceeds 164 m^2 (second node). Y and N stand for "yes" and "no", respectively. P and NP stand for "Participant" and "Non-Participant", respectively. (**b**) The fraction of residents participating in the rebate program (or "participation probability") is 3.4% if the home is owner occupied, compared to 1.1% if it is not. When owner-occupied homes are divided based on outdoor area, homes with outdoor areas of >164 m^2 or <164 m^2 have corresponding participation probabilities of 3.7 and 1.5%, respectively. The number of parcels included in the calculation of participation probability is shown for each category (solid bars on upper chart).

2.4.3 Participation Probability

To explore the functional relationship between participation probability and outdoor area, we sorted all owner-occupied SFR parcels (N=38,255) by outdoor area, assigned the parcels into 11 equal-sized bins, and then calculated the participation probability and median outdoor area for each bin. For outdoor area < 400 m^2, the participation probability is strongly correlated (R^2=0.91) with median outdoor area, increasing 1.2% for every 100 m^2 increase in outdoor area (**Figure 2.5a**); the participation probability levels off for outdoor area > 400 m^2. For non-owner occupied SFR parcels (N=8,658), the participation probability increases with outdoor area, but the correlation is weaker (R^2=0.67) and the slope is reduced (0.39% increase in participation probability for every 100 m^2 increase in outdoor area, **Figure 2.5a**). In summary, program participation increases monotonically with median outdoor area, but the magnitude of the response (and strength of the correlation) is especially striking for SFRs that are owner occupied.

Once a resident decides to participate in the rebate program, the lawn area they replace also increases with outdoor area. This conclusion was reached by sorting and binning all participants in IRWD's rebate program (N=1,366) by outdoor area, and then calculating for each bin the median values of outdoor area and lawn area replaced. For parcels with outdoor areas < 600 m^2, the median lawn area replaced increases linearly with outdoor area (**Figure 2.5b**). In contrast to the participation probability (blue and red filled circles, **Figure 2.5a**), the dependence of lawn area replaced on outdoor area is not altered by owner occupancy status (blue and red filled circles, **Figure 2.5b**)). From the latter slopes we can infer that residents replace, on average, 10 to 15% of their outdoor area with drought tolerant landscaping.

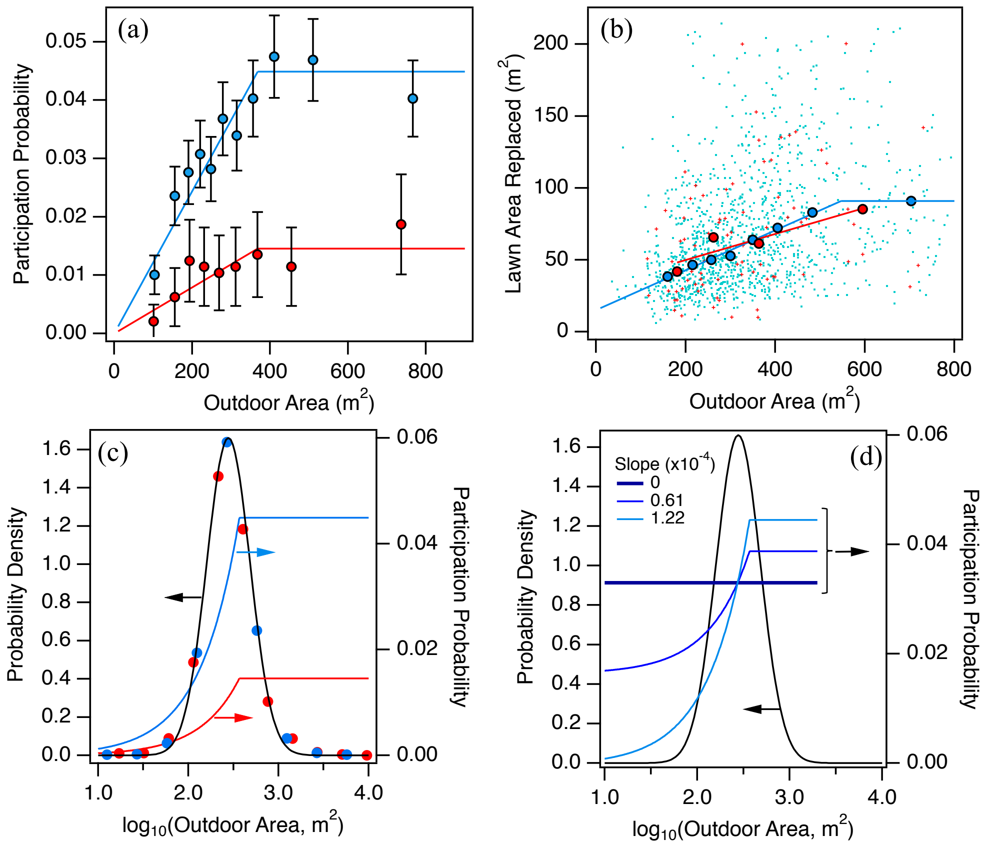

Figure 2.5. Participation probability increases monotonically with outdoor area

(**a**) Participation probability increases monotonically with median outdoor area, but the initial slope and maximum value depends of this relationship depends on whether the home is owner occupied (blue filled circles and line) or not (red filled circles and line). (**b**) The median lawn area replaced also increases with outdoor area, but there is little difference between owner occupied (blue filled circles and line) and non-owner occupied (red filled circles and line) homes. At the parcel scale, there is considerable variability between parcels (blue and red dots). (**c**) The number distribution of outdoor areas in owner occupied (blue circles) and non-owner occupied (red circles) homes closely follows a log-normal distribution (black curve). The participation probability curves from (a) are superimposed on this graph (blue line corresponds to owner occupied homes and red line corresponds to non-owner occupied homes). (**d**) Model simulations of total water savings were carried out for the three participation probability curves with the different initial slopes indicated. The number distribution of outdoor areas from (b) is superimposed on this graph (see Section 2.3.5 for details).

2.4.4 Size Distribution of Outdoor Area

How does the dependence of participation probability on outdoor area compare with the distribution of outdoor areas in IRWD's service area? Histograms of the parcel-scale outdoor areas of owner-occupied and non-owner-occupied homes (blue and red points, **Figure 2.5c**) are well described by a single log-normal distribution (median parcel area $10^{2.5}$ or 300 m^2, solid black curve in the figure). There is substantial overlap between outdoor areas that are most common in IRWD's service area (i.e., outdoor areas with the highest probability density, solid black curve) and outdoor areas with the highest participation probability (blue and red curves in the figure). However, the highest participation probabilities are skewed toward parcels with the largest outdoor areas and higher household incomes (see **Figure C.2**), consistent with previous reports that environmental rebate programs are utilized disproportionately by wealthier residents (DeShazo, Sheldon, & Carson, 2017; Pincetl et al., 2019).

From a theoretical perspective, it is interesting to ask: how might we alter the incentive structure of cash-for-grass programs to motivate more equitable participation? Under the fixed unit rebate approach employed by IRWD, rebates increase linearly with the lawn area replaced (up to a maximum of $3000 during the study period). This may incentivize the participation of residents with large yards (and higher household incomes), consistent with the results presented in **Figures 2.5c** and **C.2**. From an equity perspective, we would like to "flatten" the participation probability curve (i.e., decrease its slope and increase its intercept), for example, by transitioning from a fixed unit rebate (which incentivizes the replacement of large lawns) to a fixed dollar rebate (to incentivize the replacement of all lawns)). On the other hand, by targeting smaller lawns for replacement, the average lawn area replaced per rebate could decline, possibly leading to a net reduction in overall water savings. In the next section, we describe a modeling framework that can guide the development of rebate strategies that attain both equity and water savings goals.

2.4.5 Model of Outdoor Water Savings

The results presented above demonstrate that owner occupancy and outdoor area are key controls on the water savings achieved by IRWD's cash-for-grass rebate program. Outdoor area plays a role in all aspects of the program examined here—the probability that a resident will participate (**Figure 2.5a**), the lawn area replaced with drought tolerant landscaping (**Figure 2.5b**), and the number of SFR parcels in the utility's service with an outdoor area of a particular size (**Figure 2.5c**). Owner occupancy affects the slope and intercept of the participation probability curves (**Figure 2.5a**), but otherwise has little influence on either the lawn area replaced (**Figure 2.5b**) or the number-distribution of outdoor areas (**Figure 2.5c**). In the United States, parcel scale data on outdoor area and owner occupancy are easily accessed through the local county tax assessor office. Therefore, our research approach should be readily applicable to other cities and regions of the country.

Our results also point to a simple mathematical framework for predicting water savings achieved by cash-for-grass rebate programs. To this end, we begin by specifying, for any incremental change in outdoor area (from a to $a+\Delta a$, units of square meters), the incremental water savings ΔW (units of liters per year) accrued from a cash-for-grass rebate program. This incremental water savings ΔW can be expressed as the product of the water savings achieved by replacing a unit area of lawn with drought tolerant landscaping (w'', units of liters per square meter per year), the probability that a randomly chosen resident will participate in the rebate program ($p(a)$, unitless), the lawn area that a participating resident will replace with drought tolerant landscaping ($\ell(a)$, units of square meters), and the number-distribution of outdoor areas $n(a)$ (units of inverse square meters) across the service area, where $n(a)\Delta a$ is the number of SFR parcels with outdoor areas in the incremental range a to $a+\Delta a$: $\Delta W = w'' p(a)\ell(a)n(a)\Delta a$. Taking the limit $\Delta a \to 0$ and integrating, we arrive at the following simple model for total water savings:

$$W = w'' \int_{a_{\min}}^{a_{\max}} p(u)\ell(u)n(u)du \tag{1}$$

The variable u is a dummy integration variable and the limits of integration $a_{\min}$ and $a_{\max}$ (units of square meters) represent the range of outdoor areas of interest:

The unit water savings w'' captures the influence of local climate (K. Sovocool & Morgan, 2005), cultural preferences for outdoor plants (Hurd, Hilaire, & White, 2006; McClintock, Mahmoudi, Simpson, & Santos, 2016; Nassauer, Wang, & Dayrell, 2009), and water use behavior (K. Sovocool & Morgan, 2005; K. A. Sovocool et al., 2006) on the water savings realized when a unit area of lawn is replaced with drought tolerant landscaping; for their service area, IRWD adopts a value of $w''=1711$ liters per square meters per year. The participation probability increases linearly with outdoor area, $p(a)=b_p+m_p a$; the slope (m_p, units of inverse square meters) and intercept (b_p, unitless) in this expression depend on the owner occupancy status of an SFR parcel and the range of outdoor areas of interest (**Figure 2.5a**). Likewise, the lawn area that a resident replaces with drought tolerant landscaping increases linearly with outdoor area, $\ell(a)=b_\ell+m_\ell a$; the slope (m_ℓ, unitless) and intercept (b_ℓ, units of square meters) do not depend on owner occupancy status (**Figure 2.5b**). Finally, the number-distribution of outdoor areas, $n(a)$, follows a log-normal distribution (solid black curve in **Figure 2.5c**). Substituting these results into equation (1), our model predicts that owner and non-owner occupied SFR parcels in the IRWD service area should achieve a total water savings of 134 and 9.8 ML per year, respectively (see Appendix C for details). These model predictions are within 22% of the estimated water savings for these two groups, calculated by summing up the lawn areas replaced and multiplying by $w''=1711$ liters per square meters per year (163 and 12 ML per year for owner and non-owner occupied parcels, respectively).

One advantage of equation (1) is that it can simulate "what if" scenarios. For example, returning to the equity concern mentioned above, we can ask: how would the rebate program's overall water savings change if IRWD "flattened out" the participation probability curve by moving to a fixed cash rebate? To simulate this scenario, we decreased the initial slope m_p of the participation probability curve while holding the average service area participation probability constant at 3.3% (consistent with the average participation probability reported for owner occupied SFR parcels in **Figure 1.1b**). Surprisingly, the model predicts very little change in overall water savings (from 133 to 123 ML per year) as the initial slope is reduced from the value inferred from IRWD's dataset ($m_p=1.22\times10^{-4}$ m^{-2}) to a completely flat line ($m_p=0$ m^{-2}). The reason for this, evident in **Figure 2.5d**, is that a small reduction in the participation of SFRs with large outdoor areas is balanced by an increase in the participation of *many more* SFRs with small outdoor areas; recall, the number-distribution of outdoor areas in IRWD's service area is positively skewed by virtue of being log-normally distributed (Ang & Tang, 2007).

Thus, according to the model, there is no inherent trade-off between equity and water saving goals. However, it remains to be seen if financial incentives alone can alter the shape of the participation probability curve and, even if this were possible, other factors (e.g., administrative costs for water managers associated with vastly more rebate inspections) might make such a change impractical. Research is presently underway to extend equation (1) to address additional factors known to influence the success of cash-for-grass programs, including temporal variability (e.g., associated with news coverage of drought (Hollis, 2016; Quesnel & Ajami, 2017)), demand hardening (Lund, 1995), and neighborhood adoption effects (Graziano & Gillingham, 2014; Pincetl et al., 2017).

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CHAPTER 3

Turf Patch Distribution Study

3.1 Introduction

In early 2017, IRWD commissioned a study to produce a high-resolution GIS land use classification dataset that delineates the locations, boundaries, and areas of ten distinct land use categories. In this chapter, I examine the size distribution of individual “turf patches” associated with single-family residences (SFRs) in the Irvine Ranch Water District (IRWD) service area in Orange County, California. Due to the fixed unit rebate and the large capital costs of landscape retrofits, there may be little financial incentive to replace small turf patches. My working hypothesis is that much of the turf area in the service area is associated with small patches and that large turf patches have already been converted to drought-tolerant landscaping, resulting in “demand hardening” or a decreasing participation rate from an ever-smaller group of potential participants (Lund, 1995). By isolating for the category of turf patches and generating distributions from these data, we can begin to understand the existing turf landscape and the potential of demand hardening in the service area. The results described in this chapter could help water managers improve future implementation of their turf rebate programs and provide alternative metrics of success beyond total area of turf grass replaced.

3.2 IRWD Land Use Classification Dataset

As mentioned above, IRWD commissioned a land use classification study in February 2017. In the first part of the study, IRWD hired a consulting firm called Eagle Aerial Solutions to collect 3-inch resolution LiDAR topographic information for the IRWD service area. From May to June 2017, Eagle Aerial conducted aerial flyovers over the entire service area, covering an area of approximately 181 mi^2 or 469 km^2. Quantum Spatial (QSI) then converted the aerial imagery data into a Digital Elevation Model (DEM) and used Near-Infrared-emphasized raster symbology (NIR) to distinguish vegetation cover and artificial turf (Quantum Spatial, 2017) (see **Figures D.1 and D.2**). Using proprietary software, QSI delineated ten land use categories, delivered to IRWD in the form of GIS shapefiles, which were then shared with me for the purpose of this study. These categories are: (1) Impervious Surface, (2) Swimming Pools, (3) Irrigated Landscape - Non-Turf, (4) Irrigated Landscape - Lawn/Turf, (5) Natural Lands/Vegetation, (6) Irrigable - Potentially Irrigated, (7) Artificial Turf, (8) Horse Corrals and Arenas, (9) Open Water, and (10) Agriculture (Quantum Spatial, 2017).

3.3 Theoretical Framework

This study seeks to characterize and analyze the turf size distribution in relation to the range of turf areas that are included in IRWD's turf rebate program. We begin by carefully laying out a mathematical framework for analyzing the turf size distribution. Let $n(a,t)da$ represent the number of all turf patches in the IRWD service area with areas in the range a to $a+da$. The function $n(a,t)$ is a turf area distribution function (units: number of turf patches per area), analogous to the particle size distribution function used to describe the state of aggregation in a coagulating suspension (for example, see (Grant, Kim, & Poor, 2001)). We have included time t in the argument of the turf area distribution function in recognition of the fact that the distribution will change with time as turf grass is replaced with drought tolerant landscaping. Note that $n(a,t)$ is not a probability density function (PDF), because it does not integrate to unity. However, a PDF can be easily constructed from the turf area distribution function by dividing by the total number of turf patches in the IRWD service area, $N_{\text{total}}(t)$: $f_a(a,t)=n(a,t)/N_{\text{total}}(t)$. The

PDF of turf area $f_a(a,t)$ has units of inverse area; the quantity $f_a(a,t)da$ can be interpreted as the fraction of all patches of turf in the IRWD service area with sizes in the range a to $a+da$. Depending on the analysis of interest, we will use either $n(a,t)$ or $f_a(a,t)$ to describe the distribution of turf patch sizes.

A complication that we may run into is that turf patches may vary in size by several orders of magnitude (e.g., from 1 to 100 m^2, or larger). In this case, it is convenient to represent the turf area distribution function on a logarithmic (base 10) basis, as follows:

$$\frac{dN_{\text{total}}}{d\log_{10} a} = 2.303\frac{dN_{\text{total}}}{d\ln a} = 2.303a\frac{dN_{\text{total}}}{da} = 2.303an(a,t)$$

where $n(a,t) \equiv \frac{dN_{\text{total}}(t)}{da}$

The last equation follows from the definition of the turf area distribution; i.e., the number of patches with areas in the range a to $a+da$.

An empirical turf area distribution function $n(a,t)$ can be easily constructed from the list of turf patch areas exported from ArcGIS (see Section 3.4) using standard procedures for the construction of histograms (e.g.,(Ang & Tang, 2007)). This empirical distribution of turf patch sizes is of immediate practical interest, because it allows us to estimate: (1) the total turf area associated with SFRs in the IRWD service area; (2) the total water savings that could be realized if all of that turf was replaced with drought tolerant landscaping; and (3) the fraction of (1) and (2) that is currently included in IRWD's turf rebate program.

The total turf area available for replacement (item 1 above) can be obtained by simply summing all of the turf patch areas exported from the ArcGIS step above, or more formally, by taking the first moment of the empirical turf area distribution function:

$$A_{\max}(t) = \int_0^{\infty} a\, n(a,t)\, da$$

The corresponding maximum water savings can be obtained by multiplying the total turf area by an estimate of the per unit area water savings achieved by replacing turf grass with drought tolerant landscaping, here denoted by the variable w'' (the double prime indicates per unit area). For example, IRWD uses values in the range of $w'' = 1002$ to 1711 liters per square meter per year (Tull, Schmitt, & Atwater, 2016). We can imagine cases where w'' might vary with turf area (e.g., small turf patches may lose more irrigation water from overspray, compared to large turf patches, and thus the small patches would be subject to greater water savings, all else being equal). However, in the absence of any other information we will assume that same per unit area water savings applies across the spectrum of turf areas. In that case, the maximum annual water savings that can be achieved by replacing all turf in the IRWD service area is given by the following equation:

$$W_{\max}(t) = w'' \int_0^{\infty} a\, n(a,t)\, da$$

Again, we recognize that this maximum annual water savings is a function of time, depending on when the patch area distribution is assessed (e.g., from the LiDAR aerial survey mentioned earlier). In other words, $W_{\max}(t)$ represents the maximum additional annual water savings that could be achieved if all turf area existing at time t was replaced with drought tolerant landscaping.

IRWD's turf rebate program restricts the range of turf areas that are eligible for a rebate. This raises the question: *what fraction of the total turf area - and potential annual water savings - is IRWD capturing in its turf rebate program*? If a large fraction of the turf area falls below IRWD's minimum eligibility threshold ($a_{\min}$) and/or above their maximum threshold ($a_{\max}$) for rebates, then under the best of circumstances (for example, assuming 100% program participation) the resulting water savings will fall short of $W_{\max}$. Indeed, the fraction of turf area (f_{area}) and potential annual water savings (f_{water}) captured by IRWD's turf rebate program can be calculated from the empirical turf area distribution function as follows:

$$f_{\text{area}}(t) = f_{\text{water}}(t) = \frac{\int_{a_{\min}}^{a_{\max}} a\,n(a,t)\,da}{\int_{0}^{\infty} a\,n(a,t)\,da}$$

In writing this last result, and consistent with our earlier discussion, we have assumed that the per unit area water savings w'' does not vary with turf patch size. One of the primary contributions of this study will be to determine what range of turf patch sizes that should be targeted, if the goal is to maximize the total turf area replaced and annual water savings realized. To contextualize these results, we will work with IRWD staff to understand what factors led them to adopt specific threshold values of $a_{\min}$ and $a_{\max}$, and also explore potential complications associated with including turf patches smaller and larger than $a_{\min}$ and $a_{\max}$, respectively (e.g., given budget and staff constraints, it may not be feasible to process and inspect hundreds to thousands of turf rebate applications for very small turf patches).

3.4 Methods

To produce the necessary GIS data for this study, we queried a GIS parcel shapefile updated as of October 29, 2018 (data provided by IRWD), which contains a plethora of built environment information at the parcel scale for every parcel within the IRWD service area. In this query, we first isolated the variables that represented the parcel type and imposed a definition query to filter the data so that only SFR parcels remained. From this subset of the data, we then imposed an additional constraint so that vacant lots were not included either. Then we filtered the data even more so that parcels with incomplete information would be excluded. Because lot size represents the area of the parcel and is therefore an important piece of information in this shapefile, we imposed an additional definition query so that the parcels with lot size of 0 would be excluded. We also excluded those parcels with no information for the year that the structure was built to account for the possibility that the parcel may be zoned as residential but may not actually have a physical structure on the property. Of the 60,528 SFR parcels, a total of 1,138 parcels (or 1.88% of the SFR parcels) lacked sufficient "lot size" or "year built" data and were therefore excluded from the analysis. The remaining 59,390 SFR parcels were used to later produce the empirical turf patch distribution.

Within the land use classification layer, we applied a definition query to isolate turf patches only. Then, using Spatial Join tools within ArcMap (Esri, ArcGIS version 10.5, Redlands, California). We intersected the filtered SFR parcel layer (containing 59,390 SFR parcels) with the filtered land use classification layer (containing only turf patches) based on location, yielding a new GIS layer that displays only turf patches within the filtered SFR parcels. We then exported the turf patch data into IGOR Pro, where we sorted the turf patches by area, then plotted histograms of the empirical turf patch size distribution. The following sections go into more depth about the results and implications of the empirical turf patch distribution.

3.5 Key Results

Our key results point to interesting features of the IRWD turf patches that are not readily apparent. Of 1.74 million turf patches within the IRWD service area, only 91,700 of them fall within SFR parcels (see **Figure 3.1**).

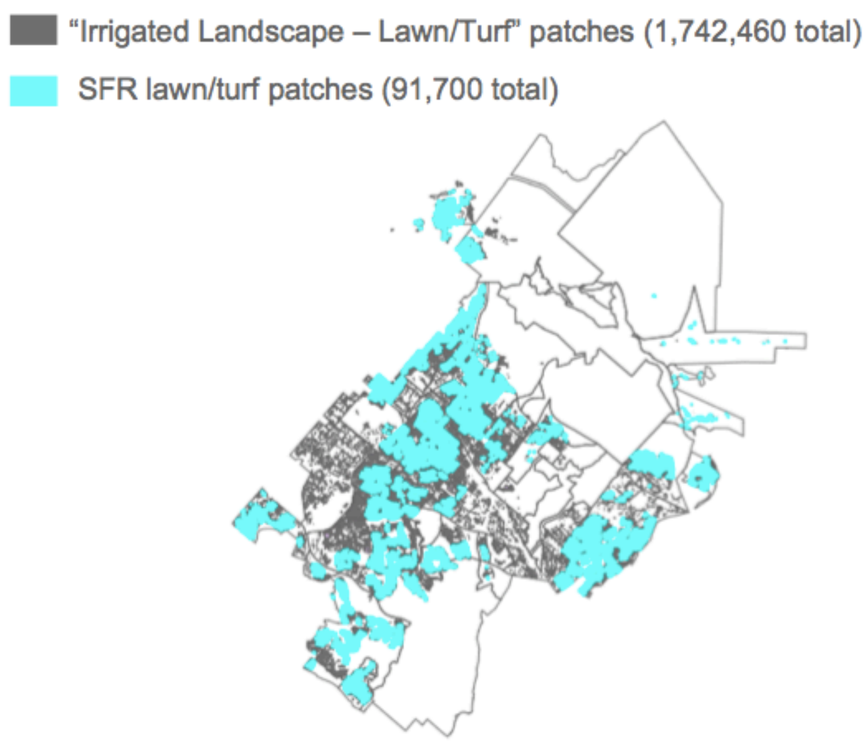

Figure 3.1. SFR turf patches in the IRWD service area

Over 1.7 million distinct turf patches were identified in the IRWD land use classification dataset. When intersected with the locations of SFR parcels in the service area, results yielded only 91,700 turf patches within the SFR parcels (about 5% of the total number of turf patches).

Using an empirical distribution of turf patches (see **Figure 3.2**), we focus on three different thresholds. The first corresponds to turf patches that are less than 250 ft^2 (IRWD's minimum requirement for participation in their turf rebate program). The second corresponds to turf patches that are greater than 1500 ft^2 (IRWD's maximum for participation in their turf rebate program). The last corresponds to the turf patches that fall within the IRWD program limits, between 250 and 1500 ft^2.

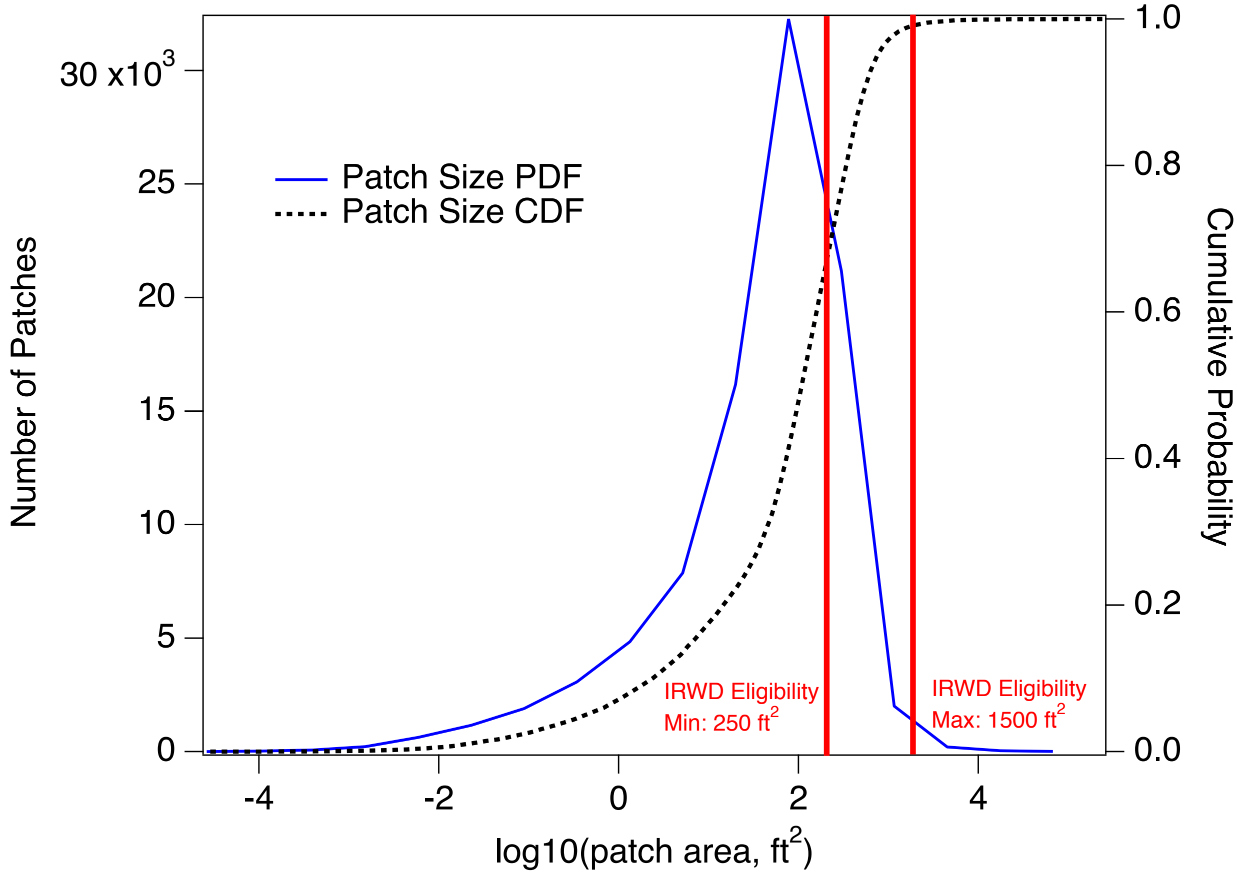

Figure 3.2 Empirical turf patch distribution

The empirical turf patch distribution, where the turf patch area on the x-axis is log-transformed due to a range spanning over 8 orders of magnitude. The left axis shows the number of patches, corresponding to the patch size PDF (solid blue line). The right axis displays the cumulative probability corresponding to the patch size CDF (dotted black line). The red vertical lines denote eligibility limits for IRWD's turf rebate program: participants must retrofit at least 250 ft^2 of turf grass (minimum) and no more than 1500 ft^2 (maximum).

Among those 91,700 SFR turf patches, the number of turf patches smaller than 250 ft^2 vastly outnumbers patches larger than 250 ft^2. In fact, 72% of the turf patches are smaller than

250 ft^2. However, when summed, these small turf patches comprise just under 20% of the total SFR turf area (about 5.06 million ft^2). The majority of the turf patch area is associated with a very small percentage of the turf patches. Only 0.07% of the SFR turf patches (or 64 individual turf patches) are larger than 1500 ft^2 (the IRWD maximum limit for turf rebates), yet they comprise 13% of the total SFR turf patch area (about 3.66 million ft^2). We also learn that only 30% of the SFR turf patches fit within the bounds of the IRWD turf rebate program (250 to 1500 ft^2, see dashed red vertical lines in **Figure 3.2**), comprising 67.6% of the total SFR turf patch area (about 17.3 million ft^2). This fraction was mentioned earlier in Section 3.3 as f_{area}, the fraction of turf area that is captured by IRWD's turf rebate program.

Using equations outlined in Section 3.3, we can quickly calculate $A_{\max}$ and $W_{\max}$ using the empirical turf patch distribution and IRWD's unit water savings value of $w'' = 1711$ liters per square meter per year. For the 91,700 SFR turf patches, $A_{\max} = 2.42 \times 10^6$ m^2 and $W_{\max} = 4.13 \times 10^9$ L/year.

Participation in IRWD's turf rebate program resulted in approximately 130,000 m^2 of drought tolerant landscaping, leading to an estimated water savings of 22.2×10^6 L per year. However, this accounts for less than 1% of the potential water savings if all SFR turf patches were converted to drought tolerant landscaping. Even if all of the turf patches within IRWD's eligible range were converted, the resultant water savings would be at most two-thirds of the potential water savings. The implications of these fascinating results could reframe the conversation about water savings and participation in turf rebate programs. To capture even more water savings, IRWD should consider inclusion of turf patches outside of their eligibility range.

3.6 Discussion and Policy Implications

Although residents can convert multiple turf patches on their property, understanding the distribution of individual turf patches may illuminate gaps in participation from residents that own a particular turf patch size. For example, under IRWD's turf rebate program guidelines, SFR parcels with total turf area less than 250 ft^2 are only eligible to participate if the entirety of the turf area is replaced with drought-tolerant landscaping, forcing residents to face an "all-or-nothing" decision. More often than not, the capital costs associated with turf retrofit projects include fixed costs independent of the size of the turf area (IRWD, personal communication). Therefore, the cost per area for a smaller retrofit project may be prohibitively high.

Considering that the majority (over 70%) of the SFR turf patches are below the minimum requirement for eligibility in the IRWD turf rebate program, one may wonder how to effectively design the program and by what metric of success IRWD should consider. If that metric relied on the percentage of participants relative to the population (e.g., 2.6% of SFRs participated), IRWD may be inclined to focus their efforts on large-scale marketing campaigns designed to persuade more residents to participate. Conceivably, IRWD may be more focused on participation by numbers in an effort to promote widespread shifts in cultural norms for outdoor landscaping (Hurd, 2006; McClintock, Mahmoudi, Simpson, & Santos, 2016; Nassauer, Wang, & Dayrell, 2009). Perhaps their aim is to engage their customers in these programs to promote a culture of water efficiency. Yet when pressured during a drought or by regulatory requirements to conserve more water, IRWD's larger priority may be to reduce water demand within the service area or shift water use away from outdoor irrigation. In this case, a better metric of success could be the relative turf area removed. IRWD may preferentially target certain residents with large turf patches (who were otherwise eligible), such as the 64 individual turf patches that together comprise 13% of the total SFR turf patch area. Given the limitations of the IRWD staff to process turf rebate applications and conduct inspections, this approach may be spur more water savings in a shorter period. However, because of the relative rarity of these large turf patches, demand hardening is also a problem for future water conservation. When large turf patches are no longer available, a shift towards reducing barriers of participation for residents with very small turf patches (perhaps by introducing different rebate structures) could be the next logical target for the turf rebate program. Although this chapter does not characterize the ideal turf rebate program structure, it does introduce a framework to allow water managers to modify their programs depending on their priorities, limitations, and goals whether the emphasis is on water conservation, broader participation, or landscape transformations.

Additionally, over 1.6 million turf patches in the IRWD service area are associated with non-SFR parcels. The 91,700 SFR turf patches make up only 3.79% of the total turf area. Despite the emphasis in this thesis on SFR turf rebates, it’s undeniable that the vast majority of the turf area in the service area resides elsewhere. Turning attention to other places where turf resides is another important step towards attaining long-lasting water savings in this urban setting.

The methodology applied in this paper could very well be scaled up to larger regions, such as the service area of the Metropolitan Water District of Southern California (MWD), a wholesaler and the largest supplier of treated water in the United States, serving 19 million people across 26 cities and retail suppliers (Metropolitan Water District of Southern California). Considering the hundreds of millions of dollars spent on turf rebate programs during the last major drought in California (Matt Stevens, 2015), the results of this work could help inform policy reform on local and regional scales where turf rebate programs are implemented. By understanding where and what type of turf patches are lacking program participation, water managers can develop strategies to better address specific audiences and hopefully cultivate more participation in the turf rebate program.

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CHAPTER 4

Summary, Conclusions, and Future Research

4.1 Summary and Conclusions

In this thesis, I focus on urban water sustainability from the perspective of reducing urban water demand through turf rebate programs. During my time at UC Irvine, I completed three major studies. The first is described in Chapter 1, where I discuss the village-level spatial patterns of participation in the IRWD turf rebate program, as well as temporal patterns of participation and their parallels with mass media coverage on the California drought. From the analysis, we show that two key variables – "home age" and Google Trends search rates for the term "turf rebate" – account for 96% of the spatial and temporal variability in participation probability, respectively. The analysis draws a connection between temporal patterns of IRWD turf rebate program participation and Google Trends, which serves as a proxy for California Governor Jerry Brown's unprecedented emergency drought proclamations, mass media coverage of the California drought, and local water conservation and education programs (such as IRWD's) that provided an outlet for residents to participate in local water conservation. Similar connections between water conservation and mass media coverage have been described in other studies (Quesnel & Ajami, 2017).

Chapter 2 is an analysis that explores the spatial patterns of participation probability of the IRWD turf rebate program at the parcel scale, employing several sources of built environment, demographic, and political GIS data to do so. Using a machine learning algorithm called CART (classification and regression trees), a forest of 33 decision trees were generated from the participation status and the explanatory variables of the SFR participants and an equal number of randomly chosen non-participants. 70% of these decision trees split the dataset according to whether a SFR parcel is owner-occupied or not (first node) followed by whether the parcel's outdoor area is greater than 164 m^2 or not (second node, **Figure 2.4a**). Furthermore, results show that participation probability is three times higher for owner occupied SFRs and increases monotonically with larger outdoor areas across all SFRs. Lawn area replaced also increases with outdoor area – on average, 10 – 15 % of a resident's outdoor area is replaced with drought tolerant landscaping. We also see that the number-distribution of outdoor areas follows a log-normal distribution (positively skewed). Because the highest participation probabilities are skewed towards parcels with higher household incomes and larger outdoor areas, we explore a scenario wherein we introduce a fixed cash rebate in an effort to encourage more equitable participation. Using a simple water savings model (see Section 2.4.5), we predict very little change in water savings, attributable to the fact that reduced participation from SFRs with large outdoor area is balanced by higher participation from many more SFRs with small outdoor area. Thus, this example demonstrates the potential for alternative rebate structures to improve equity and still achieve considerable water savings. Of course, there may be other factors that make such an alternative rebate structure suboptimal (such as the additional administrative burden on water managers to conduct more inspections and process more rebate applications), but this serves as an interesting framework for exploring alternative structures of the existing turf rebate program.

In Chapter 3, I describe the turf patch distribution study and potential implications for program implementation and policy reform for turf rebate programs generally. After laying out a theoretical framework and constructing an empirical turf patch distribution, I find that less than one percent of the potential water savings is captured by participation in the turf rebate program thus far. Moreover, even if all the SFR turf patches that fall within IRWD's eligibility range (250 to 1500 ft^2) were converted to drought tolerant landscaping, the resultant water savings captures only about two-thirds of the total potential water savings. This then leads to a discussion on the potential water savings under different scenarios and alternative metrics of success to help water managers improve their turf rebate programs.

Outdoor water conservation programs are well-funded programs and extremely common in times of drought. Their dynamics are of high interest to water managers. My dissertation is focused on the spatial and temporal patterns of turf rebate programs for the IRWD service area, but the analysis could be scaled up to a larger region, such as southern California or even the entire arid Southwest. Collaborations with economists and water managers could provide more insight into increasing the amount of turf replaced through turf rebate programs.

4.2 Topics for Future Study

The analysis completed on the turf rebate program was illustrative to me as a researcher. Not only did it provide a real-world application to the spatial, temporal, and statistical analysis tools that I used to complete this work, it also opened up a universe of further questions and topics of future study. In this section, I describe three potential directions for future research that build on my thesis.

4.2.1 Parcel scale analysis of turf rebate programs at larger scales

In and of itself, the parcel scale analysis in Chapter 2 is a very interesting study. It also demonstrates a generalizable approach and the relatively easy accessibility of the source data (i.e., parcel-scale data from the county tax assessor, voting data, and census block group data). Though the results pointed to owner occupancy and a certain outdoor area size as the most important variables in participation probability, it begs the question whether that is also true for other regions. Therefore, the next step in this vein of work is to facilitate a larger-scale analysis to evaluate whether these results still hold true or whether other drivers will emerge. More importantly, in the second iteration of this analysis, an additional variable should be included – the cost of water. IRWD employs a tiered rate structure in which the first tier (corresponding to small amounts of water use) has the lowest water rates (dollars per volume of water), the second tier (corresponding to larger amounts of water use) has a higher unit price, and so on. It would be an interesting study to replicate this approach for a study area that has a different water rate structure.

Authors of a recent study on turf rebate programs in southern California noted a critical need for research looking at the factors determining a resident's participation in cash-for-grass programs, including "building density, lot sizes, and other characteristics" (Pincetl et al., 2019). The comparison between IRWD's results and those of a larger study area, like the service area of the Metropolitan Water District of Southern California (a wholesaler and the largest supplier of treated water in the United States, serving 19 million people across 26 cities (Metropolitan Water District of Southern California) could illuminate both commonalities and distinct differences between drivers of participation probability in each study area. It would also be interesting to complete a similar analysis for a region that has vastly different climate or cultural norms around outdoor landscaping. Such comparisons across different regions could draw out important distinctions that could help water managers in those regions tailor their turf rebate programs based on the drivers influencing their local area.

4.2.2 Demand hardening in turf rebate programs

Water managers are keenly aware of "demand hardening" in which efforts to induce water conservation become progressively more difficult over time because the pool of potential participants shrinks as more residents complete the program. We can think of two fundamental causes of demand hardening. First, among the target population there will be a distribution of interest and willingness to participate in the turf rebate program. As individuals opt into the program, they leave behind a more "hardened" population that is less likely to participate. From the perspective of our modeling framework, we would say that the participation probability is, itself, distributed amongst the population, and the mean value of p declines over time. Second, generally speaking, customers that have previously applied for a rebate are not eligible to apply for a rebate again; i.e., they will have already replaced their turf grass. Because the pool of eligible applicants within any village, and within the IRWD service area as a whole, is finite, this "sampling without replacement" leads to a reduction in the rate at which turf rebates are awarded, *even if the probability an individual will apply for a rebate remains constant over time*. The influence of sampling without replacement can be seen in the formula we derived earlier (in Chapter 1) for the total number of turf rebates received from the i-th village by the j-th month:

$$N_{i,j} = n_{\mathrm{SFR},i} \sum_{k=1}^{j} p_{i,k} - \sum_{k=1}^{j} p_{i,k} \times N_{i,k-1} \qquad (1)$$

Here, sampling without replacement manifests as the second term on the right hand side of equation (1), and has the effect of slowing the rate at which turf rebates are awarded over time; i.e., it is another mechanism of "demand hardening" that does not require the probability $p_{i,j}$ to decline with time.

This paper could bring out these two mechanisms of demand hardening, illustrate their relative influence with our probability model (equation (1)), and use the IRWD dataset to evaluate the evidence for and against each of these mechanisms. For example, we would expect that demand hardening from the “sampling without replacement” mechanism will only be significant when the fraction of the population participating in the turf rebate program is relatively high. Importantly, our modeling framework can reveal at what participation fraction we would expect to begin seeing a sampling without replacement effect—a result we can compare directly. If participation in IRWD’s turf rebate program is far below that threshold, then presumably any hardening that is occurring at present is due to the first mechanism; i.e., a decline in the participation probability over time.

Because IRWD is a model for other water agencies in the region – and because the State of California has recently modified water use efficiency legislation for water agencies statewide (California State Assembly, 2018), the results of this paper could inform Californian water conservation policy reform and provide quantitative feedback on how to improve broader participation in outdoor water conservation measures.

4.2.3 Structural vs. non-structural water conservation

We can categorize water conservation into two broad categories – structural and non-structural. Structural water conservation (also called “water use efficiency”) involves changes to the built environment that result in less water used in the long term, e.g., water-efficient showerheads or drought tolerant landscaping. This type of water conservation typically involves an upfront capital cost (such as installation of a new appliance or retrofit of an existing appliance or landscape) but largely does not involve day-to-day conscious effort to sustain the water conservation. On the other hand, non-structural water conservation involves changes to behavior that are typically temporary, e.g., taking shorter showers or skipping car washes during a drought. My hypothesis is that the turf replacement is a structural water conservation measure because there is minimal reversion (the threshold defining minimal reversion to be addressed later).

I will test this hypothesis by evaluating reversion rates and how those rates vary by village. To do this, I will first filter the IRWD land use classification GIS layer to isolate the "Irrigated Landscape - Non-Turf" landscape category, then intersect that with another GIS layer that shows the location of SFRs in the service area. This yields a GIS layer that shows the location of SFR irrigated non-turf patches. Then I will compare the post-inspection area (measured by IRWD staff) of turf retrofits of the program participants between October 2010 and March 2017 with the corresponding amount of irrigated non-turf patches on their properties in the IRWD landscape classification GIS layer. After preliminary analysis, I will impose a buffer (to be decided in consultation with IRWD staff) to account for inaccuracies in the classification data. Then I will graph the post-inspection areas of the turf retrofits versus the irrigated non-turf patches from the land use classification data. If the post-inspection areas are more than the buffer radius but smaller than the irrigated non-turf patches for that particular residence, then it is a potential site of "reversion" back to turf grass. Other factors may play a role in the post-inspection areas being smaller than the irrigated non-turf patches, an aspect which warrants further exploration.

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APPENDIX A

Obstacles to Wastewater Reuse: an Overview

Abstract

With growing water scarcity worldwide, reclaimed wastewater is an increasingly attractive option for meeting household water demand, especially in urban areas. However, reluctance by households to use treated wastewater persists. In this article, we discuss the 'yuck factor,' health risk concerns, and cost considerations, which are key obstacles to wastewater reuse by households. We then summarize successful and unsuccessful case studies of wastewater reuse around the world. Reasons for the success (or failure) of each case study draws upon unique contextual, historical, and cultural circumstances. Direct potable reuse—where purified wastewater is added to the potable water supply directly—is rare; most successful projects are nonpotable wastewater reuse schemes—where purified water is placed into an environmental buffer before entering a drinking water distribution system. Our review of experiences around the world suggests approaches for improving public acceptability of wastewater reuse schemes. The literature also suggests that there is an urgent need to collect more wastewater treatment and reuse data, to research ways of better assessing and reducing health risk associated with emerging pollutants in reclaimed wastewater, and to better price both drinking water and recycled wastewater.

Text A.1. Introduction

As outlined in a recent United Nations report (United Nations Development Program, 2006), clean water is essential to human development; yet over one billion people do not have access to clean water and 2.6 billion people lack access to adequate sanitation. Reasons for this dire situation include poverty, inequality, and flawed water management policies that exacerbate scarcity (United Nations Development Program, 2006). As the cheapest natural sources of freshwater have already been tapped and given projected increases in urban populations combined with global climate change (McDonald et al., 2011; United Nations, 2014), it is essential to use existing water resources more efficiently (e.g., by reducing leaks and managing demand) and to find new sources of water. Although there are other alternatives such as desalination, one of the most promising options for increasing water supplies is to reuse wastewater (water whose quality has been adversely affected by human activities), especially in urban areas where most of the world's population is now concentrated (United Nations, 2014).

In this article, we call 'treated wastewater' wastewater that has been treated to a quality suitable for beneficial reuse. It is common to distinguish between greywater—wastewater generated from laundries, showers, bathtubs, and hand basins (but typically not kitchen sinks)—and blackwater that includes human waste (Allen, Christian-Smith, & Palaniappan, 2010). It is also important to distinguish between direct potable reuse—where purified water is introduced directly into a potable water distribution system or into the raw water supply just upstream of a water treatment plant—and indirect potable reuse—where purified water is discharged into an environmental buffer for some time before it is withdrawn for potable uses (George Tchobanoglous, 2011). Reusing wastewater allows better matching the quality of water with its use; it yields economic benefits (by deferring additional water infrastructure) and environmental benefits (by reducing or postponing the withdrawal of water from the environment) (Bruvold, Olson, & Rigby, 1981; Grant et al., 2012).

Wastewater has *de facto* long been reused indirectly after being discharged in rivers upstream of communities, but this reuse has been implicit. Although it has been reclaimed, recycled, and reused in many parts of the world for centuries, as evidenced by the elaborate infrastructure of the Minoan civilization (Angelakis & Spyridakis, 1996), explicit wastewater reuse has mostly been for irrigating crops. This practice is attractive because it provides both water and nutrients, whose value may exceed the value of the water itself (Dalahmeh & Baresel, 2014). However, there are a number of other uses for reclaimed wastewater, including industrial applications, environmental uses, and urban uses.

Industrial use of treated wastewater is especially important in sectors that require a large volume of water for uses such as cooling, including the manufacturing of metals, paper, and plastics; in that case, treatment is needed to avoid rusting, biological fouling, and scale formation(Rebhun & Engel, 1988). Environmental uses include supplementing stream flows to sustain aquatic life, supplying water to wetlands, and recharging aquifers. Residential uses include outdoor uses such as irrigating parks, golf courses, and gardens, as well as indoor uses for flushing toilets, and—depending on water quality—cleaning vehicles and washing clothes. Treated wastewater can also be used for firefighting or for melting snow. The purpose of this article is to explore what is known about obstacles to wastewater reuse, with an emphasis on households. Starting with keyword searches in Google Scholar and in databases such as Water Resources Abstracts and the Web of Science, and then extending our search based on citations and cited papers, we attempted to review more recent sources and to provide a broader geographic coverage than currently available papers that provide an overview of obstacles to wastewater reuse (Asano, 2005; Hochstrat, Wintgens, Melin, & Jeffrey, 2006; Khan, Schäfer, & Sherman, 2004; Po, Nancarrow, & Kaercher, 2003).

A review of the literature on wastewater reuse suggests that the main obstacles to treated wastewater reuse by households include public acceptance (the so-called ‘yuck factor’), perceptions of risks from reclaimed wastewater, and cost concerns (Po et al., 2003). We examine these issues in turn before summarizing some salient case studies. The last section summarizes lessons learned.

Text A.2. The Yuck Factor

To gain public acceptance for wastewater reuse, it is critical to overcome instinctive disgust, also called the 'yuck factor,' i.e., repugnance triggered by the idea of consuming the water that was once flushed down a toilet. In their exploration of the nature of disgust, Curtis and Biran (Curtis & Biran, 2001) argue that it can best be understood as an evolutionary mechanism to defend against infectious diseases.

The phrase 'yuck factor' is attributed to the bioethicist Arthur Caplan who coined it to describe instinctive aversion against new technologies (Schmidt, 2008); it has also been invoked to explain public opposition to genetically modified foods, animal or human cloning, and pollution trading programs. It may combine instinctive disgust (reaction to drinking recycled wastewater, for example) with moral aversion to having humans tamper with the natural order (Schmidt, 2008). According to Marks(J. S. Marks, 2003), the rejection of reclaimed wastewater—especially for drinking—clashes with cultural norms that over the past century and a half have called for separating the supply of drinking water from the removal of sewage.

The 'yuck factor' has been invoked at least since the 1970s as an obstacle to wastewater reuse by households in public perception studies, with 'psychological repugnance' and concerns over 'purity' as the most frequently cited reason for opposing the use of reclaimed wastewater in California (Bruvold & Ward, 1972). Similar concerns have been recorded in countries around the world, but not to the same degree, which suggests that geographical—and cultural—differences matter. For example, a recent survey of households in Kuwait (Alhumoud, Behbehani, &

Abdullah, 2003) found that the top two reasons why 96% of respondents oppose using reclaimed wastewater for human use (regardless of its quality) are health risks (69%) and psychological repugnance (44%). In contrast, in her 2004–2005 survey of urban Australians, Marks (J. Marks, Martin, & Zadoroznyj, 2008) found that nearly three-quarters of respondents would be willing to use recycled water for various household purposes (including drinking), although most would do so with some reservations.

The intended use of reclaimed wastewater matters: in general, most studies of public acceptance of reclaimed wastewater agree that people are open to considering recycled water if it involve limited personal contact, such as watering public parks or nonedible plants in their gardens, but they are reluctant to adopt it for personal uses such as showering, cooking, or drinking (J. Marks et al., 2008).

Approaches to win over public support include public education (Bruvold & Ward, 1972) (the public needs to be informed about water scarcity and the safety of reclaimed wastewater), wide participation by all stakeholders (Ashley, Souter, & Hendry, 2001), and marketing techniques (Dolnicar & Saunders, 2006). The Australian experience also suggests that the effectiveness of public campaigns by water agencies is enhanced by support from recognized experts and from a heightened sense of water scarcity triggered by a crisis (Dolnicar & Hurlimann, 2009). Viewing the 'yuck factor' as part of the social norms surrounding water issues, Ching (Ching, 2010) explains how the stigma associated with wastewater reuse was removed in Singapore by renaming it 'NEWater,' and by ensuring consistency in official discourses that emphasized the importance of 'NEWater' for continued economic growth and increased independence from Malaysia (Dingfelder, 2004).

Russell and Lux (Russell & Lux, 2009) contest the usefulness of framing the public debate about reclaimed wastewater around the notion of disgust. They critique psychometric methods, attitude causation models, and theories of disgust that claim the existence of an intrinsic response to reclaimed wastewater. To more effectively engage the public, they advocate instead a sociology-grounded cultural approach that examines local practices of water provision and waste handling to understand mismatches between current practices and proposed changes in wastewater reuse. Overall, they recommend interactive forms of consultation and education that enable people to develop their opinions on specific wastewater reuse projects.

Text A.3. Health Risks

The 'yuck factor' evokes the fear of pathogens and contamination, both of which can adversely impact health and well-being, so let us now examine what is known about health risks linked to wastewater reuse and their perception by the public.

Text A.3.1. An Overview of Health Risks

Concerns about wastewater reuse are currently centered on microbiological pathogens and pharmaceuticals/ personal care products (PPCPs). The latter include any health (prescription and over-the-counter therapeutic drugs), cosmetic (e.g., hair colorant, lipsticks, or fragrances), or personal care (e.g., deodorants, shampoos, or toothpaste) products used by people, or products used by agribusiness to enhance the growth and health of livestock (e.g., veterinary drugs such as antibiotics and steroids) (United States Environmental Protection Agency, 2010).

For microbial pathogens, the risk of water-borne infection depends on the quantity and dispersion of bacteria in the water, as well as the susceptibility of the exposed population and the amount of treatment prior to exposure. Because microbial pathogens are randomly distributed, detection can be very difficult and risk assessment may overestimate the actual risk in order to safeguard against possible infections. Intestinal parasites can also pose substantial risk when human fecal matter serves as a fertilizer for growing vegetables (Toze, 2006).

The importance of PPCPs' contribution to the combined load of chemicals in the environment has been recognized relatively recently (United States Environmental Protection Agency, 2010) and many questions remain about pathways to exposure, bioavailability and uptake, effects characterization, and risk, not to mention how to prioritize research among the thousands of chemicals in PPCPs (Boxall et al., 2012). It is now widely acknowledged that PPCPs enter the environment via many pathways, including treated wastewater from municipal treatment plants, hospital effluents, runoff from livestock activities, landfill leaks, or sludges spread on soils as fertilizers (Vulliet & Cren-Olive, 2011).

Analyses have shown that concentrations of PPCPs in reclaimed wastewater are usually quite small. Although low concentrations typically do not pose any acute risks to human health, they may drastically affect other living organisms: e.g., the exposure to a synthetic estrogen of a fish population resulted in the feminization of males and near extinction of the population in just two years (Kidd et al., 2007). Long-term exposure to low doses of pharmaceuticals may present unknown adverse effects (Rabiet et al., 2006). Moreover, these effects may worsen over time as treated effluent becomes more concentrated due to increasing population density, a wider use of pharmaceuticals, and a decrease in dilution during droughts, or as various pharmaceuticals interact (Vulliet & Cren-Olive, 2011).

Antibiotics and hormones are particularly of concern. For the former, 30–90% of antibiotic doses pass through the human body as urine and find their way into sewage. Antibiotics in wastewater encourage the proliferation of resistant bacteria, which can breed widespread resistance (Costanzo, Murby, & Bates, 2005), hinder the performance of microbial organisms during nitrogen fixation in aquatic ecosystems, and inhibit microbial processes in wastewater treatment(Le-Minh, Khan, Drewes, & Stuetz, 2010). Hormones have already been found in large enough concentrations to create a risk for human health (Vulliet & Cren-Olive, 2011).

For information about environmental and health risks related to urban stormwater harvesting, see (Jiang, Lim, Huang, McCarthy, & Hamilton, 2015).

Text A.3.2. Overcoming Health Risks

A first step for understanding human health risk linked to microbial pathogens in reclaimed wastewater is to assess the magnitude of this risk for various concentrations and types of pathogens; this is the purpose of quantitative microbial risk assessment (QMRA) (Haas, 2002). QMRA includes five steps: identifying pathogens of concern, assessing exposure, modelling dose–response relationships, characterizing risk by integrating results of the first three steps, and managing risk (Haas, 2002). QMRA is the recommended procedure for assessing required pathogen reductions in wastewater used in agriculture (World Health Organization, 2006). Applications of QMRA to crops irrigated with reclaimed wastewater are becoming increasingly popular (Barker et al., 2013; Hamilton, Stagnitti, Premier, Boland, & Hale, 2006; Mara & Sleigh, 2010; Mok & Hamilton, 2014).

After assessing the acceptable concentration of pathogens for a specific use, wastewater can be treated appropriately. The most common and effective barrier against microbiological pathogens is treatment and disinfection. The level of treatment depends on the source of water, the potential for fecal contamination and for contact with people (Toze, 2006). Recycled water treated to a standard below the tertiary level should not be used for purposes that involve direct human contact because it may still contain pathogens. Reverse osmosis and ozonation often effectively remove antibiotics. Activated sludge processes also effectively remove antibiotics and pharmaceuticals, especially with longer retention times (Le-Minh et al., 2010; Rabiet et al., 2006). Wastewater treatment processes, such as clarification, disinfection, and granular-activated-carbon filtration, treat organic compounds, such as caffeine or pharmaceuticals to nondetectable levels (Stackelberg et al., 2007).

Risk can also be minimized by imposing physical barriers between recycled wastewater and human contact, such as restricting irrigation, barring access to areas where lower-quality water is used, and processing goods watered with recycled wastewater (Toze, 2006).

Testing for unregulated contaminants, such as pharmaceuticals, can help policymakers establish priorities for future monitoring (Stackelberg et al., 2007). Because the long-term effects of many compounds are unknown and not all chemicals-of-concern may have been identified (Toze, 2006), more data, analysis, and regulations are necessary to properly assess risk from unregulated contaminants and to develop mitigation strategies (Rodriguez-Mozaz & Weinberg, 2010).

Text A.3.3. Risk Perception

Given the scientific uncertainty about some potential health risks of reclaimed wastewater and the complexity of the environmental fate of the pollutants it contains, it is not surprising that public perceptions of risks do not agree with expert assessment. In fact, a literature review indicates that risk perception issues dominate community acceptance of alternative water sources (Mankad & Tapsuwan, 2011).

Social scientists rely on three main approaches to model risk perception by the public (J. Marks et al., 2008). The first approach (labeled scientific-objective) considers risk as an objective phenomenon that can be scientifically identified and measured; it has been adopted by engineers, economists, and some psychologists (Slovic, 1987). Researchers who rely on this approach to study public perceptions of risks have reported that risks tend to be more acceptable to the public if they are visible, familiar, voluntary, controllable, fair, forgettable, and if their impacts are experienced quickly rather than in an uncertain future (Fischhoff, Slovic, & Lichtenstein, 1982; Gould et al., 1988; Marris, Langford, & O'Riordan, 1996).

Proponents of the second approach (labeled here cultural-relativist) believe instead that risk perception is better understood as a reflection of broader social processes embedded in cultural and historical environments (Douglas, 1986; Douglas & Wildavsky, 1983; Lash, 1994). For Douglas (Douglas, 1986) in particular, the acceptability of risk involves complex factors that include moral and ethical judgments, aesthetic dimensions, and the symbolic nature of 'purity', 'danger', 'pollution', and 'dirty'. For her, the latter is better understood as a cultural construct that reflects a specific social order rather than as a reflection of hygienic knowledge. People are more likely to reject what they perceive to be 'out of place.'

The third approach (labeled realist) partly bridges the other two (Beck, 1995; Beck, Lash, & Wynne, 1992). It sees merit in the empirical assessment and calculation of risks but acknowledges that these objectively measured risks may not reflect actual public perceptions of these risks, which are colored by mistrust of experts, limited understanding of very complex situations, and, in some cases, fear.

In recent years, a number of studies have assessed public perceptions of risks linked to wastewater reuse. In the UK, e.g., Jeffrey and Jefferson (Jeffrey, Jefferson, & Iwa Programme, 2003) found that people were more willing to reuse their own wastewater rather than wastewater from a pooled source. This finding also applies to the United States, where Hartley (Hartley, 2006) reported that people are more accepting of wastewater reuse when the degree of human contact is minimized, public health is promoted, and the reclaimed water is not associated with wastewater. In Australia, Marks (J. Marks et al., 2008) found that the realist view, which is often adopted by water professionals and policymakers, and even more so the scientific-objective view have limited applicability to understand public acceptance of wastewater recycling. In contrast, the cultural-relativist interpretation of different forms and uses of water appears consistent with expressed opinions about water recycling. The importance of health concerns and the complexity of perceptions are further illustrated by results of a survey of urban residents' attitudes towards wastewater reuse in Israel, where some long established and safe uses such as orchard irrigation received less support than higher contact alternatives (Friedler, Lahav, Jizhaki, & Lahav, 2006).

Text A.4. Cost Concerns

One major obstacle to (centralized) wastewater recycling is the cost of the infrastructure needed (i.e., pipes, sensors, water meters, and pumps) to bring this water where it can be productively used. Another potential problem is how to price reclaimed wastewater to make it attractive to potential users (who may be concerned about its potential risks) while recovering the fixed costs to treat and transport it.

Several studies have examined household willingness-to-pay (WTP) for reclaimed wastewater (Blamey, Gordon, & Chapman, 1999; Dupont, 2013; Gibson & Burton, 2011; Hurlimann, 2009; Tapsuwan, Burton, Mankad, Tucker, & Greenhill, 2014). Results show that WTP depends on the intended use of this water, on available alternatives, and on the occurrence of a crisis. For example, Blamey et al. (Blamey et al., 1999) report that households in Australia's Capital Territory have a negative WTP for reclaimed wastewater used for combined indoor and outdoor uses. Gibson and Burton (Gibson & Burton, 2011) obtain a similar result in Perth for potable water supply augmentation. However, WTP becomes positive for outdoor purposes

(Blamey et al., 1999) and when the proposed wastewater reclamation project is seen to be fairer than alternatives (e.g., desalination) (Gibson & Burton, 2011). Encouragingly, Hurlimann (Hurlimann, 2009) found that office workers in Victoria (Australia) have a WTP for recycled wastewater equal to several times the cost of drinking water if it allows them to avoid severe drought restrictions. In Canada, Dupont (Dupont, 2013) estimated that households are willing to pay approximately a 30% premium over average annual water bills for recycled wastewater used to flush toilets if it allows them to avoid summer water restrictions. A recent study (Tapsuwan et al., 2014) suggests, however, that household WTP (in Queensland Australia) may not be sufficient to cover the cost of greywater systems, even in severe drought conditions.

The study conducted by Menegaki et al. (Menegaki, Hanley, & Tsagarakis, 2007) in Crete (a Mediterranean island) is particularly enlightening. They surveyed farmers for their willingness to use and pay for recycled wastewater for irrigation, and consumers for their willingness to use and pay for products irrigated with that water. They found that the labelling of reclaimed wastewater ('recycled water' vs 'treated wastewater') impacted: (1) the willingness-to-use recycled wastewater by farmers and the resulting products by consumers and (2) the WTP for these products by consumers but not the WTP of reclaimed wastewater by farmers (i.e., respondents were much more willing to use and pay for 'recycled water' than for 'treated wastewater'). This result suggests that successful marketing strategies for reclaimed wastewater need to take into account the cultural background of potential consumers. In another study in Crete, Genius et al. (Genius, Menegaki, & Tsagarakis, 2012) evaluated farmers' willingness to pay for a local wastewater treatment plant. They found that farmers valued the possibility of additional irrigation water (from treated wastewater) and that their willingness was positively influenced by water shortages in the region. However, some farmers preferred the status quo over constructing a wastewater treatment plant because of cost concerns.

To stimulate the use of recycled wastewater, subsidies could be provided (Genius et al., 2012; Mekala, Davidson, Samad, & Boland, 2007). Unfortunately, nearly 40% of water utilities around the world have rates that are too low to compensate for operational and maintenance costs (Sergio Jellinek, 2006). Although subsidized prices are meant to provide greater accessibility to meet basic sanitary needs, low water tariffs often do not benefit the poorest segment of the population in developing countries, because its members are often not connected to the water distribution network and they pay much more for water than more affluent households (Genius et al., 2012). In this context, subsidizing recycled wastewater so it can compete with drinking water would further degrade the financial health of water utilities.

A better approach would be to first price freshwater appropriately, which entails balancing economic efficiency, revenue sufficiency for water utilities, political feasibility, and fairness (Hanemann, 1997). To reconcile these conflicting objectives, Hall (Hall, 2009) recommends two-part tariffs (as in Coase (Coase, 1946)) for different homogeneous groups based on observable characteristics such as climate zone and lot size (which are correlated to outdoor water use) and family size (linked to indoor water use). The price in the higher block equals the long-term marginal cost of water (inclusive of all relevant costs, including environmental costs), and the price in the lower block is designed to cancel monopoly profits. The threshold between the two tier-prices is chosen so that on average, different homogeneous groups (e.g., based on lot size and climatic sub-areas as in Los Angeles) pay a similar amount for water for political feasibility reasons (see Hall (Hall, 2009), p. 540).

Reclaimed wastewater could then be priced with respect to this benchmark, based on WTP; incentives may be considered in the short run to entice potential users to overcome their apprehensions. A recent study in Israel illustrates the complexity of finding the right price for recycled wastewater (Lawhon & Schwartz, 2006).

Text A.5. Case Studies

This section briefly reviews various case studies of wastewater reuse, starting with the United States (California and Florida) and Australia. Table A.5.1 presents an overview of obstacles to wastewater reuse by households and how they were addressed. In many countries, treated wastewater is used mostly for crop irrigation, environmental applications, and industrial activities, but not to increase the supply of drinking water because of the 'yuck factor,' fear of health risks, and inappropriate regulations. In low-income countries, only 8% on average of wastewater is treated (Sato, Qadir, Yamamoto, Endo, & Zahoor, 2013), and approximately 80% of the treated wastewater produced is used for irrigation (India, 2007).

Table A.5.1 Overview of Obstacles to Wastewater Reuse by Households and How They Were Addressed

		Obstacles considered			
Reference	Location	Public Acceptance	Perceptions of Risks	Cost Concerns	How obstacles were addressed
23, 70	Brisbane, Queensland, Australia	X			Public Acceptance: • perceived lack of choice: respondents in Brisbane, who were asked about their opinions of drinking recycled water, claimed they would probably have no choice (Dolnicar & Hurlimann, 2009) • Premiere of Queensland issued a statement in 2007 to authorize recycled water for drinking supplies without a consultation process, citing emergency situation of dam

					levels below 40%(Beattie, 2007) • predicted climate variability for the region to result in lower rainfall than in past (Beattie, 2007)
71	Melbourne, Australia	X			Public Acceptance: • aggressive government campaigns broadcasting severity of Millennium Drought invoked urgency of the water shortage and necessity of alternate water sources, such as wastewater recycling (Low et al., 2015) • severe potable water restrictions for outdoor use encouraged acceptance of alternative water sources (Low et al., 2015) • Victorian government issued education programs for schools and homes (Low et al., 2015)
72	Hong Kong	X			Public Acceptance: • demonstration scheme in Sheung Shui, which provided reclaimed water for local residents, schools, and communities (Yue & Tang, 2011)
24	Singapore	X	X	X	Public Acceptance (Ching, 2010): • partnership between water agency (PUB) and political officials • strong support from media outlets • decreased dependence on imported water from Malaysia • consistent terminology and positive message between political leaders and water officials • NEWater bottled in attractive packaging • Public education campaign through NEWater Visitor Centre **Perceptions of Risk:** • terminology changed from "wastewater" to "NEWater" to avoid invoking "yuck factor" • advanced new water technologies emphasized • indirect potable reuse instead of direct potable reuse • detailed science behind treatment processes

					presented • successful wastewater reuse projects elsewhere emphasized **Cost Concerns:** • sixfold price increases for imported water from Malaysia spurred Singapore to develop its own water sources • after inception, media reports focused on new water recycling technologies that would produce NEWater at a cheaper price
73-75	Orange County, California, USA	X	X	X	**Public Acceptance:** • reduced dependence on imported water (Markus & Deshmukh, 2010) • GWRS managers emphasized benefits of protecting local groundwater (Markus & Deshmukh, 2010) • network of openly supportive health officials, water officials, and local politicians (Markus & Deshmukh, 2010) **Perception of Risks:** • public tours of facility allow visitors to see the technology working in real time (Orange County Water District (OCWD)) • injection of treated water into groundwater recharge basins remove association with "yuck factor" (Orange County Water District (OCWD), 2014) • water quality monitoring (Orange County Water District (OCWD), 2014) • research laboratory for developing new technologies (Orange County Water District (OCWD), 2014) **Cost Concerns:** • water produced at the GWRS costs less than half of that of imported water from Northern California (Markus & Deshmukh, 2010)
76, 77	Windhoek, Namibia	X	X		**Public Acceptance:** • water demand management campaign with media coverage (du Pisani, 2006) • lack of alternatives due to few water resources (du Pisani, 2006)

					Perception of Risks: • regular water quality monitoring and testing (du Pisani, 2006) • school visits at the local water reclamation plant (Rygaard, Albrechtsen, & Binning, 2009) • student projects related to wastewater reuse (Rygaard et al., 2009) • state-of-the-art facilities to ensure high quality standards (du Pisani, 2006)

Text A.5.1. The Americas

In the United States, wastewater is reused mostly in drier areas (e.g., Arizona, California, Colorado, and Texas) or in growing areas experiencing strained water supplies (e.g., Georgia and Florida) (Hartley, 2006).

Motivated by droughts, saltwater intrusion in coastal aquifers, and difficulties meeting a soaring water demand, Florida currently produces the most recycled wastewater of any state (Parsons, Sheikh, Holden, & York, 2010). It began reusing wastewater in 1977 after the Wilson-Grizzle Act mandated that wastewater discharges into Tampa Bay must meet drinking water standards. In 2013, Florida's 482 domestic wastewater treatment plants provided recycled wastewater for public access areas (54%), industry (17%), groundwater recharge (14%), agriculture (10%), and other uses (5%) (Florida Department of Environmental Protection (FDEP) Water Reuse Program, 2014). Florida's success with recycled wastewater was bolstered by fewer irrigation restrictions on reclaimed water during droughts and no reported illnesses related to its agricultural uses (Parsons et al., 2010).

Although it has the largest population of any state in the U.S. and it was a pioneer in the use of recycled wastewater, California is in second place (669,000 acre-feet in 2009 (California Environmental Protection Agency, 2012) vs 746,900 acre-feet for Florida in 2008 (Parsons et al., 2010)) by volume for recycled wastewater, which is used for agriculture (37%), landscape and golf course irrigation (24%), groundwater recharge (12%), industry, and prevention of seawater intrusion (7% each) (California Environmental Protection Agency, 2012; Parsons et al., 2010).

California has known successes and failures for reclaiming its wastewater. Selected examples of the latter include the Bay Area Water Recycling Program, the Dublin San Ramon Clean Water Revival, and the City of Los Angeles East Valley Water Reclamation Project (Po et al., 2003). San Diego also experienced pain with its wastewater reclamation projects. Following fierce opposition to an indirect potable reuse scheme in the 1990s and legal requirements to reclaim its wastewater, it proposed instead a direct potable project. Strong public opposition (which rallied around the 'yuck factor') led to the abandonment of this project. Several reasons explain this failure: public concerns were not adequately addressed; the project appeared to serve predominantly a minority area, leading to accusations of environmental racism; and experts aired publicly conflicting opinions (Hartley, 2006).

Some of California's most successful wastewater reclamation projects were implemented in Orange County in southern California. In 1976, the Orange County Water District (OCWD) began injecting treated wastewater in coastal aquifers to halt saltwater intrusion (Water Factory 21). In the 1990s,OCWD partnered with the Orange County Sanitation District (OCSD) to build a new facility that produces 70 millions of gallons per day (MGD) of drinkable water for both halting saltwater intrusion and recharging a local aquifer (See Text A.5.1.1.). This facility—the Groundwater Replenishment System—which began operating in January 2008, has won a number of awards and is known for excellent public outreach (Markus & Deshmukh, 2010).

In Canada, wastewater is reused at a relatively small scale with regional variations that depend on water supply availability and regulatory flexibility (Schaefer, Exall, & Marsalek, 2004); in Alberta, e.g., reclaimed wastewater cannot be used inside buildings (Authority). Indeed, even though Canada has abundant water resources (Sullivan, 2002), many municipalities regularly experience water shortages. The main applications of treated wastewater include crop irrigation, golf course and urban landscape irrigation, and toilet flushing (Exall, Marsalek, & Schaefer, 2006).

In Latin America, few water reclamation projects have been implemented (Bixio et al., 2005). Over 500,000 ha of agricultural land are irrigated with raw wastewater (Van der Bruggen, 2010), but the lack of treatment makes it unsafe. According to the Pan-American Health Organization, the percentage of wastewater treated before it is discharged in the environment is under 14% in the region (Van der Bruggen, 2010).

Text A.5.1.1. GWRS: A California Success Story

The success of the Groundwater Replenishment System (GWRS) highlights the importance of active community involvement. In 1976, the OCWD, which supplies potable water to over 2 million people, began injecting treated wastewater into the coastal edge of its groundwater basin to halt saltwater intrusion. However, in the 1990s, more water was needed. At the same time, the ocean outfall of the OCSD was nearing capacity. An opportunistic partnership formed between OCWD and OCSD: it freed some capacity in OCSD's ocean outfall pipe by diverting some treated wastewater to a new facility (the GWRS) that created a reliable source of drinking water (this water is first injected in the local aquifer to further reassure the public). Learning from the failure of other wastewater reuse projects in southern California, GWRS project managers highlighted the benefits of protecting local groundwater, the need to reduce Orange County's dependence on imported water, and forged a coalition of health officials, water officials, and politicians in support of the GWRS, detracting attention away from the yuck factor

(Markus & Deshmukh, 2010). They emphasize transparency by encouraging public visits, which continue to this day (Orange County Water District (OCWD)). With a production of 70 million gallons of water per day (MGB), which is enough to supply almost 600,000 people, the GWRS is the world's largest water purification system for indirect potable reuse (Orange County Water District (OCWD), 2014). An expansion, scheduled to be completed by 2015, will increase its capacity to 100 MGD(Orange County Water District (OCWD)).

Text A.5.2. Australia

In Australia, a number of cities have successfully implemented wastewater reuse schemes. Adelaide sources some of its water (through indirect potable reuse) from the Murray River, which receives treated wastewater from several rural communities(Cullen, 2004). In Brisbane, the Queensland Government announced in 2007 the implementation of an indirect potable reuse scheme, skipping the consultation process altogether (Beattie, 2007; Dolnicar & Hurlimann, 2009). In New South Wales, two coastal towns (Gerringong and Gerroa) share a wastewater treatment plant that can yield up to 80% of recycled water. This water provides irrigation water for a local dairy farm's pasture and discharges the remainder to local receiving waters. High quality water in this coastal region is important because it is a popular tourist destination with beaches and local streams (Boake, 2006). For an overview of Melbourne's reliance on reused wastewater, see Low et al. (Low et al., 2015)

Despite several successful cases, Australia has also experienced some failed wastewater reclamation projects. In July 2006, e.g., Toowoomba (in Queensland) held a referendum to decide on the construction of an indirect potable wastewater recycling plant. Residents voted against the scheme after media coverage mentioned the 'yuck factor' (Dolnicar & Hurlimann, 2009). This project's failure was attributed to cultural and management issues, and to a lack of support from some local political leaders.

Text A.5.3. Asia

In Asia, Japan started experimenting with wastewater reuse in 1951 for an industrial paper mill in Tokyo. Large-scale reuse efforts began in 1964 in response to severe droughts that affected several regions of the country (Ogoshi, Suzuki, & Asano, 2001). In spite of this relatively long history, only 1.4% of treated municipal wastewater is currently recycled in Japan (vs 79% of industrial water) (Hiroki Yamagata). Whereas in most other countries reclaimed wastewater is predominantly used to irrigate crops, in Japan wastewater reuse is dominated by environmental, nonpotable urban, and industrial applications ((UNEP), 2005): in 2006, the top three uses of reclaimed wastewater were (1) enhancing urban streams (32.5%), (2) landscape irrigation (27%), and (3) melting snow (18%) (Hiroki Yamagata). However, with the Japanese population declining slightly, the volume of reclaimed municipal wastewater has remained stable in recent years along with the demand for freshwater.

Two success stories in Asia deserve special attention, although they may be difficult to reproduce elsewhere. The first one is Singapore, which implemented in 2001 a wastewater reuse scheme for nonpotable industrial uses, in order to decrease its water dependence on Malaysia. The recycled water was branded 'NEWater' to remove negative connotations associated with 'wastewater.' By 2003, NEWater provided 1% of Singapore's water via indirect potable reuse. This program owes its success to an emergency situation and publicity campaigns where newspapers praised NEWater, touted new water technologies, and highlighted the benefit of reduced dependency on Malaysia. Political leaders adopted a consistent message to reassure the public and successful wastewater reuse projects elsewhere were emphasized to underscore that recycled water is safe and reliable (Ching, 2010).

The second success story is Hong Kong. To reduce its reliance on imported water from China (Yue & Tang, 2011), Hong Kong broadened its water supply portfolio by using seawater for toilet flushing, reusing wastewater, and starting a pilot desalination project. It also implemented a three-tier tariff structure for fresh water, required individual meters for households, repairs leaks, created education campaigns to foster water conservation, and opened a tertiary sewage treatment plant (Yue & Tang, 2011). Overall, Hong Kong successfully coupled conservation measures with education and public awareness campaigns to gain acceptance for nonpotable wastewater reuse.

Unfortunately, the wastewater recycling situation is not very bright in the rest of Asia. In spite of severe water problems that include institutional weaknesses, low water quality, deficient pricing, poor infrastructure, and widespread pollution (India, 2007), India has not done much to reclaim wastewater for urban uses, and some attempts at implementing wastewater reclaiming have run into public opposition, as in Chennai (K, 2008).

China began using (mostly untreated) municipal wastewater to irrigate crops in the 1940s; after a demonstration stage (from 1985 to 2000), the use of reclaimed wastewater picked up but low public acceptance has prevented it from becoming widespread (Yi, Jiao, Chen, & Chen, 2011). Groundwater pollution is a concern in more than half of China's major wastewater irrigation areas; even though China ranks low in the world for water availability, in 2008 only 8% of total treated municipal wastewater was reclaimed and reused (Yi et al., 2011). In addition to public opposition, obstacles to wastewater reuse in China include: unclear or inconsistent water quality standards for reclaimed wastewater (Mok & Hamilton, 2014), inadequate pricing;

lack of private sector investment (Yang & Abbaspour, 2007); and insufficient planning for wastewater treatment (Yi et al., 2011).

Text A.5.4. Africa

In Africa, we found only a few examples of wastewater reclaiming projects, most of which focus on agriculture. However, there are a few important exceptions. Indeed, the first major potable direct reuse project in the world was built in 1968 in Windhoek, the capital of Namibia (a country located along the south-western coast of Africa, north of South Africa) (See Text A.5.4.1.) (du Pisani, 2006). After a 2002 upgrade that saw the installation of cutting-edge technology, Windhoek's wastewater recycling plant produces up to 21,000m^3/day of high-quality drinking water, which represents up to a third of the city's daily potable water needs (du Pisani, 2006). Although by all accounts this project has been quite successful, it remains the only large-scale example of direct potable wastewater reuse in the world (Rygaard, Binning, & Albrechtsen, 2011). Overall, however, sanitation remains insufficient in Namibia, where two thirds of the population (including 298 schools) lacks access to improved sanitation (T, 2014).

Another exception is Durban, a major industrial city in South Africa, with a history of periodic droughts, where high-quality recycled water has been provided for industrial use since 2001 (Friedrich, Pillay, & Buckley, 2004).

In Egypt (and a few other Mediterranean countries), an international organization called Zer0-M has been providing technology to achieve optimized closed-loop usage of water flows in small municipalities without central wastewater treatment (Regelsberger, Baban, Bouselmi, Shafy, & El Hamouri, 2007). Apart from these examples, it appears that few African countries rely on reclaimed wastewater in spite of the dire water situation on this continent.

Text A.5.4.1. Windhoek: The Only Large-Scale Direct Potable Wastewater Reuse System In The World

The City of Windhoek that counts approximately 322,000 inhabitants is located in central Namibia, a very arid area that is approximately 465 miles from the closest perennial river (Rygaard et al., 2009). Most of Windhoek's water comes from three reservoirs supplied by ephemeral rivers; less than 11% of its water comes from groundwater. Because of the dryness of central Namibia (the average annual rainfall is 14.4', which is a fraction of the annual evaporation rate of 136') (du Pisani, 2006), stringent water restrictions that include bans on daytime irrigation, use of outdoor hoses, and car washing, are periodically imposed. Efficient water fixtures and appliances are heavily promoted, along with advice on preventing leaky water taps. As a result, although Windhoek's population grew at a 5% rate from 1967 to 2005, its per capita water consumption decreased from 315 litres/person/day (lppd) in 1967 to 196 lppd in 2005 (Rygaard et al., 2009). The public's initial reluctance to consume highly purified reclaimed wastewater was overcome partly by a lack of alternatives but also by an on-going water demand management campaign (with coverage in the media and in a municipal newsletter) that encourages water conservation. Water quality is monitored and tested regularly to ensure the quality of reclaimed wastewater (du Pisani, 2006). Moreover, visits of the water reclamation plant are periodically organized for schools, and students are involved in projects related to wastewater reuse (Rygaard et al., 2009).

Text A.5.5. Europe

Although Europe as a whole is well endowed in water resources compared to other parts of the world, marked regional differences explain that almost 70% of Europeans are exposed to water stress (excessive abstraction of water given available resources) (Bixio et al., 2006). In this context, the EU published in 2012 the ‘Blueprint to safeguard Europe’s water resources’ to foster wastewater reuse for agricultural and industrial purposes because, even though wastewater reuse has lower environmental impacts than alternatives such as desalination, it is limited by a lack of common standards and concerns about agricultural products irrigated with reused water (European Union–Environment, 2014). In Italy, e.g., wastewater recycling is only allowed for agricultural purposes, and on the condition that it can increase crop yield (Van der Bruggen, 2010).

Based on 2006 data (the latest seemingly available) (Union, 2012), 2.4% of treated wastewater was reused in Europe, with high values of 100% and ~60% in Cyprus and Malta, and lows between 5 and 12% in Greece, Italy, and Spain. Almost three-quarters of the treated wastewater was used to irrigate crops, and the remainder was almost equally distributed between environmental uses, groundwater recharge, industrial applications, and urban uses (but not human consumption) (Union, 2012). These numbers hide large regional differences: in the EU Mediterranean countries, treated wastewater was used mostly for irrigating crops, whereas in Atlantic and continental European countries, reuse occurred mainly for urban, environmental or industrial applications.

Increasing demand (often seasonal in nature, driven by tourism), severe droughts, and concerns about climate change are driving the EU to rely more on treated wastewater, but so far the focus is on environmental, agricultural, and industrial uses to compensate for drinking water restrictions (Union, 2012). Overall, a recent EU report on water reuse concludes that urban wastewater reuse is not well understood in Europe, although some coastal areas have been experimenting with indirect potable reuse (Union, 2012).

Text A.5.6. The Middle East

In the Middle East, where water scarcity is high, reclaimed wastewater is not used in urban areas (except for landscaping) but at least eight countries use it for agriculture. However, some raw sewage is still used for irrigation in Egypt, Iran, Lebanon, Palestinian Territories, Syria, and Yemen (Radcliffe, 2004). Three countries are at the forefront of wastewater recycling: Israel, Jordan, and Kuwait.

Israel is a world-leader in wastewater reuse for agriculture, not only because it has one of the oldest wastewater reuse legislations (1953) but also because its institutions and policies instilled confidence in reclaimed wastewater users (Guardiola-Claramonte, Sato, Choukr-Allah, & Qadir, 2012; Qadir, Bahri, Sato, & Al-Karadsheh, 2010). The fraction of treated wastewater reused is high (~75%) and makes up a large percentage of its water supply (20% in 1994) (Qadir et al., 2010; Radcliffe, 2004); approximately 65% of the connected sewage in Israel is reused for irrigation purposes (Van der Bruggen, 2010). Several factors contributed to public acceptance of reclaimed wastewater and to its adoption by farmers, including a dearth of alternative water resources, technical guidance provided by the government to farmers, and prices that are 20% lower than for freshwater (Qadir et al., 2010). In addition, the government has been conducting research to address the long-run salinization of groundwater caused by irrigation with reclaimed wastewater (Qadir et al., 2010).

Due to low water availability, Jordan focused early on wastewater recycling, creating in 1971 a public health framework (which has been updated and improved several times) to foster the safe use of reclaimed wastewater (Guardiola-Claramonte et al., 2012). In 1998, 95% of the treated wastewater (74 million m3/year) was reused for irrigation; most (~80%) of the treated effluents were used for irrigation in the Jordan Valley, and the remaining 20% was used on site as process water (Radcliffe, 2004).

Kuwait also has very limited water resources. In 1965, it began treating its wastewater that was used to irrigate alfalfa (Alhumoud et al., 2003). In Kuwait, treated wastewater is used to irrigate one quarter of crops and green areas using, and to recharge groundwater (Radcliffe, 2004). In spite of its history of reuse, a recent survey of Kuwait residents showed that over 80% of respondents had no basic understanding of wastewater reuse and that over 95% of respondents oppose using reclaimed wastewater (Alhumoud et al., 2003).

For more information about other Middle Eastern countries, see Guardiola-Claramonte et al. (Guardiola-Claramonte et al., 2012) and Qadir et al. (Qadir et al., 2010).

Text A.6. Concluding Remarks

More than one billion people do not have access to clean water and water scarcity is no longer reserved to arid regions. It is becoming more common with population and economic growth, combined with poor management, dysfunctional water institutions, inadequate infrastructure, and global climate change (McDonald et al., 2011; Rygaard et al., 2011; Yi et al., 2011). This stark reality highlights the need for reliable new sources of water. Reclaimed wastewater can fulfill this role (especially for uses that do not require drinking water), and it can help reduce water pollution. The idea of reusing wastewater is not new, but explicit reuse is far from achieving its potential to augment insufficient water supplies, especially in urban areas.

A number of obstacles remain before recycled wastewater can become a full-fledged component of the residential water portfolio. These include public acceptance, public attitudes towards risk, and costs. Public acceptance is also conditional on trust in water authorities, a factor we did not focus on herein, but that was examined repeatedly in the literature (Hartley, 2006; J. S. Marks, 2003, 2006; Po et al., 2003). Because of the specificities of each community and of each wastewater reuse project, there is no magic bullet for solving water supply problems worldwide (J. S. Marks, 2006), but certain key features are essential to the success of a wastewater reuse project.

First, to be effective public outreach needs to use multiple methods of communication to manage different types of information; there should be equal access to information with messages adapted to the target audience; and it is critical to have an open, fair, and transparent process to motivate citizens to participate actively in the decision-making process (Hartley, 2006). As emphasized by Marks (J. S. Marks, 2006), effective public consultation involves respectful deliberation that promotes community involvement and attempts to provide meaningful answers to community concerns, as opposed to the strategic communication approach based on 'Decide, Advise, Defend' that is often employed to market a project to the public, reducing participation to tokenism. The case studies covered in this review exhibit many methods of communication that contributed to acceptance of wastewater reuse, such as: positive media coverage in Singapore (Ching, 2010) and Windhoek (du Pisani, 2006); support from political leaders in Orange County, California (Markus & Deshmukh, 2010), Singapore, and Hong Kong (Yue & Tang, 2011); publicity campaigns by water agencies and their partners in Orange County, Singapore, Hong Kong; and education campaigns, as in Orange County, Hong Kong, and Windhoek.

Second, the need for using reclaimed wastewater should be clearly explained and motivated (Bruvold & Ward, 1972; J. S. Marks, 2006; Yue & Tang, 2011). As shown in the case studies summarized above (Beattie, 2007; Ching, 2010; du Pisani, 2006; Guardiola-Claramonte et al., 2012; Qadir et al., 2010), successful wastewater reuse projects were often conceived and realized during a water crisis that forced people to leave their comfort zone and decision makers to think creatively (Dolnicar & Hurlimann, 2009).

Third, it is critical for a wastewater reuse project to have the full support of the scientific community and of health experts in particular, as was the case, e.g., for successful projects in Orange County, California (Markus & Deshmukh, 2010) and in Hong Kong (Yue & Tang, 2011) It is also essential for elected officials to be unified in their support, as in Singapore, where political figures publicly supported the NEWater project (Ching, 2010). In other cases, such as in Sydney, Australia (2005) and San Diego, California (1990s), the lack of consistency in public officials' support led to confusion and uncertainty in the public, which allowed emotional disgust reactions (such as the 'yuck factor') to prevail (Ching, 2010; Hartley, 2006).

In addition, pricing needs to be right both for drinking water and for reclaimed wastewater (Sergio Jellinek, 2006; Yi et al., 2011; Yue & Tang, 2011). Drinking water subsidies prevent reclaimed wastewater from being cost competitive (Mekala et al., 2007). Controversy over who pays also complicates pricing: should the polluter pay for creating reusable wastewater or should the beneficiary pay for reclaimed wastewater (Lawhon & Schwartz, 2006)? A sound and progressive regulatory framework is also necessary for successful wastewater reuse projects. The lack of such frameworks may account for the paucity of successful wastewater recycling schemes in Europe, where there is no uniform standards for water reuse (European Union–Environment, 2014), and in Canada, where water reuse regulations are left to provinces (Exall et al., 2006; Schaefer et al., 2004).

Finally, detailed information about wastewater recycling projects in other jurisdictions around the world would help inform managers of water utilities, regulators, and the public. Unfortunately, information about wastewater generation, treatment, and reuse is severely lacking for most countries (Sato et al., 2013). Without adequate data about treatment and reuse, e.g., the health risks that may arise from wastewater reuse cannot be assessed. The lack of water to serve a rapidly growing population (McDonald et al., 2011) and competing interests among agriculture, urban use, and industry highlight the urgent need for more data and analysis (Sato et al., 2013).

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APPENDIX B

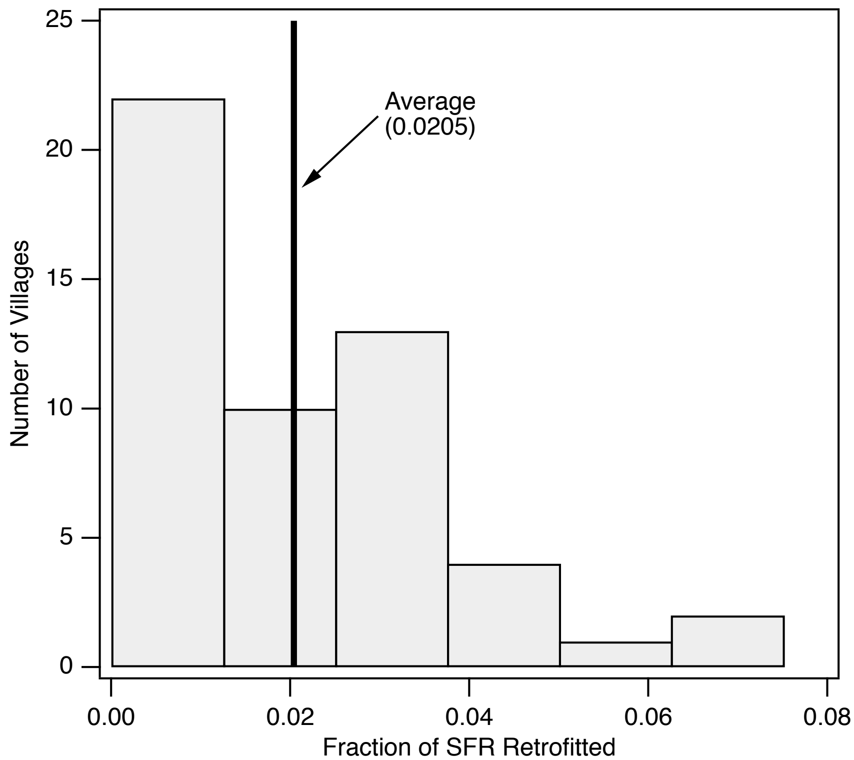

Figure B.1. Histogram of the fraction of single-family residences (SFRs) retrofitted

This histogram shows the fraction of SFRs that participated in the rebate program from the 52 villages included in this study. The distribution is positively skewed with a skewness coefficient of $\theta = 0.934$.

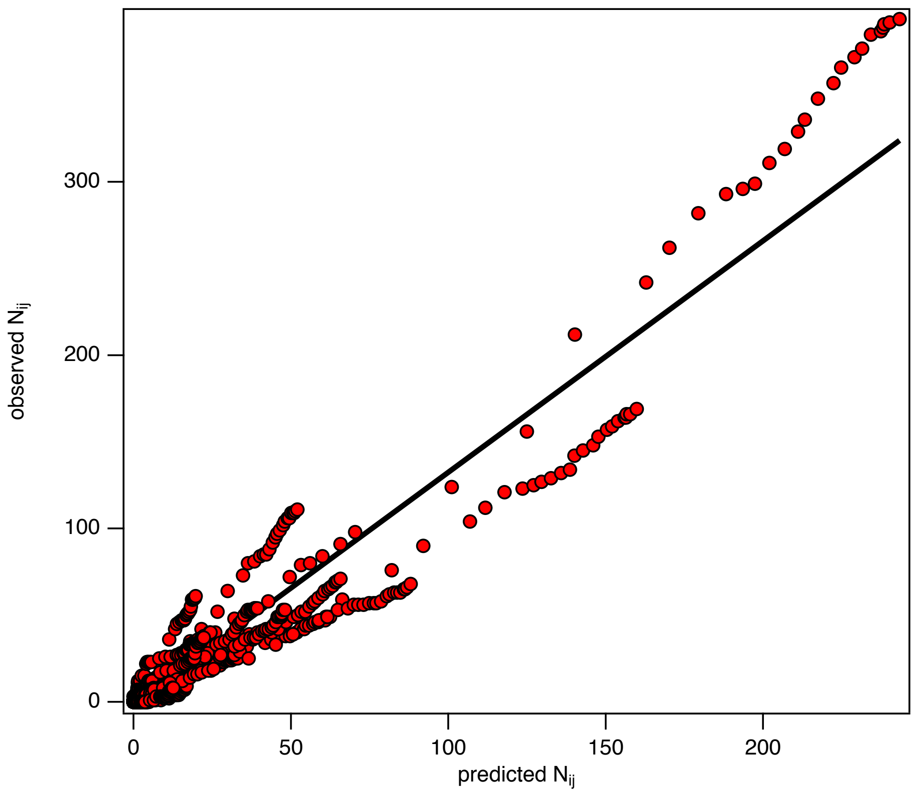

Figure B.2. Predicted vs. observed $N_{i,j}$

The Bernoulli trial model for turf retrofit applications captures 96% of the variance in the cumulative number of applications received from the i-th village by the j-th month ($N_{i,j}$). Here, the cumulative applications received from 42 villages in the IRWD service area (vertical axis) are compared with the number of applicants predicted by equations (6a) and (6b) **in Chapter 1**. Cross plot of observed vs. predicted $N_{i,j}$ (red points) for 42 villages in the IRWD service area. The diagonal line represents a one-to-one relationship. A total of 3276 points (representing different combinations of months and villages) are included in this plot.

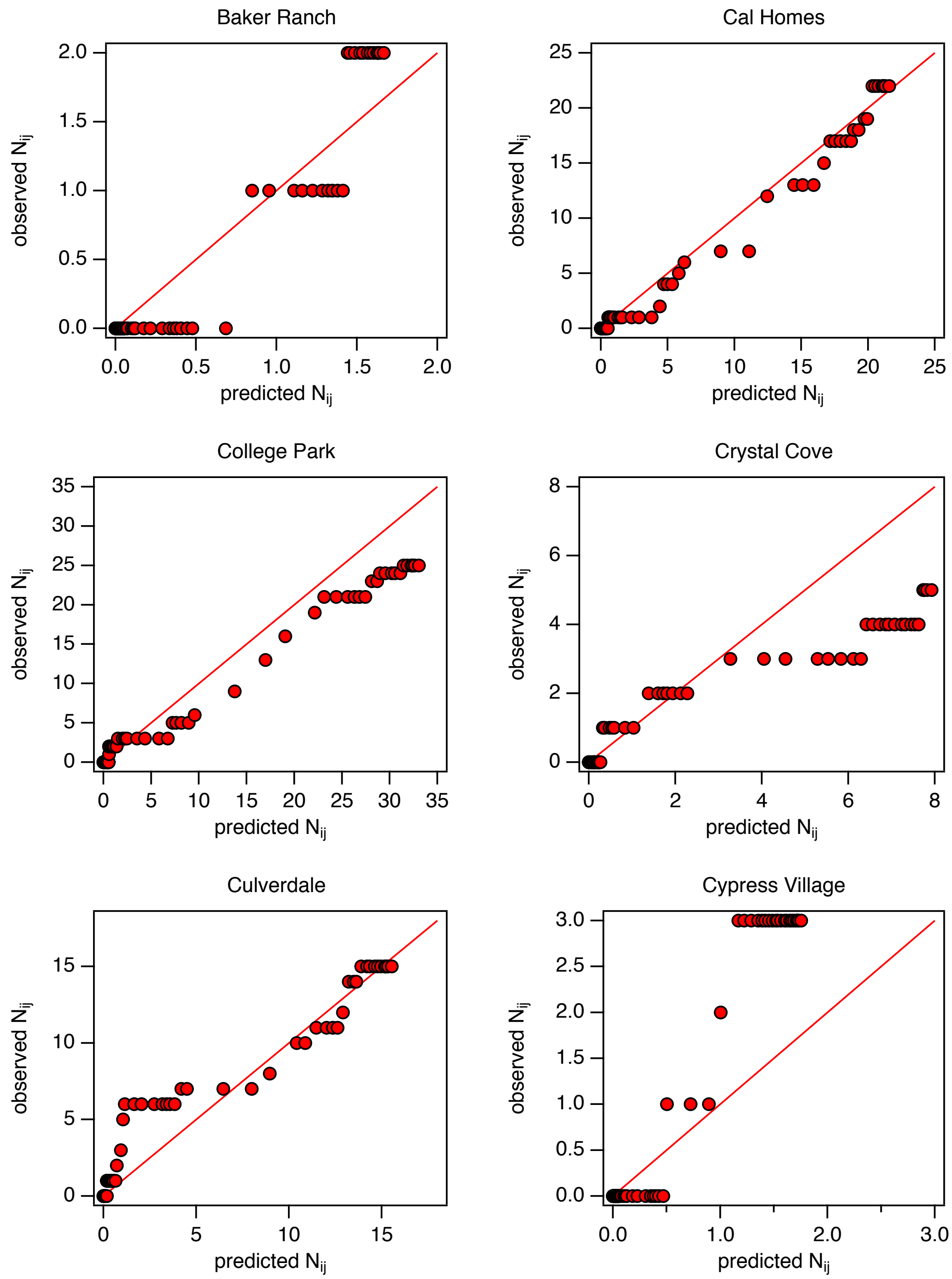

Figure B.3 Subset 1 of the data included in Figure B.2

These plots correspond to six of the 42 villages (Baker Ranch, Cal Homes, College Park, Crystal Cove, Culverdale, and Cypress Village). The diagonal lines represent a one-to-one relationship. (Note that the axes have been adjusted to reflect the data range).

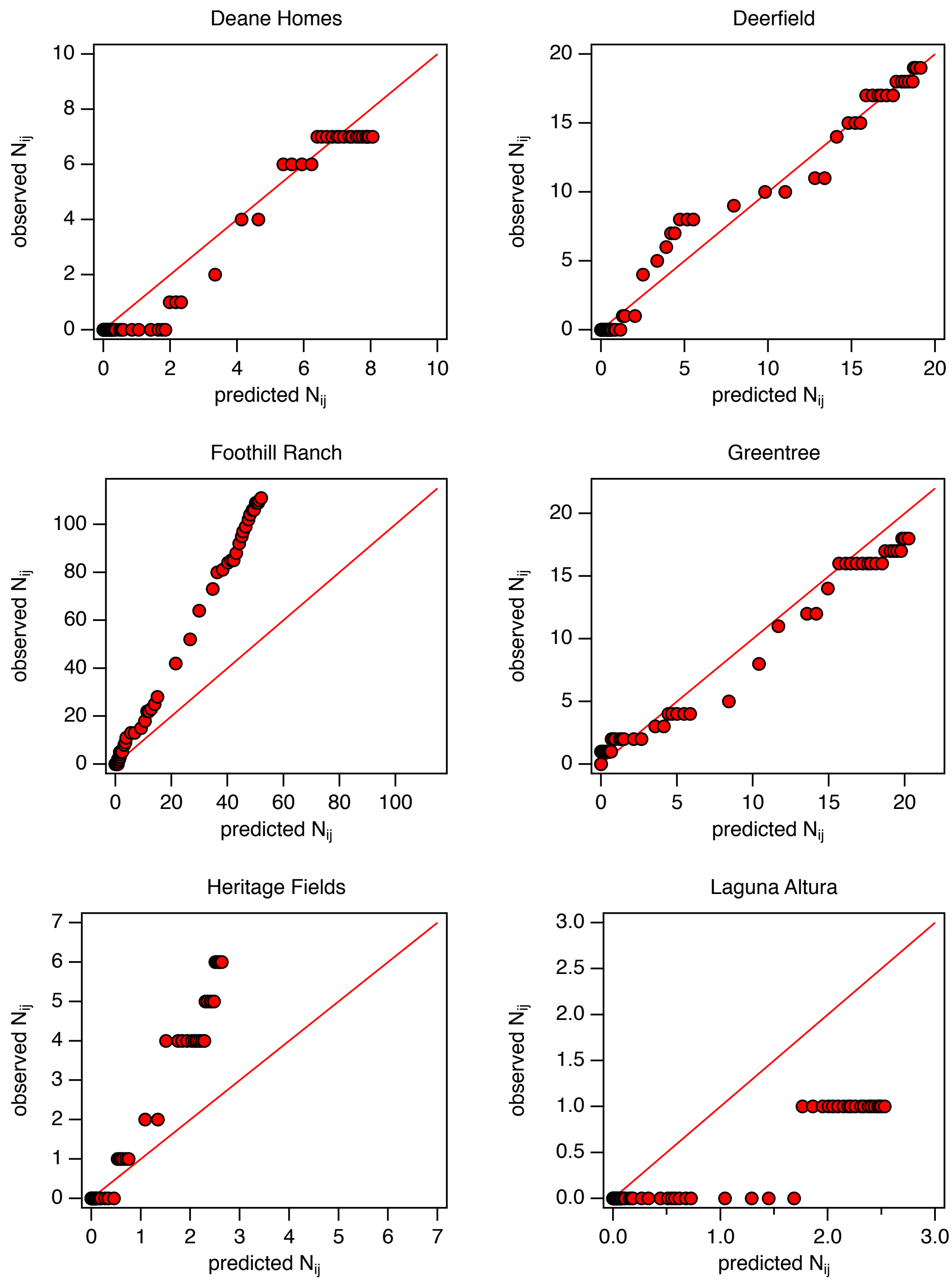

Figure B.4 Subset 2 of the data included in Figure B.2

These plots correspond to six of the 42 villages (Deane Homes, Deerfield, Foothill Ranch, Greentree, Heritage Fields, and Laguna Altura). The diagonal lines represent a one-to-one relationship. (Note that the axes have been adjusted to reflect the data range).

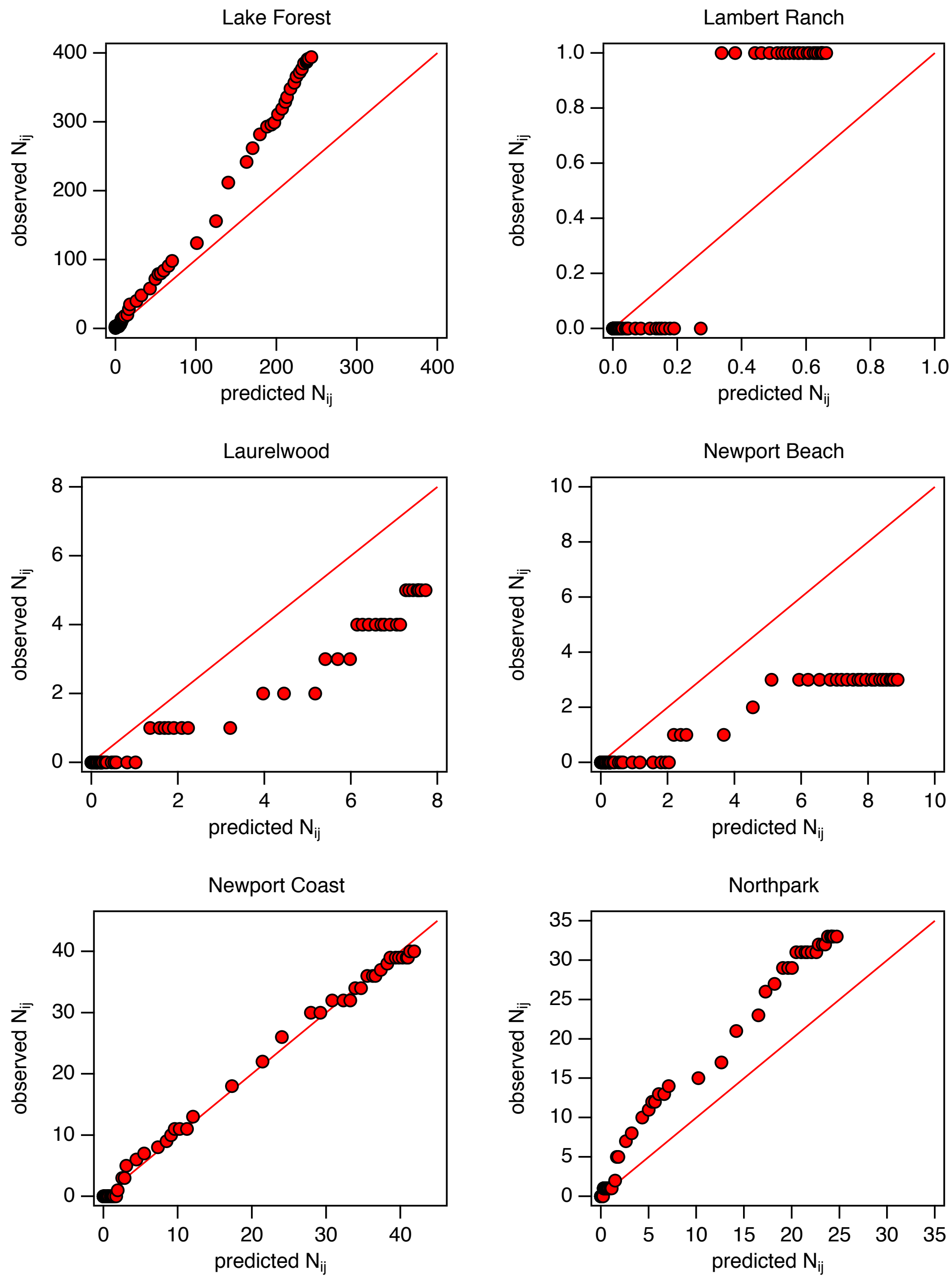

Figure B.5 Subset 3 of the data included in Figure B.2

These plots correspond to six of the 42 villages (Lake Forest, Lambert Ranch, Laurelwood, Newport Beach, Newport Coast, and Northpark). The diagonal lines represent a one-to-one relationship. (Note that the axes have been adjusted to reflect the data range).

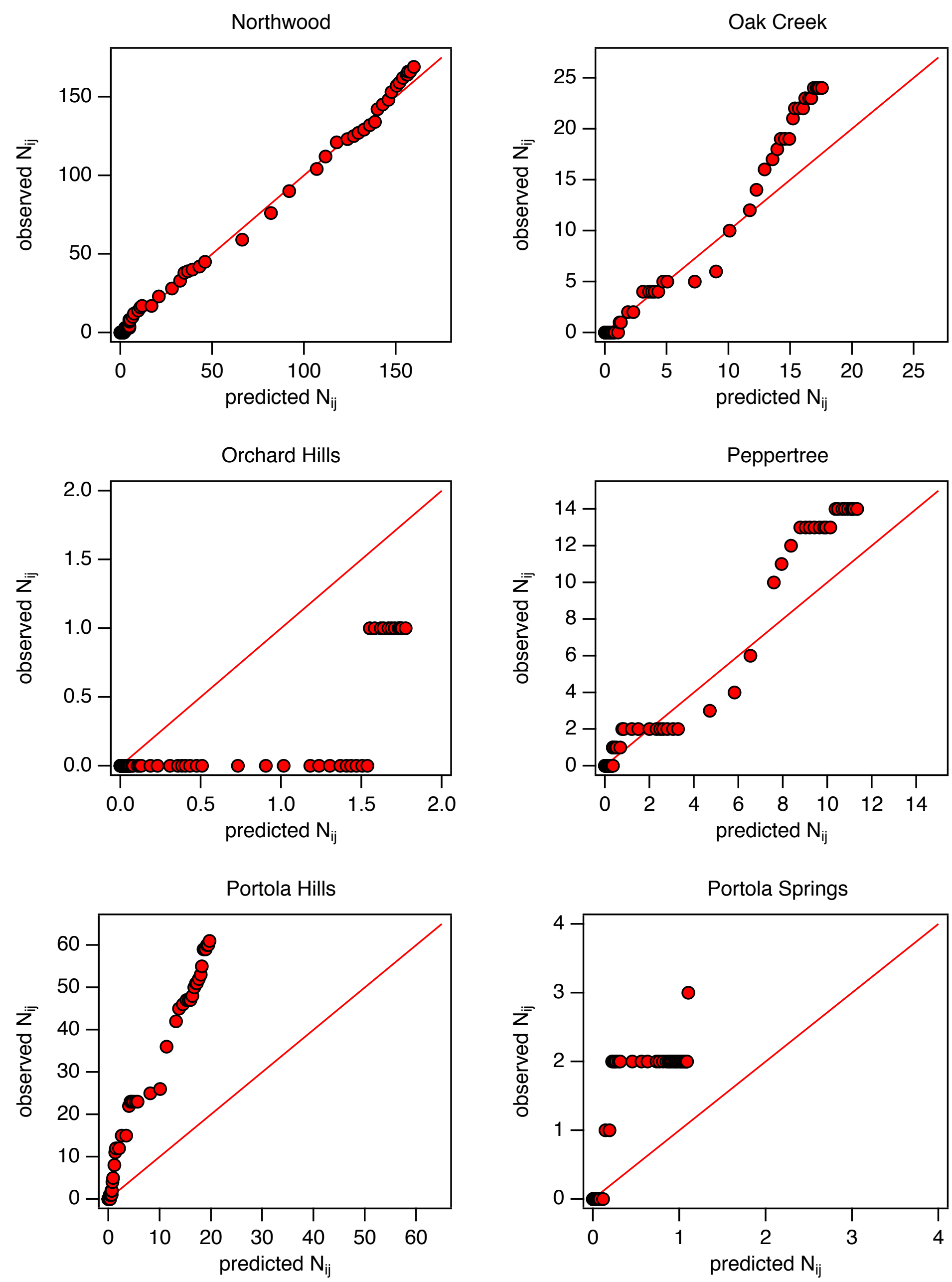

Figure B.6 Subset 4 of the data included in Figure B.2

These plots correspond to six of the 42 villages (Northwood, Oak Creek, Orchard Hills, Peppertree, Portola Hills, and Portola Springs). The diagonal lines represent a one-to-one relationship. (Note that the axes have been adjusted to reflect the data range).

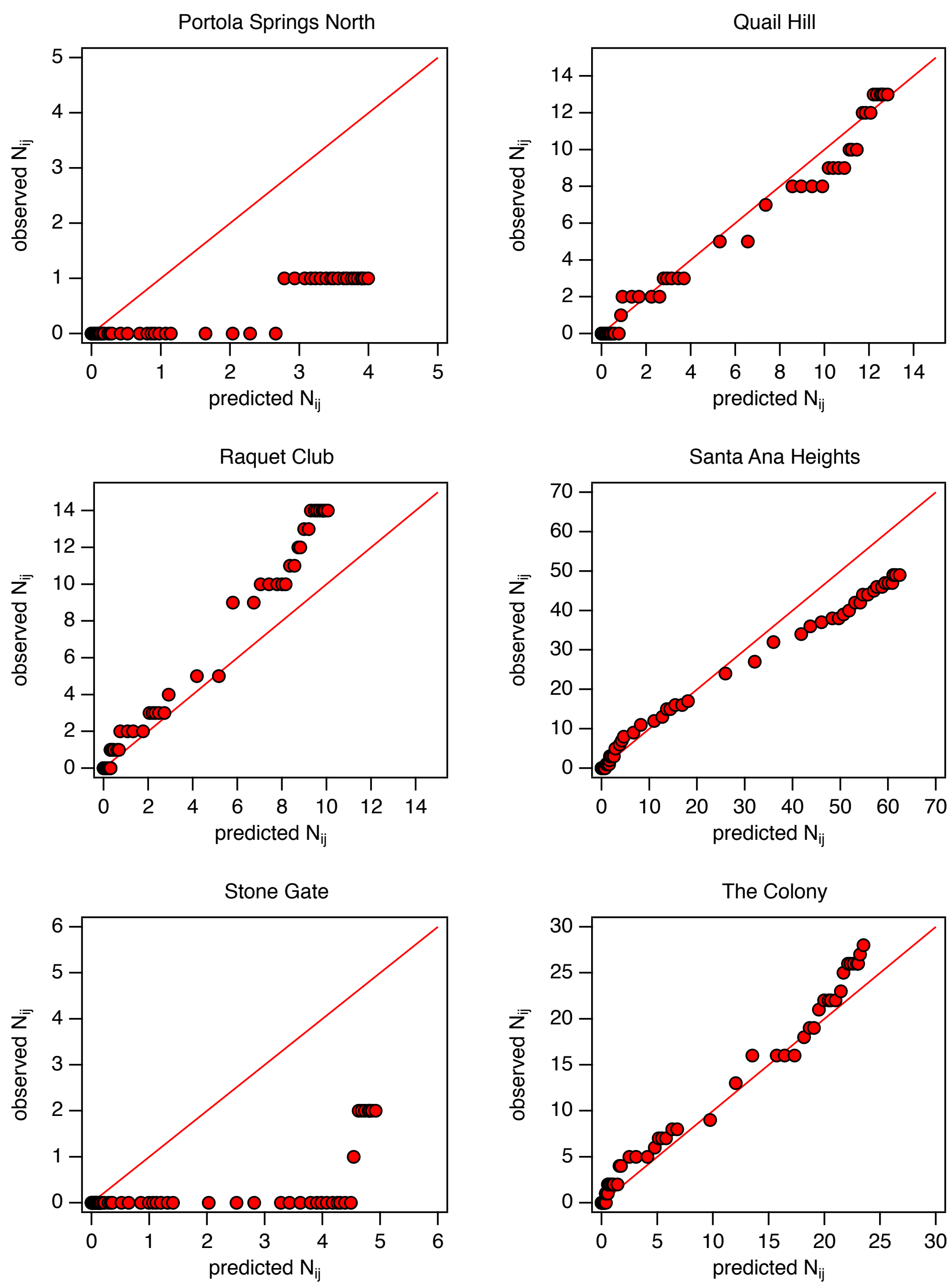

Figure B.7 Subset 5 of the data included in Figure B.2

These plots correspond to six of the 42 villages (Portola Springs North, Quail Hill, Raquet Club, Santa Ana Heights, Stone Gate, and The Colony). The diagonal lines represent a one-to-one relationship. (Note that the axes have been adjusted to reflect the data range).

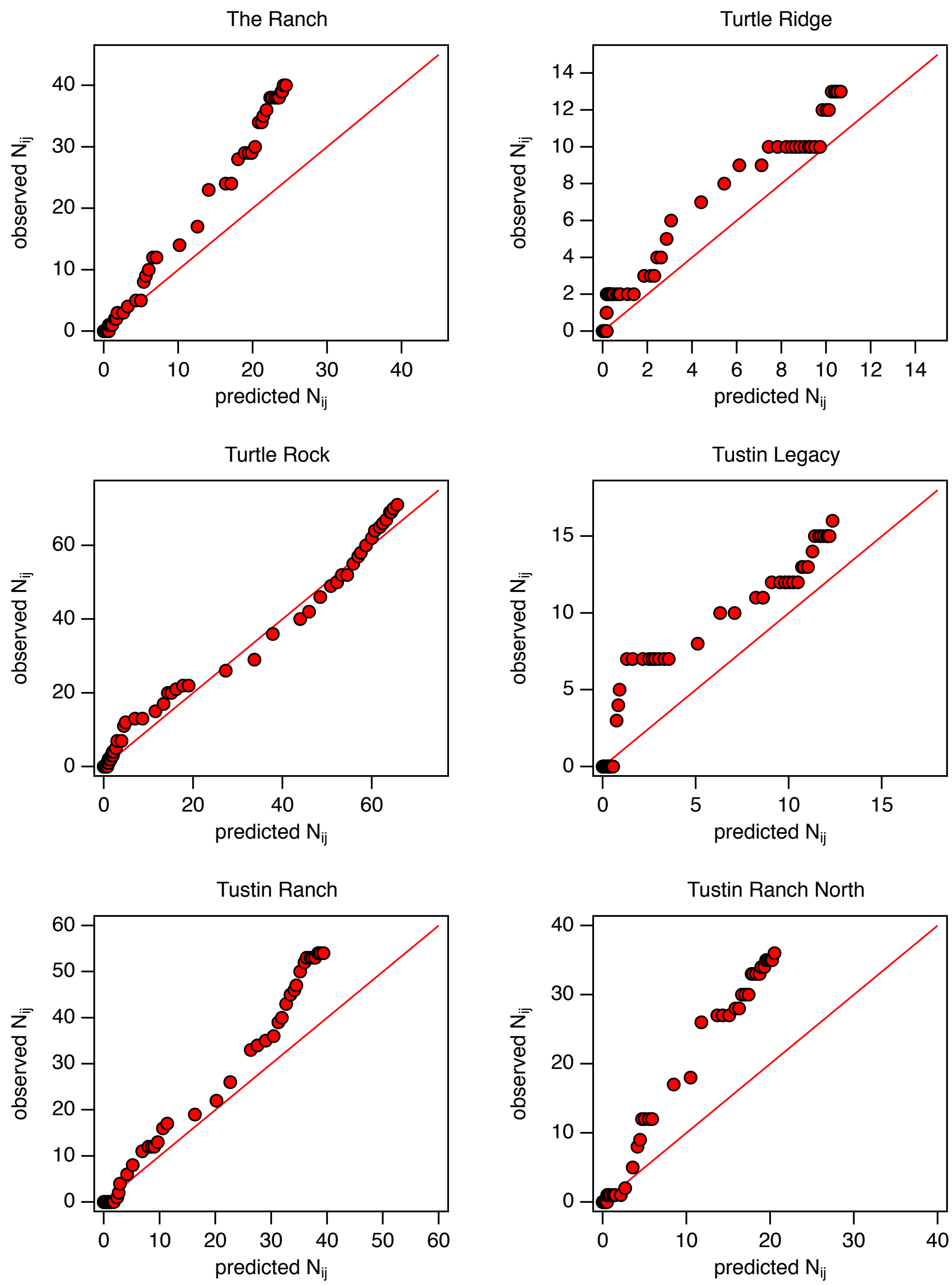

Figure B.8 Subset 6 of the data included in Figure B.2

These plots correspond to six of the 42 villages (The Ranch, Turtle Ridge, Turtle Rock, Tustin Legacy, Tustin Ranch, and Tustin Ranch North). The diagonal lines represent a one-to-one relationship. (Note that the axes have been adjusted to reflect the data range).

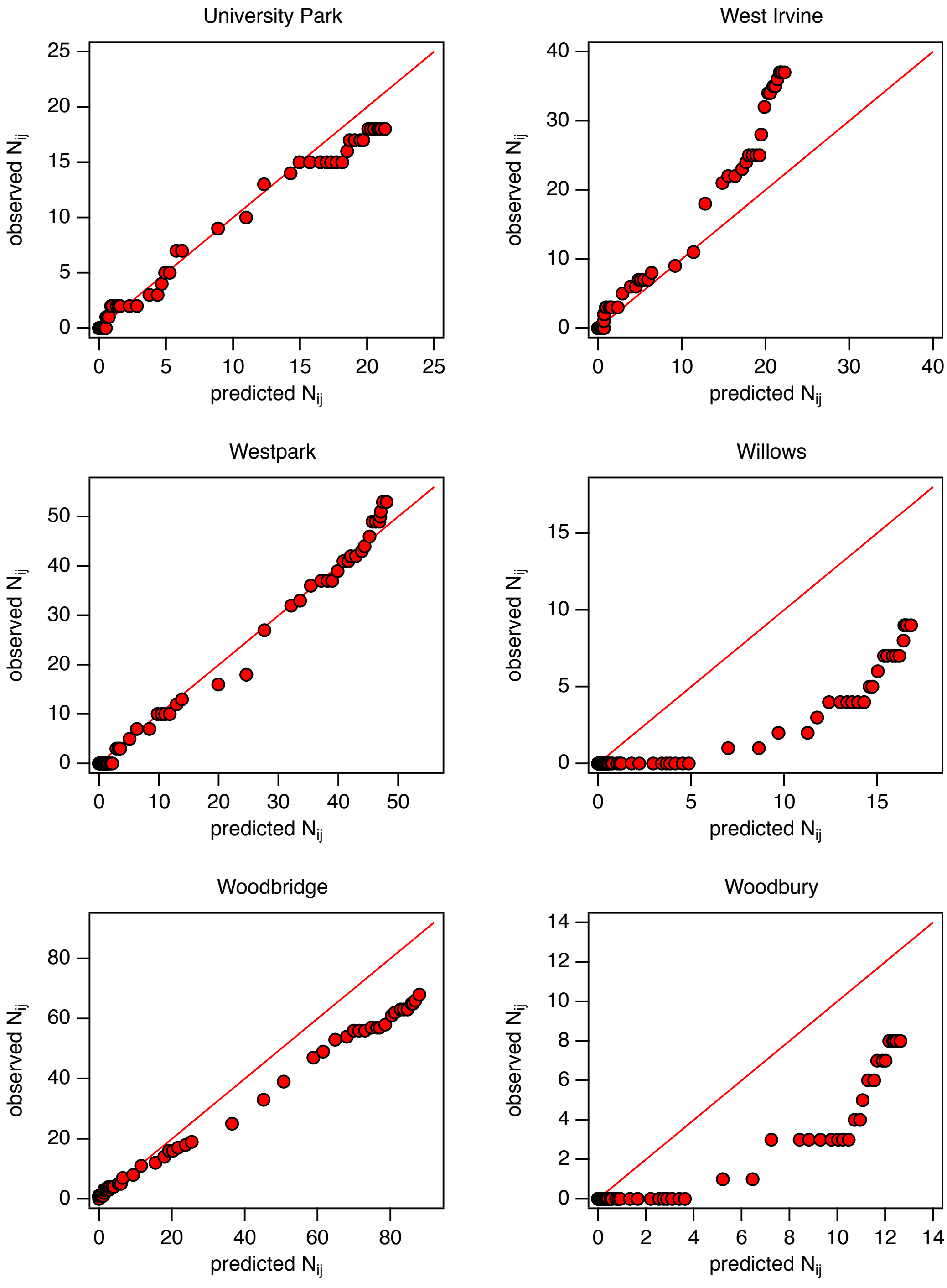

Figure B.9 Subset 7 of the data included in Figure B.2

These plots correspond to six of the 42 villages (University Park, West Irvine, Westpark, Willows, Woodbridge, and Woodbury). The diagonal lines represent a one-to-one relationship. (Note that the axes have been adjusted to reflect the data range).

APPENDIX C

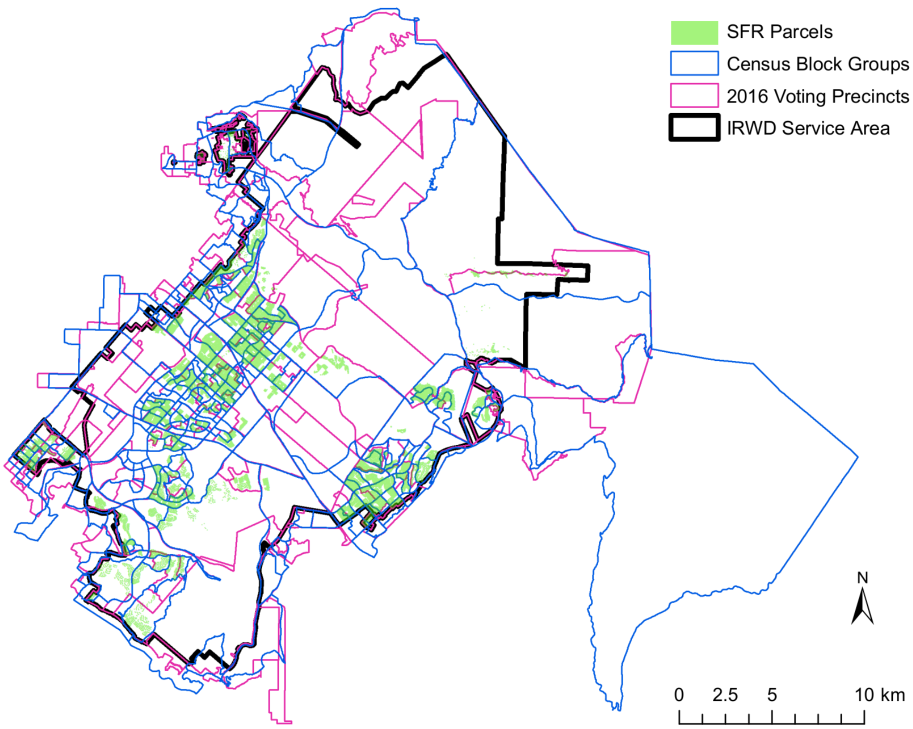

Figure C.1 GIS demographic data overlaid on the IRWD service area boundaries

Four sets of GIS data used in the analysis for Chapter 2 and Appendix C. (1) Approximately 60,000 individual SFR parcels are displayed as points (lime green). Regions with no SFR parcels are typically zoned as non-residential land for commercial purposes, parks, or wildlife. Regions of the map that appear to be solid green are actually densely populated regions with thousands of individual parcels. (2) Boundaries of the census block groups are shown (solid blue lines) where they intersect with the IRWD service area. SFR parcels that fall within a particular block group are designated with the corresponding census data for that block group. (3) Boundaries of the 2016 General Election voting precincts are shown (solid magenta pink lines) where they intersect with the IRWD service area. SFR parcels that fall within a particular voting precinct are designated with the corresponding voting data for that precinct. (4) The IRWD service area (thick black line) has an extent of approximately 470 km^2 and includes six cities (Tustin, Orange, Lake Forest, Costa Mesa, Newport Beach, and Irvine) as well as unincorporated land.

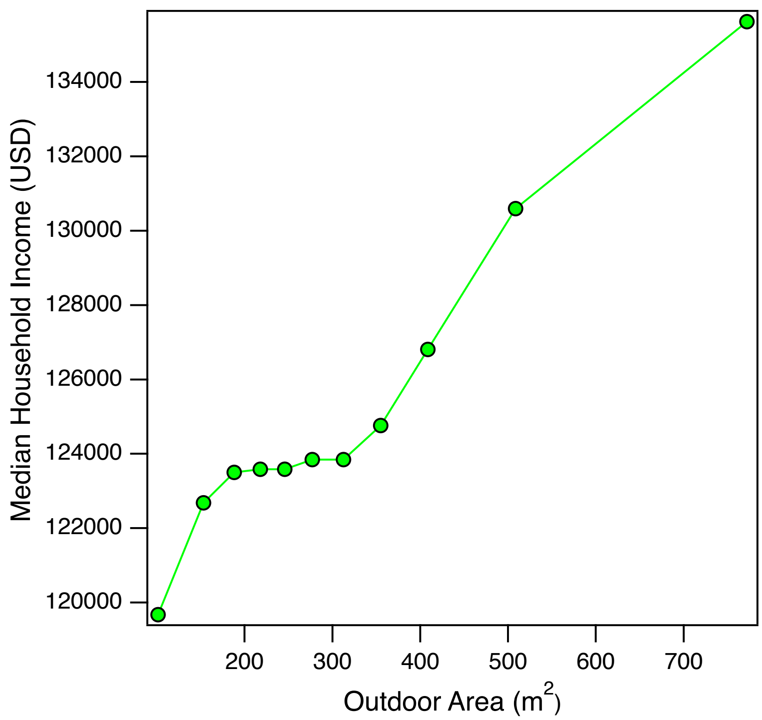

Figure C.2 Outdoor area (m^2) vs. median household income (2017 USD)

Census block group values of median household income increase linearly with county tax assessor records of parcel-scale outdoor area. This plot was generated by sorting all 46,913 SFR parcels enrolled in our study by outdoor area, binning the parcels into 11 equally sized bins (each bin contained 4,264 SFR parcels), and then computing the median household income and outdoor area associated with each bin.

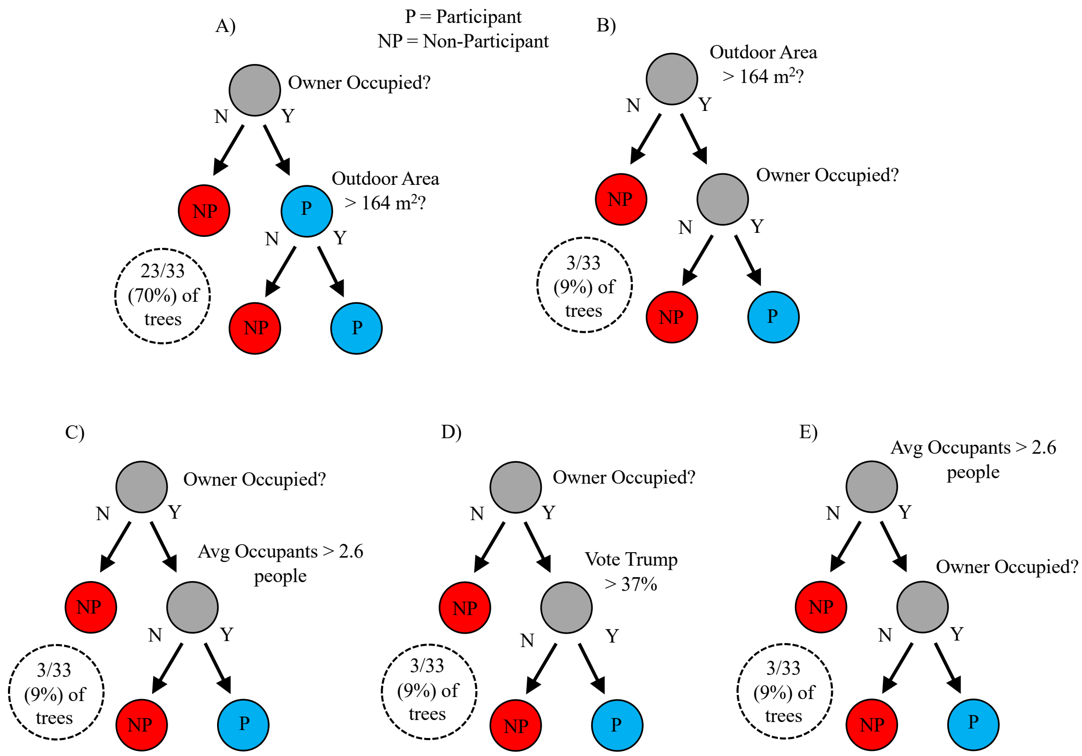

Figure C.3 CART analysis of parcel-scale participation

Each tree (A-E) depicts one possible set of best decisions for predicting the participation status of parcels. Tree A) was detected most frequently: 70% (A) > 3% (B, C, D) > 1% (E). Trees A) and B) include owner occupancy status and outdoor area as predictor variables. Trees C) and E) include owner occupancy status and average household size as predictor variables, and Tree D) includes owner occupancy status and the percentage of voters who cast ballots for Trump (2016) as predictor variables.

Text C.1 Classification and Regression Trees (CART)

A supervised machine learning approach called CART (conducted in R (R Core Team, 2019) using the package rpart (Therneau and Atkinson, 2018)) was used to assess the capacity of 11 variables (outdoor area, owner occupancy, average household size, median household income, median house value, and six voting preferences, including the percent of registered voters who voted in the 2016 General Election, and percent of voters who cast ballots for Clinton, Trump, Stein, Johnson, and independent candidates in the 2016 Presidential Election) to predict resident participation in a cash for grass turf rebate program at the parcel level. The total sample contained information from 1,366 residents that participated in the lawn rebate program and 44,484 residents that did not. Because this dataset was highly skewed towards nonparticipants, CART was performed 33 separate times on subsets of the data; each subset contained 1,348 participants and a randomly selected subset of 1,366 nonparticipants. All 33 classification trees were grown to their maximum possible depth using weighted Gini impurity as the node splitting criterion:

$$G=\frac{N_k}{N_k+N_j}\left[1-\sum_{i=1}^{c}p_{ik}^2\right]+\frac{N_k}{N_k+N_j}\left[1-\sum_{i=1}^{c}p_{ij}^2\right]$$

where k and j are two daughter nodes of a possible split, c is the number of classes (i.e., 2, participants and nonparticipants), p_k and p_j are the proportion of residents in class c for nodes k and j, and N_k and N_j are the total number of residents in nodes k and j. The split resulting in the smallest Gini impurity across both nodes is the best split. Trees were subsequently pruned using leave-one-out cross validation and the smallest tree method, which prunes trees to within 1 standard error of the minimum misclassification rate under cross-validation.

All pruned trees were assessed for consistency in split criteria and splitting order, which indicate that splits are meaningful across the entire dataset. Each split was evaluated, starting with the first and progressing in order. The first split that was not common to more than 30% of trees was used as a stopping rule; that split and all subsequent ones were excluded from further consideration.

Text C.2 Implementation of the Water Savings Model

For the calculations described in the main text, the following functional form was adopted for the participation probability, $p(a)=b_p+m_p a$. Fitting this model to the participation probabilities inferred from the IRWD dataset (see **Figure 2.5a** of the main text) we find that the intercept and slope depend on whether SFR parcels are owner occupied or not owner occupied:

Owner Occupied

$$b_p=\begin{cases} 0, & a<368\ \mathrm{m}^2 \\ 0.0449, & a\geq 368\ \mathrm{m}^2 \end{cases}$$

$$m_p=\begin{cases} 1.22\times 10^{-4}, & a<368\ \mathrm{m}^2 \\ 0, & a\geq 368\ \mathrm{m}^2 \end{cases}$$

Not Owner Occupied

$$b_p=\begin{cases} 0, & a<368\ \mathrm{m}^2 \\ 0.01455, & a\geq 368\ \mathrm{m}^2 \end{cases}$$

$$m_p=\begin{cases} 3.95\times 10^{-5}, & a<368\ \mathrm{m}^2 \\ 0, & a\geq 368\ \mathrm{m}^2 \end{cases}$$

Likewise, the lawn area replaced with drought tolerant landscaping increases linearly with outdoor area, $\ell(a)=b_\ell+m_\ell a$, but in this case the slope and intercept are the same, within error, for SFR parcels that are owner occupied and not owner occupied. The slope and intercept values inferred by fitting the linear equation to the owner-occupied data in **Figure 2.5b** (which was chosen because it had a much larger N value) is:

$$b_\ell = \begin{cases} 14.9 \text{ m}^2, \; a < 547 \text{ m}^2 \\ 90.95 \text{ m}^2, \; a \geq 547 \text{ m}^2 \end{cases}$$

$$m_\ell = \begin{cases} 0.139, \; a < 547 \text{ m}^2 \\ 0, \; a \geq 547 \text{ m}^2 \end{cases}$$

Finally, we found the number distribution of outdoor parcel areas follows a log-normal distribution (**Figure 2.5c**) which implies that the base-10 log-transformed outdoor area is normally distributed, where N_T is the total number of parcels eligible to participate in the rebate program:

$$n(a) = \frac{N_T}{\sqrt{2\pi} a \sigma_{\ln a}} e^{-\frac{(\ln a - \mu_{\ln a})^2}{2\sigma^2_{\ln a}}}$$

Inferred values of the mean and standard deviation of the base-10 log-transformed outdoor area values (see black curve in **Figure 2.5c** in main text) are $\mu_{\log_{10} a} = 2.44 \pm 0.01$ and $\sigma_{\log_{10} a} = 0.24 \pm 0.006$, respectively. Because the independent variable in the number distribution above is log-transformed outdoor area, it is convenient to represent the integral over outdoor areas (equation (1) in Chapter 2) in the same way, where $\mu_{\ln a} = 5.62 \pm 0.02$ and $\sigma_{\log_{10} a} = 0.55 \pm 0.01$:

$$W = \frac{w'' \times N_T}{\sqrt{2\pi} \sigma_{\ln a}} \times \int_{a_{\min}}^{a_{\max}} \frac{p(u)\ell(u)}{u} e^{-\frac{(\ln u - \mu_{\ln a})^2}{2\sigma^2_{\ln a}}} du$$

The total number of owner occupied and non owner occupied SFR parcels is, respectively, N_T = 38,255 and 8,658. We numerically integrated the integral using the Mathematica computing package (v. 11.20, Wolfram Research, Inc.) for outdoor areas ranging from $a_{\min}$ = $10^{1.5}$ = 31.6 m^2 to $a_{\max}$ = $10^{3.5}$ = 3160 m^2.

Text C.3. Equity versus Water Savings Simulation

The simulation described in Chapter 2 was set up as the following. In general form, the participation probability function can be written out as:

$$p(a)=\begin{cases} b_p+m_p a, & a<368\ \mathrm{m}^2 \\ p_{\mathrm{final}}, & a\geq 368\ \mathrm{m}^2 \end{cases}$$

Averaging this expression over the range of outdoor areas, $a_{\mathrm{min}}=10\ \ \mathrm{m}^2$ to $a_{\mathrm{max}}=692\ \ \mathrm{m}^2$ (this particular range of outdoor areas was chosen so that p_{ave} equals the observed service area-wide participation probability for owner occupied SFRs of 3.3%; see **Figure 2.4b** in Chapter 2), we obtain the following formula for the average participation probability):

$$p_{\mathrm{ave}}=0.525b_p+99.2m_p+0.475p_{\mathrm{final}}$$

Because p_{final} equals the participation probability evaluated at $a=368\ \ \mathrm{m}^2$, we can rewrite the last expression as follows:

$$p_{\mathrm{ave}}=b_p+274m_p$$

Combining these results, we arrive at a final formula for the participation probability that depends only on the service-wide participation probability (p_{ave}=0.33), the outdoor area, and the initial slope of the participation probability curve (m_p):

$$p(a)=\begin{cases} p_{\mathrm{ave}}+m_p(a-274), & a<368\ \mathrm{m}^2 \\ p_{\mathrm{ave}}+94m_p, & a\geq 368\ \mathrm{m}^2 \end{cases}$$

Thus, if we fix the average service-area participation probability for owner occupied homes ($p_{ave}=0.033$), the participation probability function can be represented solely as a function of the outdoor area and initial slope m_p. This formula was substituted into the integral expression above, to determine how overall water savings varied with different choices of the initial slope m_p (see main text in Chapter 2).

References

1. R Core Team (2019). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL: http://www.R-project.org/
2. Terry Therneau and Beth Atkinson (2018). rpart: Recursive Partitioning and Regression Trees. R package version 4.1-13. https://CRAN.R-project.org/package=rpart

APPENDIX D

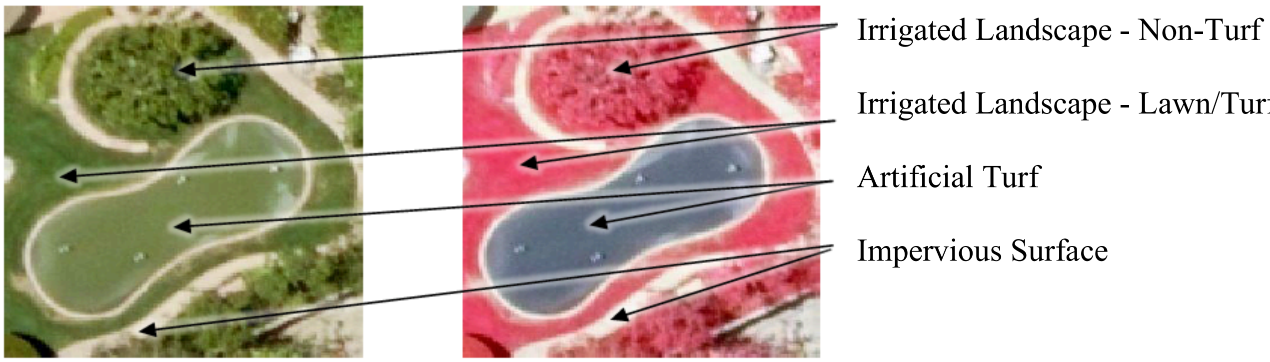

Figure D.1. Standard imagery raster RGB and near-infrared-emphasized raster symbology

Left: Standard imagery raster RGB (red, green, blue) symbology. **Right:** Near-infrared-emphasized raster symbology (NIR). The artificial turf patch in the center of the image on the right is visibly gray, while the surrounding vegetation is clearly red (Quantum Spatial, 2017).

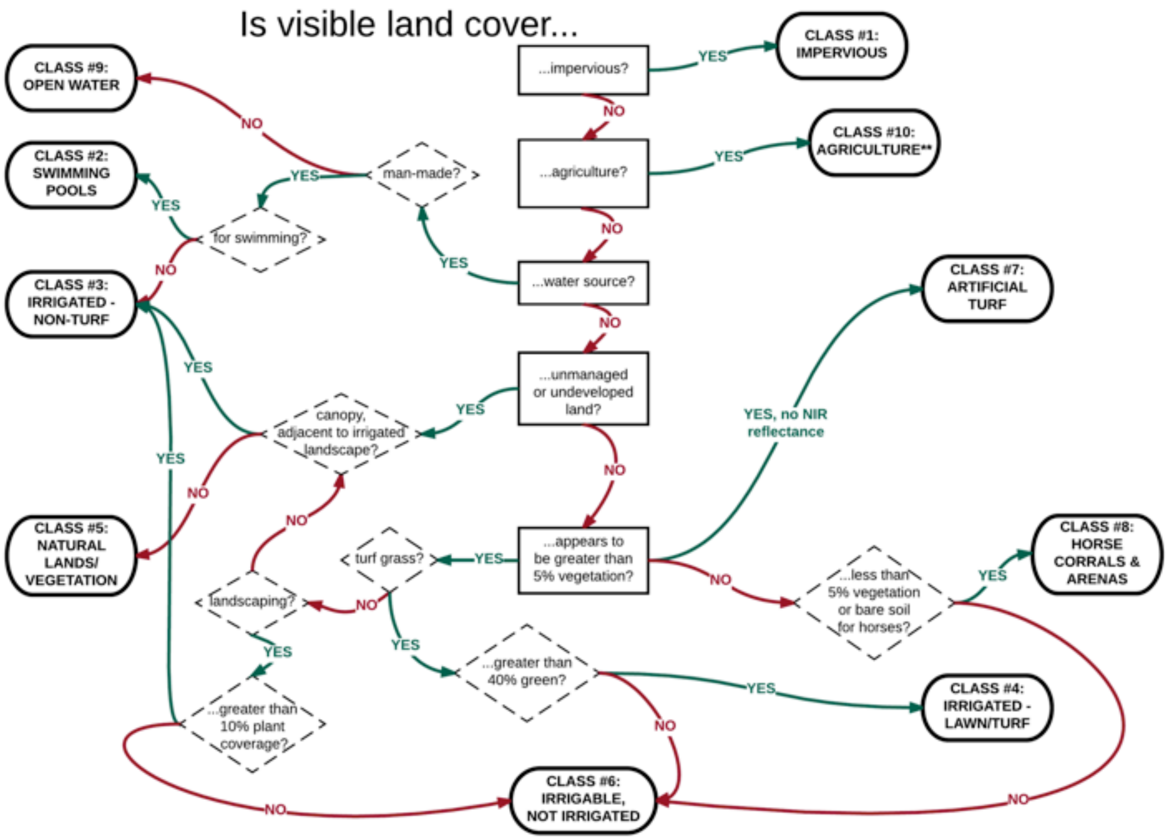

Figure D.2. A flow chart for how the land use classifications were assigned (provided by Quantum Spatial).

References

Quantum Spatial. (2017). *IRWD Land Use Classification Project Technical Data Report*. Retrieved from IRWD