WATER DEMAND IN THE RESIDENTIAL AND TOURISM SECTORS: EVIDENCE AND IMPLICATIONS FOR EFFICIENT MANAGEMENT

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Abstract

Water resource management is becoming an increasingly pertinent topic worldwide, particularly in the face of a growing population and changing climate. This is especially true on O‘ahu, Hawai‘i, where concerns about the availability of fresh water existed even before water resources were strained by urban growth, tourism, and the potential negative effects of climate change. Reduced recharge due to increased runoff and the possibility of reduced rainfall, combined with aquifer withdrawals potentially exceeding maximum sustainable yield, may result in a reduction of freshwater quantity and quality. The status of water availability on O‘ahu is thus precarious.

There is a vigorous effort to quantify the availability of fresh water and estimate the effects of climate change on aquifer sustainable yield, but less attention has been paid to the equally-important effect the climate has on water demand. These three essays attempt to help fill this gap in the literature by examining the relationships between climate and water use in the residential and tourism sectors of O‘ahu. In the first chapter, we exploit a novel quasi-natural experiment to estimate the price elasticity of water demand for single family homes, which are the largest consumer of water on the island. After demonstrating the ease with which researchers may fall victim to common data analysis pitfalls despite using the newest popular techniques, we show that the demand for water is highly price inelastic. This information will be useful for policymakers and utilities when developing water management solutions. We also examine the potential effects of local policies on consumer welfare.

The second chapter examines the relationship between climate and household water use. Unlike other similar studies which rely on comparing two regions with different climates or the same region over time, our study uses the highly varied microclimates on O‘ahu to identify links between water use and climate. We find strong relationships that are likely causal, and apply them to downscaled future climate scenarios. We suggest that the high degree of uncertainty not only between different climate scenarios, but also within scenarios, dictates that a successful water management strategy will prepare for a wide variety of potential climate outcomes.

In the final chapter, we analyze one of O‘ahu’s largest industries, tourism, and the effect it has on water use. Other studies have examined similar issues on tourism-heavy islands with limited freshwater resources. However, many of these studies focus on islands in developing nations with economies, institutions, and demographics much different than those of a highly-developed region like O‘ahu. Further, our study is, to our knowledge, the first to separate the impact of hotels and the impact of transient vacation rentals like Airbnb on the island’s water resources. We find that, although there is evidence of a positive relationship between hotel visitors and water use, hotels are one of the smallest consumers of overall water use. Residential units, many of which host the transient vacation rentals, are the largest consumers of water as a whole. Despite this, and the large number of transient vacation rentals, we do not find an economically-significant relationship between vacation rental occupancy and water use. We discuss potential reasons for this, including limitations of the data. Implications for future scenarios and additional work are discussed.

Contents

List of Tables

List of Figures

Chapter 1

Estimating water demand using price differences of wastewater services

1.1 Introduction

Growing concern about the effects of climate change and other factors impacting water availability make it more critical than ever to gain an improved understanding of water demand and how policies can better manage it. In addition to household characteristics and demographics (Balling, Gober, and Jones 2008; Chang, Parandvash, and Shandas 2010), water consumers have been shown to be sensitive to weather and climate (Balling, Gober, and Jones 2008; Mansur and S. M. Olmstead 2012; Larson et al. 2013; Breyer and Chang 2014; Lott et al. 2014). Climate change is already negatively impacting certain areas of the country like the southwest and California, where water use curtailment policies are needed as a result of shifts in the distributions of temperature and precipitation (Hanemann, Lambe, and Farber 2012). Policies that have proven effective in conserving water include non-price water use curtailment strategies, such as command-and-control measures and campaigns that persuade consumers to voluntarily alter their behavior (Gober and Kirkwood 2010; Mansur and S. M. Olmstead 2012). Other systems face growing scarcity and are ill-prepared for climate change, so a fundamental reworking of the way they are operated will be needed to adapt (Joyce et al. 2011).

Some economists argue that a market-based approach where water use is managed by adjusting prices in accordance with its scarcity would be more efficient than command-and-control policies and water conservation campaigns. A problem with many current pricing regimes is that municipalities typically do not account for the scarcity value of water when determining water price schedules (S. M. Olmstead 2010; Bell and Griffin 2011; Mansur and S. M. Olmstead 2012). Instead, municipalities are typically required under statute to recover tangible costs of delivering water, which may derive from a public source. This is the case in our study area, the Hawaiian island of O‘ahu. S. M. Olmstead, Fisher-Vanden, and Rimsaite (2016) go further to suggest that many managers aim more to maintain affordability for users than trying to recover the full opportunity cost of the resource, which may result in the need for difficult changes in resource use and suggests the need for a better understanding of how the current barriers leading to inefficient pricing can be overcome.

Since accounting for scarcity value would imply an increase in the price charged to consumers, the resulting short-term welfare loss could be difficult to sell politically. However, the price-driven measures would have considerable benefits, including reduced frequency of acute shortages requiring mandatory cutbacks, more sustainable water-conserving investments and development, like drip irrigation and xeriscaping, and better allocative efficiency, such that the highest value uses of water are always served first. There would also be surplus revenue that could be used to serve other public goods and, compared to command-and-control measures, there are reduced costs of monitoring and enforcement (S. Olmstead and R. Stavins n.d.). A price-based conservation policy is essentially costless from an enforcement perspective once it's enacted, relative to non-price programs like temporary bans on lawn irrigation, which are inherently more difficult to police.

Knowledge about the nature and structure of demand helps us to determine efficient pricing, including the prices needed for sustainable use. It also aids evaluation of non-price allocation mechanisms. Previous studies have found residential water demand to be generally inelastic. A literature review by Dalhuisen et al.(Dalhuisen et al. 2003) of 64 studies with 296 elasticity estimates published between 1963 and 2001 found that the mean and median price elasticity of water demand for residential homes is -0.41 and -0.35, respectively, with a standard deviation of 0.86. According to the authors, the variation in the estimates results from the various analysis methods used, different pricing schedules (flat, increasing block, decreasing block) of the utilities, household and consumer characteristics, and using aggregate versus household-level data. This meta-analysis finds elasticities that are slightly more inelastic than an earlier meta-analysis by M. Espey, J. Espey, and W. D. Shaw (1997), which finds a mean price elasticity of -0.51 using 124 elasticity estimates from 24 articles published between 1963 and 2001. Meta analyses, however, cannot account for the strength of the study design. Confounding and omitted variables biases are likely pervasive. As an example of how model choice matters, a study by Nieswiadomy and Molina (1989) arrives at an estimate of -0.55. Hewitt and Hanemann (1995), using the same data, use another approach and estimate an elasticity of -1.6. More recent studies that use better quasi-experimental designs have found demand to be less elastic (S. M. Olmstead, Hanemann, and R. N. Stavins 2007; S. Olmstead and R. Stavins n.d.; Lott et al. 2014; Mansur and S. M. Olmstead 2012; Klaiber et al. 2014; Ghavidelfar, Shamseldin, and Melville 2016). However, due to reasons we discuss in the next section, even recent studies may suffer from poor identification and other difficulties.

In this study, we use a unique neighbor matching technique to estimate the price elasticity of water demand for single family homes using household level data from Oʻahu. By matching neighbors who face different pricing structures due to their sewage disposal type, but otherwise have similar characteristics, we estimate demand to be highly inelastic at -0.06 to -0.08. These results are shown to be unbiased and robust, and we compare them to other traditional methods that produce robust, yet biased, estimates. The elasticity estimates are then applied to a consumer surplus scenario specific to Hawaiʻi, where the local government is offering a tax credit to homes who upgrade their sewage systems to more expensive alternatives in an attempt to improve water quality in the state. We show the current tax credit is insufficient to cover the net present value of upgrading the systems, considering installation costs and the long-term welfare implications of higher water prices resulting from the upgrades. Also discussed are broader topics of consumer welfare in the context of the water management regime, and related price adjustment scenarios.

The rest of the paper is organized as follows: in section (1.2) we further discuss the context of our study and describe in more detail the water quality issues in Hawaiʻi. Section (1.3) provides an overview of the data used in our analyses. Section (1.4) discusses the empirical strategies we implement to estimate residential price elasticity of water demand. The results are provided in section (1.5), and a discussion of the elasticity measurements and its application to water quality and climate issues, along with consumer welfare, is provided in section (1.6).

1.2 Context and Study Design

The methods used to estimate demand in many earlier studies often suffer from one or more shortcomings identified by Nataraj and Hanemann (2011):

1. Most studies obtain variation in price by comparing a cross section of two or more cities, or one city over time. A cross sectional study of many different cities may be omitting unobserved city-specific characteristics. On the other hand, estimating an elasticity using data from one city over time may fail to control for variables that are potentially correlated with price, such as weather effects. There is little focus on truly exogenous, random, or as-if random, changes or differences in water prices.

2. The complexity of block pricing schedules often used to estimate elasticity poses another problem. As mentioned later, there is disagreement in the literature about the importance of price salience and whether consumers respond to average or marginal price, which complicates or confounds elasticity calculations. Customers' elasticities and how they are calculated depend on information availability, along with how the bill is presented to the customer. Some studies choose to use average price (Billings 1990; Hogarty and Mackay 1975), while others use marginal price (Danielson 1979; Lyman 1992). Some include both (Opaluch 1982; Opaluch 1984; Martin and Wilder 1992), or use a combination of the two to create a "perceived price" for their analyses (Shin 1985; Nieswiadomy 1992).

We address these issues by identifying the price elasticity of residential water demand using a new quasi-natural experiment. According to the Environmental Protection Agency, Hawai'i has more cesspools than any other US state.[1] Homes with cesspools comprise about 75% of all homes with on-site sewage disposal systems (OSDS). Other OSDS systems include aerobic and septic systems. While most homes on O'ahu are billed for fresh water by the Honolulu Board of Water Supply, only those connected to the municipal sewer are charged a sewer service fee. Thus, the Honolulu Board of Water Supply has two groups of single-family water customers. One group has an on-site system for sewage disposal, and only pays for clean water delivered to the home. The other group is connected to the municipal sewer system and is buying a joint product: water service and sewer service, where the amount of sewer service received is determined only by the amount of water consumed.

Table (1.1) shows the current pricing schedule faced by homes with and without sewer service. All single family residential homes are charged according to an increasing block price structure plus a fixed monthly fee of $9.26. However, as shown in figure (1.1), only 18% of households consume enough water to consistently place them in the second block, and only 0.5% use enough to place them in the third block. The majority of consumers remain within the first block and face a constant volumetric charge of $4.42 per 1000 gallons. A consumer switching from a cesspool to sewer service will experience an increase in fixed cost of $77.55, and a volumetric increase of $4.63 per 1000 gallons. The fixed cost of the sewer service "represents [the] fixed cost associated with operating and maintaining the municipal sewer system," and the volumetric charge

[1] `https://www.epa.gov/uic/cesspools-hawaii`

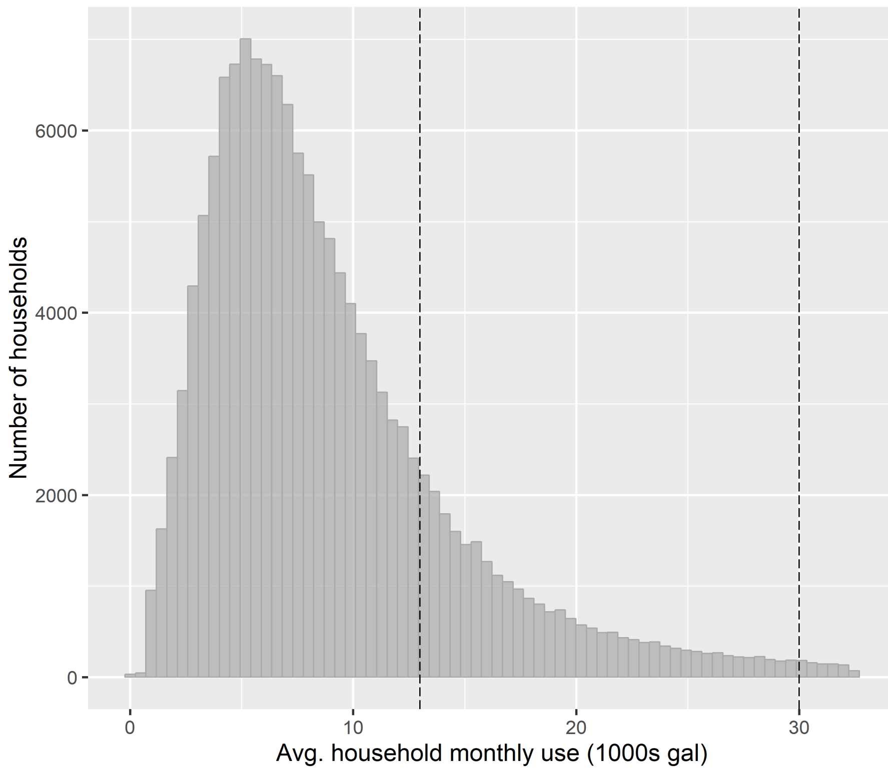


Figure 1.1: Histogram of household average monthly consumption. The vertical line at 13,000 gallons indicates the first block in the pricing structure. 18% of households have average monthly use at or greater than this cutoff. The third block starts at 30,000 gallons, which is only consistently applied to about 0.5% of homes in the sample period. The median consumption is 7500 gallons per month, and the mean is 8900 gallons per month.

"represents [the] variable cost of transporting and treating the wastewater." For homes without a sub-meter that measures water used for irrigation, the volume charged for sewer is reduced by 20%.[2]

Unlike some previous studies, which may rely on relatively small differences in price due to block cutoffs, policy changes, and the like, differences between bills for residences with sewer-connections and those with OSDS systems are substantial. If a household with an OSDS system connects to the sewer, their monthly fixed charge increases by $77.55 and the marginal volumetric charge more than doubles. This situation, where similar consumers face markedly different price schedules, provides a unique opportunity to study water demand. Not only is the price difference significant between the two groups, but the groups are also contained under one utility in the same small geographic location. Although this comparison does not constitute a perfect natural experiment—OSDS systems are not randomly assigned across residences—we use different methods for finding suitable controls for residences with OSDS systems, some of which are more compelling than others. As we show below, the most compelling natural experiment comes from comparing OSDS homes with immediate neighbors that are connected to the sewer.

We use several methods to estimate the price elasticity of residential water demand to highlight the importance of careful model selection while maintaining interpretability. First, we use OLS to control for observable differences between OSDS and sewer-connected homes, with or without census tract fixed effects,

[2] `https://www.boardofwatersupply.com/bws/media/images/about-your-bill-env-2019.jpg`

Table 1.1: Monthly residential water use charges. All water service customers are charged a fixed fee of $9.26 per month, and a volumetric charge based on the given increasing block price structure. The sewer service fee is in addition to the water service fee for applicable customers.

	Water Service			*Sewer Service*
	Block I $\leq 13,000$ gal/mo	*Block II* $13,001 - 30,000$ gal/mo	*Block III* $> 30,000$ gal/mo	
Fixed Cost	$9.26	—	—	**$77.55**
Charge per 1000 gal	$4.42	$5.33	$7.94	$4.63

and non-parametric controls trained using cross-validation and a lasso. Using these methods robust results similar to those found in the existing literature are obtained: estimated elasticities range from -0.03 to -0.34 depending on the method used. However, these results could mask the bias due to unobservable differences between OSDS and sewer-connected residences or, in the case of lasso, produce unintuitive results that are difficult to interpret. Even with local fixed effects, we find observable characteristics are unbalanced between the two types of homes. We show this bias persists even after using generalized boosted regression and a propensity score matching technique in an attempt to balance the data. Balance between the two groups is only achieved when we reduce the sample to direct neighbors that vary by sewage disposal type. With this method we estimate robust, unbiased elasticities in the range of -0.06 to -0.08, which is on the lower end of our previous estimates. However, the estimates lose some statistical significance.

In addition to our primary goal of estimating elasticity and its uses in water conservation under climate change, we use the estimates to evaluate a current effort by the local government to phase out cesspools in the state. Following evidence that cesspools contribute significantly to coastal water pollution, Hawai'i has recently become the last state to outlaw new cesspools[3]. A study by the Hawai'i Department of Health estimates that existing cesspools release about 53 million gallons of raw sewage into the ground statewide each day[4]. As shown in figure (1.2), many of these homes are located in coastal areas and the leaking waste is negatively affecting ground and nearshore water quality (Amato et al. 2016; Fackrell et al. 2016).

Current efforts by the local government are underway to reduce the pollution from cesspool leakage. In addition to the ban on new cesspools, a program has been made available to provide a $10,000 tax credit to qualifying households that replace their existing cesspools with modern systems like a septic tank or a sewer connection[5]. Septic tanks, which differ from cesspools in that the wastewater must pass through a leach field that filters the water, may be less expensive than a sewer connection and may therefore be preferred by customers looking to upgrade their systems. This connection is still expensive, however, and the cost must still be paid up front by the customer with the tax credit applying later. It is thus unclear whether the $10,000 tax credit is enough to incentivize customers to voluntarily upgrade their systems. Further, for those who wish to connect to the sewer system (the cleanest, most environmentally-friendly wastewater disposal option), it is quite clear the offered tax credit falls far short of covering the costs associated not only with

[3] https://www.civilbeat.org/2016/03/hawaii-bans-new-cesspools/

[4] http://health.hawaii.gov/wastewater/cesspools/

[5] There are 2064 homes (23% of all homes with cesspools) on O'ahu that potentially qualify for this credit. To qualify, a cesspool has to be within 200 feet of a shoreline, perennial stream, wetland, or within a source water assessment program area such that the duration of time of travel from cesspool to a public drinking water source is less than two years. http://health.Hawaii.gov/wastewater/home/taxcredit/

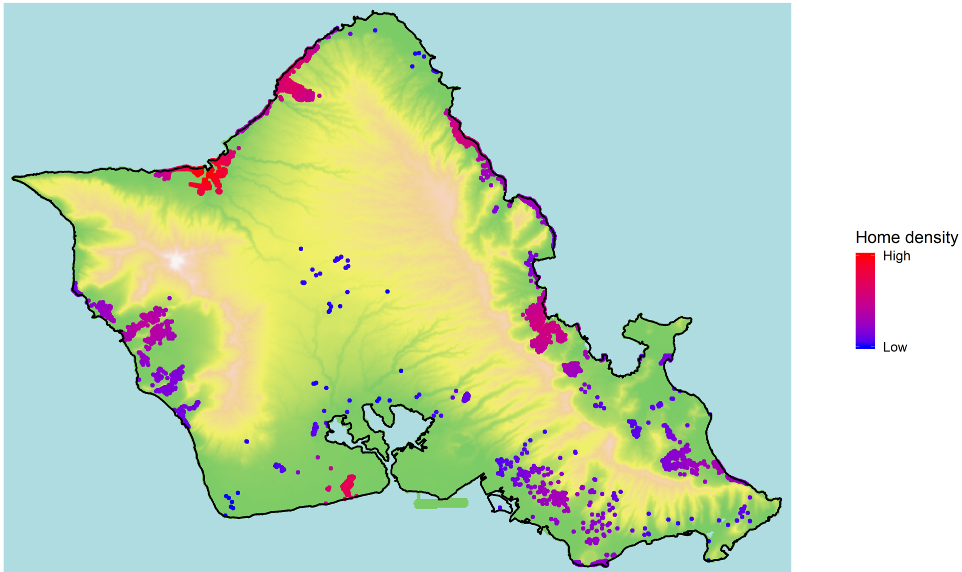


Figure 1.2: Locations of homes on the Hawaiian island of O'ahu with other than sewer service. Approximately 75% of these homes have cesspools. Point color indicates density of homes.

the initial sewer connection, but also the net present value of an increased water bill as described above. In many cases, connecting to the sewer may otherwise be impossible due to the location of the home relative to existing sewer lines.

Exactly how much consumer surplus would be lost for a household switching from OSDS to sewer depends on the elasticity of demand. Additionally the rationality of the consumers is likely bounded, whether from indifference, ignorance, or poor information communication by the utility. While economic theory tells us rational consumers will make consumption decisions based on marginal price, it is unclear in many cases whether consumers actually respond to marginal or average price. Previous studies have found different results on this topic. Several studies suggest consumers tend to base consumption decisions on average price (Shin 1985; Worthington, Higgs, and Hoffmann 2009; Ito 2014; Wichman 2014). If this is true in the case of water consumption on O'ahu, it may have significant consumer welfare implications given the steep fixed price incurred by sewer service customers. If they were to base decisions on average price, this large fixed cost may cause them to consume a lesser quantity of water than the utility-maximizing amount. The current distribution of household water use on the island seems to suggest this may be the case, since a response to marginal price would be evident by consumption bunching at the pricing blocks. Figure (1.1) shows this bunching does not exist, suggesting consumers are instead responding to average price. However, there is a literature with results suggesting some customers may react only to marginal price (Howe and Linaweaver Jr 1967; Nataraj and Hanemann 2011). Those that do respond to marginal price in this study tended to be large users with higher incomes. This makes sense, since high-income consumers using large amounts of water are more likely to have larger discretionary uses, as mentioned above. In light of these contradictory findings we consider both cases for our welfare analysis and, by comparing the consumption behavior of the two groups, it is possible to determine how much sewer customers are under-consuming if we assume they

Table 1.2: Summary of home characteristics by wastewater disposal type. In the data, there are 131,519 homes with sewer service, and 9127 with OSDS. Of the homes with OSDS, 7044 have cesspools. The t-tests suggest the difference between means of the characteristics for the two groups is significantly different from 0, and using Kolmogorov–Smirnov tests suggest the distributions are not similar.

Characteristic	Median		Mean		t-statistic	D-statistic
	Sewer	OSDS	Sewer	OSDS		
Year built	1970	1970	1973	1968	19.9***	0.14***
Effective year built	1975	1972	1977	1974	11.7***	0.10***
Home size (sq. ft.)	1656	1484	1837	1735	7.3***	0.14***
Home value ($1000s)	667	614	751	808	−6.5***	0.14***
Yard size (sq. ft.)	4517	6180	5486	9938	−19.5***	0.25***
Num. bedrooms	4.0	3.0	3.8	3.5	26.6***	0.09***
Num. bathrooms	2.0	2.0	2.2	2.0	13.4***	0.14***

*p<0.1; **p<0.05; ***p<0.01

are responding to average price. Overall, our results indicate there is little difference in welfare loss between the two cases. The loss in consumer surplus from switching from cesspool to sewer service remains much more significant.

1.3 Data

Billing data for 140,646 single family homes on Oʻahu were obtained from the Honolulu Board of Water Supply. It contains monthly data between June 2011 and March 2016. Characteristics of these homes, such as year built, effective year built[6], assessed value, and square footage, are provided for each home by the Honolulu Real Property Assessment Division, and information regarding the sewer, cesspool, and septic tank connections of these homes is from the Department of Health. A small neighborhood with a separate sewer service provider, American Hawaii Water, is charged according to a different pricing structure and were thus removed from the analysis.

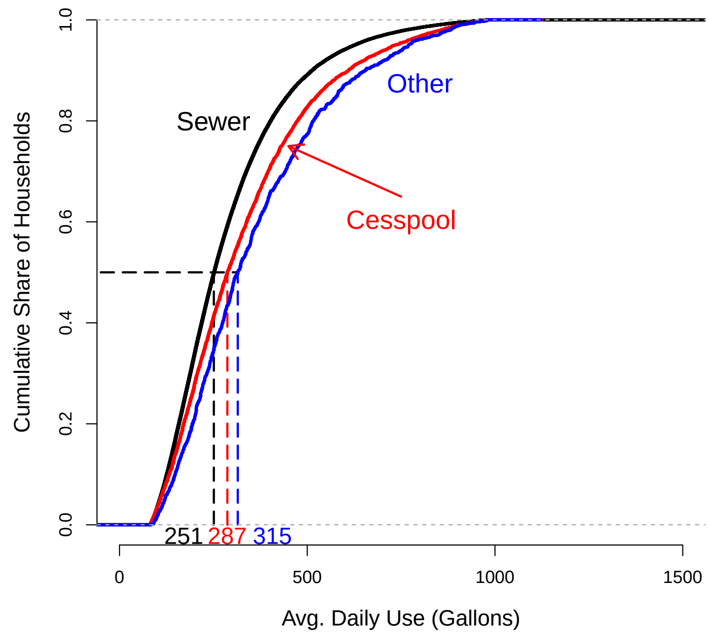
Table (1.2) summarizes select physical characteristics of the homes. Of the homes 9127, or about 6.5%, are characterized as having other than a municipal sewer connection. Approximately 75% of these are cesspools. For each characteristic, t-tests were performed to determine whether the means of the characteristics differed between the two groups. These tests suggest the means are significantly different between the two groups. Kolmogorov-Smirnov tests were also performed to test whether the distributions of the characteristics differed between homes with OSDS and homes with sewer connections. The reported D-statistic simply measures the maximum distance between the two groups' empirical cumulative distribution functions in absolute terms, so larger numbers indicate distributions that are less similar. For each characteristic, the tests suggest the distributions are significantly different from one another. This means homes with OSDS are not entirely similar to homes with sewer connections; in experimental terms, the treatment and control groups are not

[6] Many older homes have been renovated, effectively decreasing the age of the home. To account for this, the "effective" year built is provided by the Honolulu Real Property Assessment Division.

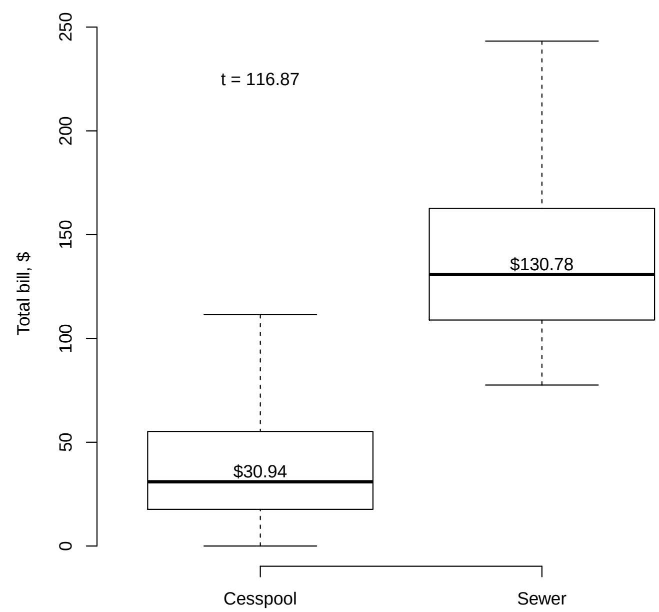
randomly assigned. We discuss the significance this difference in distributions has in more detail in the empirical strategy section below.

For water use, we aggregate consumption across all billing periods for each home. From this we find the average daily consumption of each home, and examine the basic water use patterns among homes with different wastewater disposal types. Figure (1.3(a)) shows the empirical CDF of average daily water use for homes with and without sewer connections. A basic calculation using only the raw billing data shows that homes with cesspools consume about 14% more water than homes with sewer connections. Performing a Kolmogorov-Smirnov test between the distributions of water use for homes with sewer connections and homes with OSDS (cesspools and "other" combined) yields a D-statistic of 0.15 that is significant at the 99% level, suggesting the distributions of water use between the two groups is significantly different. Using the billing data and the Board of Water Supply price schedule in table (1.1), we can also calculate the amount charged to each customer in a billing period. As expected, figure (1.3(b)) shows that the monthly bills of consumers with sewer service are typically much larger than homes with cesspools due to the increased fixed and variable costs.

One characteristic of the distribution of homes on O'ahu is that many areas have homes with cesspools interspersed among homes with sewer service. For example, consider the Black Point and Tantalus neighborhoods in figure (1.4). In panels (a) and (c), the color of the home indicates the type of wastewater disposal. In many cases, homes with cesspools are located closely to homes with sewer service in the same neighborhood. Panels (b) and (d) show us that households with cesspools tend to consume more water than homes with sewer service. One method we attempt to use in order to estimate consumer sensitivity to price is matching homes that are close to one another but differ by wastewater disposal type. However, this method may not be suitable since the type of wastewater disposal system a home has is not entirely randomly assigned. This is evidenced by the lack of balance between the two groups shown in table (1.2). The t-tests suggest the means of the characteristics of the homes are significantly different between the two groups, and the D-statistics show the distributions themselves are not the same. We also see from the figure that homes with OSDS in both neighborhoods tend to have more land, as evidenced by the large areas surrounding the points. In Black Point, all homes on the coast, which we expect to have a higher value, exclusively have OSDS. We discuss in the next section how several empirical approaches typically used to estimate elasticity may produce biased results if factors such as these are not accounted for.



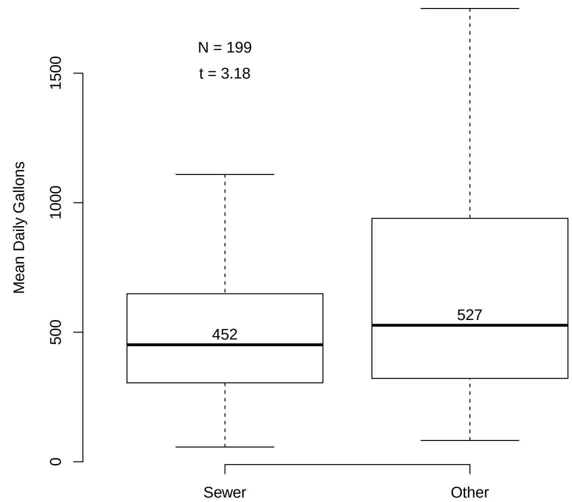
(a) Empirical cumulative distribution functions of water use by wastewater disposal type. Households with sewers typically consume the least water, with a median of 251 gallons per day. Those with cesspools consume more, with a median of 287 gallons per day. Households classified as "other", which contains aerobic and anaerobic septic tanks, among others, consume the most with a median of 315 gallons per day.



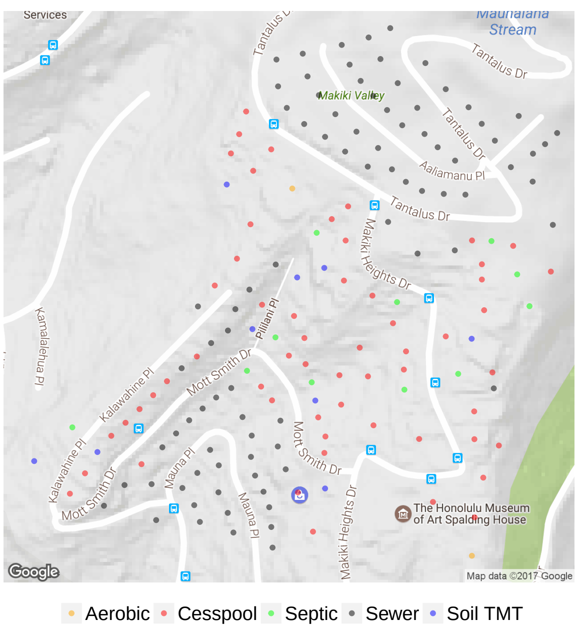
(b) Monthly water bills by wastewater disposal type. Due to the large increase in both the fixed and variable costs of sewer service, households with sewer service pay a median of $130.78 per month on their total water bill, compared to a median of $30.94 for households with cesspools. Water bills were calculated manually using the BWS pricing schedule.

Figure 1.3: Simple comparison of wastewater disposal groups.

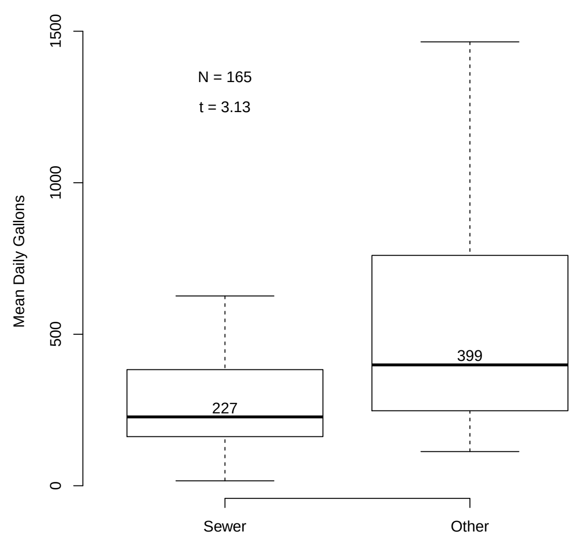
(a) Locations of Black Point homes of various sewage types. Many of these homes, particularly those along the coast, are very large (median 2761 sq. ft., compared to the Oʻahu median of 1638 sq. ft.) and have other characteristics not typical of a home on Oʻahu, such as being on the coast. Note that all the coastal homes have OSDS.



(b) Average daily water use of Black Point homes in gallons. Of the 199 homes on Black Point, those with sewer connections consume a median 452 gallons per day, and those with cesspools 527 gallons per day.



(c) Locations of Tantalus homes of various sewage types. These homes are also quite large (median 2756 sq. ft.), and we see homes with OSDS tend to have more surrounding property than those with sewer connections.



(d) Average daily water use of Tantalus homes in gallons. Of the 165 homes, those with sewer connections consume a median 227 gallons per day, and those with cesspools 399 gallons per day.

Figure 1.4: Examples of neighborhoods with mixed sewage disposal types.

1.4 Empirical strategy

Often, we face a tradeoff between models that are easy to interpret and those that produce robust, unbiased results. For example, a simple linear OLS model is very easy to interpret, but may not accurately reflect relationships in the data. Alternately, more advanced methods like modern machine learning techniques tend to produce unbiased and robust results, but are complex and lack interpretability. For our study, in order to estimate an unbiased price elasticity of residential water demand, we must account for the imbalance between the characteristics of homes with sewer connections and homes with on-site sewage disposal systems. Our goal is to do this in a way that retains the intuitive nature of linear regression while having the robustness of more advanced techniques. We first demonstrate the methods that produce robust, sensible results, but hide the bias or are difficult to interpret. These methods include simple OLS, lasso regression, and propensity score-boosted regression models. Then, we show that accounting for the differences between the two groups of homes, using an application of the nearest neighbor matching technique, produces a robust elasticity estimate that produces an unbiased result while also being intuitive and easy and interpret.

The first method we attempt to use to estimate elasticity is traditional OLS. The model takes the form

$$\log(w_i) = \alpha_0 + \alpha_1 S_i + \boldsymbol{\beta X}_i + \varepsilon_i, \tag{1.1}$$

where w_i is the average monthly water use of household i, S is the sewage type dummy variable, and X is a vector of household characteristics. These characteristics include the physical characteristics from table (1.2) above, along with other controls for climate and household demographics. To control for other unobserved demographic characteristics of the households, a model with census block and census tract dummy variables was also tested. In this log-linear model the coefficient of interest, α_1, then tells us the relative water use between homes with sewer and homes with OSDS. We can then take the characteristics of a median home to calculate $\widehat{\log w_i}$ for homes with and without OSDS. Using the pricing schedule in table (1.1) and these estimated quantities, we can finally arrive at an estimate for price elasticity of demand[7].

We then try nonlinear regression using splines as a more robust method to estimate price elasticity controlling for household location and characteristics. With the log of water use as the dependent variable, B-splines were created for each continuous control variable. With these splines, each possible combination of interactions between them were also created, resulting in approximately 60 splines tested in our model. Additional home characteristics that were included as linear terms were the number of bedrooms and the number of bathrooms in the home. The explanatory variable of interest, whether or not the home has a sewer connection or an OSDS, is included in the regression as a dummy variable. The model takes the general form

$$\log(w_i) = \alpha_0 + \alpha_1 S_i + \boldsymbol{\beta} \begin{bmatrix} b(X_1) \\ \vdots \\ b(X_n) \end{bmatrix} + \varepsilon_i, \tag{1.2}$$

[7] The elasticity is calculated using predicted water use for a median home. As was found with most homes in the data, these predicted values remain within the first block of the rate schedule in table (1.1), simplifying the elasticity calculation.

where the vector $[b(X_1)\cdots b(X_n)]^{\mathrm{T}}$ contains B-splines of home characteristics (and their interactions) X which were chosen through a LASSO cross validation process.

The model with the best out-of-sample predictions is selected using lasso with cross-validation at the ahupuaʻa level. Ahupuaʻa are traditional Hawaiian subdivisions of land that typically run from the coast to the mountains. Figure 1.5 shows a map of ahupuaʻa within the major districts of Oʻahu. There are 64 ahupuaʻa on the island with single family homes. Given the geography and development patterns of the island, these land divisions span a wide range of microclimates and home characteristics and vintages (figure (1.6)). Adding ahupuaʻa fixed effects to our models allows us to control for unobserved characteristics unique to these neighborhood-like divisions. Using the results from this model, we find the median predicted water use for homes with and without an OSDS. Again, the price charged to the homes can be calculated using the water and sewer rates from BWS. These quantity and price values are combined to estimate the price elasticity of residential water demand.

The final traditional technique we show is propensity score matching with generalized boosted regression. Whether or not the household has an OSDS is used as treatment. Generalized boosted regression, a machine learning technique, is used for model selection and estimating the propensity scores. Covariates are the same used in the regression models. The resulting treatment effect is used to estimate a price elasticity in a similar manner to the regression techniques.

The results of the regression and propensity score techniques are then compared to those of a one-to-one nearest neighbor matching method. The difficulty encountered with the previous techniques is that the two groups of homes are not balanced; even the propensity score matching method used was unable to effectively account for the differences in characteristics between homes with OSDS and those with sewer connections. As already noted before, homes with OSDS are often grouped with one another, and have no suitable matches to homes with sewer connections. However, in some cases, there are homes with OSDS that have direct neighbors with sewer connections. This was clearly seen in figure (1.4), where homes were largely grouped by sewage disposal type, but there are several cases where direct neighbors had different sewage disposal systems. We thus restrict our matching method only to homes that are direct neighbors, but differ by the type of sewage disposal system. Ties (cases where a home with OSDS has more than one neighbor with a sewer connection) are broken by matching to the home with the closest yard size, which was chosen since it created the best balance between matches among the covariates tested. The robustness of the choice of this tie-breaking characteristic is tested in the appendix on page (77). This is important to check, since over half of all homes with OSDS neighboring a home with a sewer connection, neighbors more than one home with a sewer connection. That is, more than half of all homes on OSDS who have a neighbor with a sewer connection have two or more neighbors with a sewer connection. In our analysis, we only perform one-to-one matching so must break many ties.

We show the balance of home characteristics between these neighbors is much improved under the matching method. Also worth noting in support of using a nearest neighbor matching method is that unobserved characteristics, such as demographics and location relative to the urban center of Honolulu, are likely to have significant effects on water use. Households in relatively wealthy neighborhoods, like the Black Point neighborhood previous discussed, may have very different uses for water than those in the more rural areas of the island. Normal OLS does not account for these differences, but a nearest neighbor method is able to address them by making better comparisons and yield less biased results. Using OLS with dummies to control for the matched home pairs, we obtain a robust, unbiased estimate for elasticity that is much less

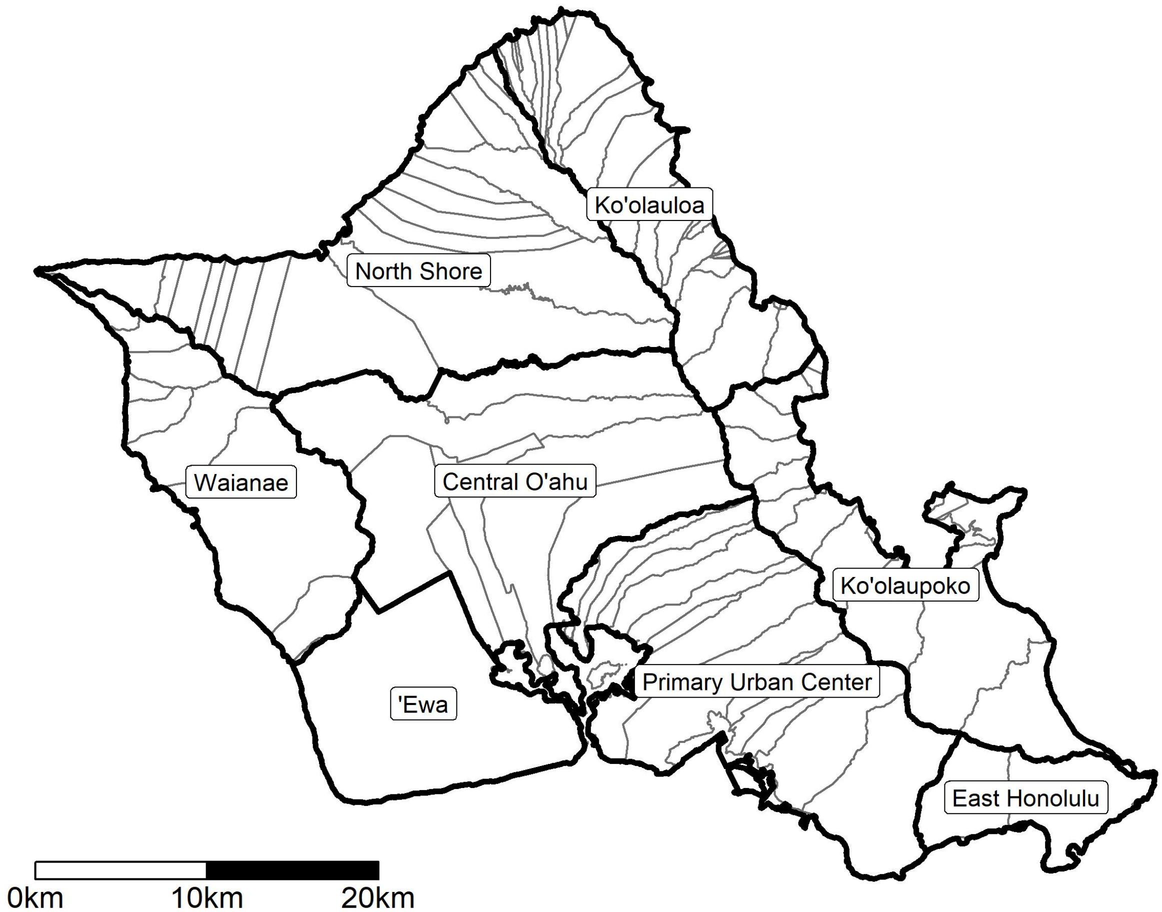
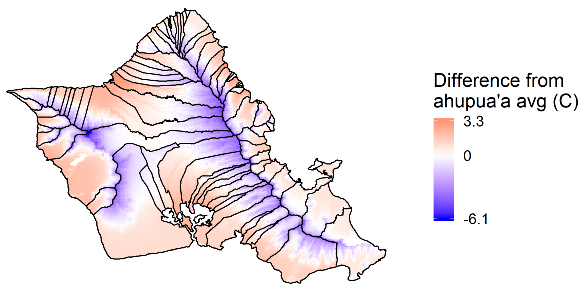
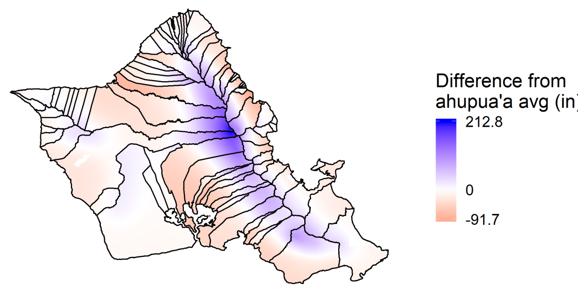


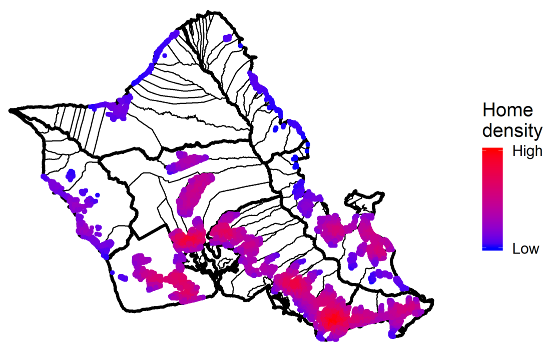
Figure 1.5: A map of ahupuaʻa within Oʻahu's major districts.



(a) Relative temperature



(b) Relative rainfall



(c) SFD locations

Figure 1.6: Ahupuaʻa characteristics. Maps show the relative temperature and rainfall within ahupuaʻa, and the locations and density of single family homes. Generally, higher elevation areas are relatively cool and wet. Homes can be seen to span across a wide variety of these microclimates, even within a small geographic area.

elastic than what was found using the regression and propensity score techniques.

1.5 Results

Table (1.3) summarizes the results of all models described in the last section. Columns (1) through (3) correspond to equation (1.1) using all homes in the dataset. Column (1) is a simple comparison of the two groups, where the only variable on the righthand side is a dummy indicating if the homes has an on-site system. Column (2) adds the home's physical characteristics and local climate as controls, and column (3) includes physical characteristics and census tract dummies that aim to control for unobserved demographic characteristics of the households. The full regression tables for these results can be found in table (A.1) in the appendix on page (78). These regressions produce statistically significant results for the OSDS coefficient, indicating homes with on-site systems consume between 7% and 23% more water than homes with sewer connections. If we use the median characteristics of a home[8], we calculate elasticities between -0.031 and -0.31 for these models using the BWS water rate table. However we know that these estimates are biased, since in table (1.2) we saw there is an imbalance between the characteristics of homes with OSDS and those with sewer connections.

Next, we use lasso regression with cross validation at the ahupuaʻa level which is not shown in the summary table. As discussed in the empirical strategy section, splines were developed for each continuous variable and their interactions. This resulted in 63 splines. The method allows the individual coefficients to reduce to 0, resulting in a large sparse matrix that is impractical to display. However, the coefficient on OSDS was estimated to be 0.1518, meaning homes with OSDS use, on average, about 15% more water than their counterparts with sewer service. An elasticity estimate can be derived from this result using the same strategy used with OLS: we take the median characteristics for a home and use the results to estimate water use for a home with and without OSDS. With robust errors clustered at the ahupuaʻa level, the elasticity is estimated to be -0.28, with a 95% confidence interval of $(-0.20, -0.37)$. This is robust to both choice of cross validation grouping and error clustering: no significant difference was observed when 2010 census tracts were used instead of ahupuaʻa. Again, however, these results are based on imbalanced data, which we attempt to fix using propensity score matching and neighbor matchign techniques.

Columns (4) and (5) in table (1.3) show the results of the propensity-score weighted GLM models. No controls are used in model (4), but model (5) includes home characteristic and climate covariates. In both cases the statistical significance of the coefficient estimates drop considerably, with corresponding elasticity estimates of -0.028 and -0.058. Imbalance between the characteristics of the homes with cesspools and the homes with sewer connections remained even after using boosted regression. Table (1.4) compares the balance of characteristics of the entire dataset with the balance resulting from the boosted regression. Overall, the t-statistics improved after matching. However, statistically significant differences between the two groups still remain. Note also that the D-statistics from the Kolmogorov-Smirnov tests are omitted since this method weights individual observations, and thus a empirical CDF of the characteristics which is needed to calculate the statistic is not informative.

[8]This hypothetical median home has 1648 square feet, a 4555 square foot yard, is 44 years old, has an annual household income of $83,472, has an average annual temperature of 23.4°C, and experiences an average annual rainfall of 34.7 inches.

Table 1.3: Summary of regression models. Elasticity calculated using daily gallons consumed by a median home with a sewer connection ($\hat{y}$ | median characteristics and $OSDS = 0$) and using the OSDS coefficient to estimate the water use if it had OSDS. Associated prices used in the elasticity estimate were calculated using the BWS rates. For the models, columns (1) through (3) use standard OLS using all data. Columns (4) and (5) use the propensity score-weighted boosted GLM model, and columns (7) and (8) use OLS on the matched neighbors dataset. Robust errors clustered by census tract except for model (8), which uses only robust standard errors since the matched data are already neighbors and thus spatially clustered. Only complete cases were used across all like models. *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:							
	Log mean daily water use (gallons)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OSDS coefficient	0.214***	0.230***	0.071**	0.021	0.045	0.041	0.059	0.040
(SE)	(0.010)	(0.025)	(0.029)	(0.036)	(0.045)	(0.060)	(0.051)	(0.074)
Data	All	All	All	All	All	Neighbors	Neighbors	Neighbors
Model	OLS	OLS	OLS	PS wtd. GLM	PS wtd. GLM	OLS	OLS	OLS
Home characteristic controls	No	**Yes**	**Yes**	No	**Yes**	No	**Yes**	**Yes**
Climate controls	No	**Yes**	No	No	**Yes**	No	**Yes**	No
Census tract dummy	No	No	**Yes**	No	No	No	No	No
Neighbor pair dummy	No	No	No	No	No	No	No	**Yes**
Observations	109,875	109,875	109,875	109,875	109,875	559	559	559
R^2	0.005	0.214	0.274	0.000	0.237	0.001	0.373	0.812
Adjusted R^2	0.005	0.214	0.270	0.000	0.237	−0.001	0.362	0.414
Elasticity estimate	−0.31	−0.34	−0.031	−0.028	−0.058	−0.059	−0.083	−0.057
(95% CI)	(−0.18, −0.46)	(−0.26, −0.41)	(−0.027, −0.036)	(0.063, −0.122)	(0.056, −0.179)	(0.105, −0.236)	(0.058, −0.233)	(0.269, −0.326)

Table 1.4: Summary of home characteristics by wastewater disposal type before and after boosted regression propensity score matching. Since the boosted regression weights the observations according to how well they match under the propensity score matching method, weighted means and t-statistics are reported for the matched pairs. The t-tests suggest the difference between means of the characteristics for the two groups are significantly different from 0, even after boosted regression propensity score matching. D-statistics from the Kolmogorov-Smirnov tests are not reported since observations are weighted by the model.

Home characteristic	Mean (all data)		Wtd mean (matched pairs)		t-statistic	
	Sewer	OSDS	Sewer	OSDS	All data	Matched pairs
Year built	1973	1968	1974	1968	19.9***	12.5***
Effective year built	1977	1974	1975	1974	11.7***	5.2***
Home size (sq. ft.)	1837	1735	1855	1739	7.3***	8.0***
Home value ($1000s)	751	808	948	873	−6.5***	6.1***
Yard size (sq. ft.)	5486	9938	13,802	9759	−19.5***	12.3***
Num. bedrooms	3.8	3.5	3.7	3.6	26.6***	8.4***
Num. bathrooms	2.2	2.0	2.2	2.0	13.4***	9.7***

*p<0.1; **p<0.05; ***p<0.01

The neighbor matching method, whose results are shown in columns (6) through (8) of table (1.3), resulted in matches that were much more similar in terms of home characteristics, as is shown in table (1.5). The results with this method are much more stable across specifications, and the two groups of homes are much more balanced. The differences in the characteristics were mostly reduced to statistically insignificant values, except for yard size and the number of bedrooms. However, the balance between even these characteristics were improved compared to the previous method. This suggests the estimated effect of sewage disposal type on household water use will be much less biased than the results from the previous methods. Applying results from this method to all homes in the dataset must be done with caution though since, as shown in table (1.6), the homes used in this method may not be representative of the homes in the full dataset. There are statistically significant differences in many of the characteristics of these homes, both with and without OSDS. For homes with sewer, homes in the matched neighbors dataset are typically older, larger, more valuable homes with larger yards compared to the population. On the other hand, homes with OSDS in the matched neighbors dataset are slightly newer, larger, and more valuable, but have smaller yards.

Table 1.5: Summary of home characteristics by wastewater disposal type before and after neighbor matching. The t-tests suggest the difference between means of the characteristics for the two groups overall are significantly different from 0, and Kolmogorov–Smirnov tests suggest the distributions are not similar. However, after matching using the neighbor method, these differences become insignificant except for yard size and the number of bedrooms.

Home characteristic	Mean (all data)		Mean (matched pairs)		t-statistic (matched pairs)		D-statistic (matched pairs)	
	Sewer	OSDS	Sewer	OSDS	All data	Matched pairs	All data	Matched pairs
Year built	1973	1968	1969	1970	19.9***	−0.69	0.14***	0.11*
Effective year built	1977	1974	1974	1976	11.7***	−1.05	0.10***	0.09
Home size (sq. ft.)	1837	1735	2058	1952	7.3***	0.43	0.14***	0.05
Home value ($1000s)	751	808	967	993	−6.5***	−0.33	0.14***	0.06
Yard size (sq. ft.)	5486	9938	6832	6177	−19.5***	2.02**	0.25***	0.18***
Num. bedrooms	3.8	3.5	4.0	3.7	26.6***	2.18**	0.09***	0.11*
Num. bathrooms	2.2	2.0	2.4	2.3	13.4***	0.33*	0.14***	0.01

*p<0.1; **p<0.05; ***p<0.01

Table 1.6: Mean values of each characteristic for all homes in the data and those used in the match. In general, homes used in the matching method do not share similar characteristics with the rest of the population, as there are statistically significant differences between the neighbors group and all homes in the data.

Home characteristic	Sewer				OSDS			
	Neighbors	All	t-statistic	D-statistic	Neighbors	All	t-statistic	D-statistic
Year built	1969	1973	-3.52^{***}	0.16^{***}	1970	1968	1.51	0.17^{***}
Effective year built	1974	1977	-2.55^{**}	0.14^{***}	1976	1974	1.30	0.14^{***}
Home size (sq. ft.)	1994	1837	2.37^{**}	0.10^{***}	1952	1735	3.04^{***}	0.10
Home value ($1000s)	967	751	4.04^{***}	0.15^{***}	993	808	3.12^{***}	0.17^{***}
Yard size (sq. ft.)	6832	5486	5.96^{***}	0.22^{***}	6177	7405	-4.87^{***}	0.17^{***}
Num. bedrooms	3.96	3.84	1.68^{**}	0.07^{**}	3.72	3.50	2.66^{***}	0.06
Num. bathrooms	2.32	2.19	2.04^{**}	0.09^{***}	2.29	2.03	3.58^{***}	0.10^{**}

* $p< 0.1$; $^{**}p< 0.05$; $^{***}p< 0.01$

The lasso regression was also attempted using only the matched neighbors subset of the observations but the OSDS dummy variable was thrown out during the cross validation process, indicating demand would be estimated to be perfectly inelastic. Overall, both OLS and LASSO produce statistically significant, but biased, results when all observations are used. The propensity score matching reduced, but did not eliminate, bias in the data and produced a much smaller elasticity. The OLS model with the least amount of bias, where the observations are limited to those chosen in the neighbor matching method, produced similarly small elasticities. Although the results with the unbiased data are not statistically significant at the 10% level, they allow us to provide an estimate of the bounds of the elasticity. That is, for OLS, we estimate residential water demand to be no more elastic than -0.33 when we include the neighbor pair dummy variable. This is slightly more inelastic than many current estimates for water demand in the literature.

1.6 Discussion

Having an accurate estimate of the price elasticity of water demand is becoming increasingly critical as governments and utilities explore options for conserving water under a changing climate. This is especially true in Hawai‘i, where currently the only viable source for fresh water is the island's aquifers which are replenished by rainfall. With less precipitation and warmer temperatures expected (Izuka and Keener 2013), a decrease in water supply and increase in demand will require a more careful water management strategy until other sources like desalination become more viable. Regulating prices to influence water use is one way this can be accomplished, but relies heavily on consumers' sensitivity to these prices. Without accurate estimates of price sensitivity, it will be impossible to reach water sustainability goals with these measures. Since, in most cases, prices would have to be raised in order to conserve water, this leads to the potential for a loss in consumer surplus with no benefit to the water resource. Due to the variety of methods used, data availability, pricing structures, and consumer characteristics, there is an extensive range of estimates of price elasticity of water demand. Indeed, as we have seen in previous studies and this study, the estimate can vary widely when different models are used with the same underlying data.

Our inelastic demand estimates suggest it may be worthwhile to explore alternative conservation strategies, at least under the current pricing. Although a price increase may be justified since the scarcity value of the water isn't taken into account in the current pricing scheme (i.e. the price of water is entirely based on the costs incurred by the utility), our results suggest that the extremely inelastic demand makes price adjustment as a tool for water conservation much less feasible. However, it may be that demand becomes more elastic at higher prices. For example, the demand for water by single family homes may actually be convex, and we only observe the inelastic portion at lower prices in our study. More work in this area would need to be done to determine the shape of demand at all prices. Knowing this information would be invaluable for analyzing the welfare impacts of a price increase and how it would relate to the currently-ignored scarcity value of water. If demand is inelastic at all prices, then increasing the price to account for the scarcity value may result in an unreasonable loss in consumer welfare. On the other hand, if demand is convex, the loss in welfare would be less when the price is increased to match the scarcity value. In this case, increasing the price to a level closer to that which accounts for the scarcity value of water may be more feasible.

For analyses on a longer time horizon, studying the impact of conservation, the evolution of groundwater extraction over time, increasing reliance on alternative sources of water, and the impact on consumer welfare will be critical. Given the continually-falling cost of renewable energy (Branker, Pathak, and Pearce 2011;

Trancik 2015) and energy storage (Ralon et al. 2017; Gardner et al. 2016), alternative water management solutions may become more viable. In particular, desalination may become an increasingly affordable alternative to groundwater extraction as energy costs decrease. Therefore, in the long run, if we abstract from other concerns like ecological and cultural impacts, issues regarding consumer welfare may become more critical than the specific source of the fresh water. Even without alternatives like desalination, the optimal use of a renewable resource like water will typically reach a state where the growth of the stock is equal to the extraction rate. In the case of the aquifers of O'ahu, water may continue to be drawn until it reaches its sustainable yield, defined by parameters such as acceptable salinity measures. In theory the head level will be reduced to the limit (plus some safety margin for water salinity standards, etc.), since any stock not extracted may be lost to groundwater discharge to the ocean. The path taken from our current status to the backstop, where we reach minimum head level and desalination becomes more affordable than extraction, that also maximizes consumer welfare is another question altogether (J. A. Roumasset and C. A. Wada 2010). That is, not only is the problem of maximum sustainable yield important, but the optimal extraction and investment in conservation from now until we reach that level can have significant impacts on consumer welfare. Additionally, the timing of the transition, and how quickly it is done, from pure groundwater extraction to a hybrid of extraction and desalination can have significant effects on consumer welfare as well (J. Roumasset and C. A. Wada 2014).

In the meantime, other studies examining the efficacy of non-price strategies show these programs are promising alternatives to price controls. Persuasive means of reducing water use have been shown to be effective at developing positive attitudes toward compliance, and these attitudes can be used as predictors of water use (Landon, Kyle, and Kaiser 2016; Landon, Woodward, et al. 2018). That is, water conservation campaigns can be used as an effective means to persuade customers to reduce their water use. In one study (Otaki, Ueda, and Sakura 2017), showing the customer's usage with emoticons indicating the level of use, and their use relative to other customers, was found to be an effective way to reduce consumption. Another study (Woltemade and Fuellhart 2013) found similar results for outdoor water use, where customers are shown estimates of how much water they should need for irrigating their lawns, and the water use of their neighbors. This effect was shown to grow stronger over time through repetition.

By significantly simplifying the consumer surplus problem at hand and ignoring potential relationships with optimal pricing and groundwater extraction, our results can help estimate the economic impact of the statewide ban on cesspools. Hawai'i has banned the construction of new cesspools on all islands, and is providing tax incentives to customers to upgrade their systems to either a septic tank or sewer connection. Using back-of-the-envelope calculations, we can show that the offered tax credit of $10,000 is not enough to cover the installation of either upgraded system, let alone the net present value of increased monthly charges incurred by those who upgrade to sewer.

In December 2018, SB2567[9] went into effect, requiring owners to upgrade any cesspools on the property within 180 days of the sale of the home. In many cases, homes will more likely upgrade to a septic tank than connect to the sewer system. This is because, with a septic tank, there is no additional monthly cost the customer must pay, like there is if they upgrade to sewer service. The bill states that the average owner pays $20,000 to upgrade the system, but this may vary drastically depending on the system being installed, location relative to existing sewer lines, and geography. In certain cases, it may be impossible to upgrade to

[9] `https://www.capitol.hawaii.gov/session2018/bills/SB2567_.HTM`

a sewer connection due to the lack of existing sewer lines in the area, or the location of the home relative to the sewer line.

In any case, the cost of installing the new system alone exceeds the existing tax credit which provides little incentive for owners to voluntarily upgrade, especially since the owners will initially have to front the cost and receive the tax credit at a later time. If we consider the net present value of future monthly sewer service payments, the difference becomes even larger. Figure (1.7) shows the effect upgrading from cesspool to sewer connection will have on the surplus of the consumer. As noted earlier, there is disagreement about whether consumers respond to average or marginal price, but we show here that the difference would be minimal if consumers were acting completely rationally. Despite discussions of conservation and reducing water use, this figure suggests an increase in welfare may be observed if consumption is *increased*, since the evidence suggests residences are currently responding to average price.

Using back-of-the-envelope calculations with a discount rate of 3% and an infinite horizon, the net present value of sewer costs (not including the initial installation costs) would be

$$(\$77.55 + \$40.47 + \$1.77) \times 12/0.03 = \$47,916,$$

where the monthly \$40.77 comes from the welfare loss associated with the conversion in figure (1.7). Even without the initial installation costs, this amount far exceeds the tax credit currently offered. This would be in addition to the installation cost of the sewer connection, bringing the total net present value to about \$67,916. An important note is that the actual amount that would need to be offered as a credit would likely be less than this, since there are costs associated with maintaining an OSDS which includes emptying, repairing, and replacing the system. However, these costs vary widely depending on system age, system type, location, and other idiosyncratic factors that make an exact calculation difficult to perform. If we extend this value to all single family homes on Oʻahu with cesspools (7044 homes), the island-wide net present value of the upgrades totals over \$337 million. Again, this would be an upper limit to the value since the costs associated with the maintenance of on-site systems is ignored due to their complexity. However, this also excludes the idiosyncratic initial upgrade costs.

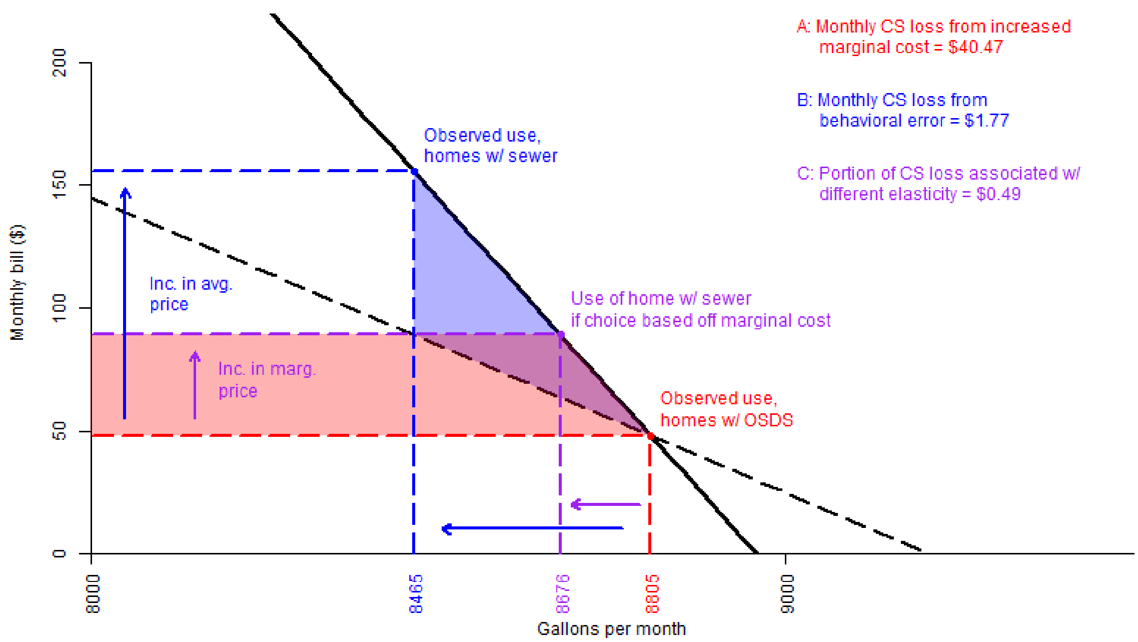


Figure 1.7: Loss in consumer surplus when switching from OSDS to a sewer connection. The solid line is the estimated demand curve, assuming consumers respond to average price *as if* it were marginal price. The dashed demand curve shows what the response to marginal cost would look like with the assumption customers actually respond to average price.

Chapter 2

How will climate change affect water demand? Evidence from Hawai‘i microclimates

2.1 Introduction

With significant changes expected for global climate by the end of the century, interest is growing in topics concerning efficient management of water resources. Shifting rainfall patterns are expected to impact watersheds and aquifers globally, some of which, like the Southwestern United States, are already increasingly strained due to growing population, intensive agricultural production, and greater drought frequency. This has spurred a growing literature that aims to quantify the effects of climate change on available water resources (Arnell 1999; Taylor et al. 2013; Dettinger, Udall, and Georgakakos 2015).

Climate change, or the gradual shifting of historical distributions of weather outcomes in a given region, may add to existing concerns about optimal groundwater extraction and conservation. The island of O‘ahu in Hawai‘i is a region where supply and demand of fresh water is precariously balanced and concerns about water resource management have existed even before consideration of climate change. Monitoring of aquifer head levels and extraction, starting the late 19th century (Gingerich and Voss 2005), show how intensive farming of pineapple and sugarcane extracted considerably more groundwater than the rate of recharge, raising concern about future water availability. Although a new water rights regime was established and in subsequent decades intensive agricultural activity largely ceased, a growing population, tourism, and urban expansion into drier, warmer areas of the island have acted to keep aquifer head levels diminished.

Later in the 20th century, computational models of the island's aquifers were developed to estimate maximum sustainable yield and have attempted to determine the agricultural and population capacity of the island. Over time, these modelling efforts have become more sophisticated (A. I. El-Kadi and Moncur 1996; Liu, L Stephen Lau, and John F Mink 1981; Thomas W Giambelluca 1983; J. Mink and L. Lau 1990; Ridgley and Giambelluca 1990; Liu 2006). Some studies have used climate models to investigate the potential impacts on future aquifer recharge. Some of these projections indicate shifting trade wind patterns may have a significant effect on associated rainfall and aquifer recharge rates, and thus the optimal extraction pathway

(J. A. Roumasset and C. A. Wada 2010; Burnett and C. A. Wada 2014; A. El-Kadi 2014; J. Roumasset and C. A. Wada 2015; Bateni 2016; Leta, A. I. El-Kadi, and Dulai 2017; Tsang and Evensen 2017; C. A. Wada et al. 2017). At the same time, increasingly large forests of invasive trees and plants have deeper roots and may transpire more soil moisture. This phenomenon, plus a large number of channeled streams that have been lined with concrete, may be reducing aquifer recharge conditional on rainfall. Given the complex hydrology and long time lag between rainfall and aquifer recharge, there is great uncertainty about the true maximum sustainable yield and how it will change with climate.

To our knowledge, this study is first to consider how a changing climate will affect water *demand*, which could be equally important to management solutions as the impact of climate change on water supply. Indeed, many previous studies have found that weather and climate variables affect water use (Gato, Jayasuriya, and P. Roberts 2007; Kenney et al. 2008; Mieno and Braden 2011; Ozan and Alsharif 2013; Ouyang et al. 2014; Ghimire et al. 2015). These studies, however, mainly include weather and climate variables in their models as controls rather than as variables of interest; the typical purpose is to estimate the effects of a change in price or policy on water use.

In this study we link residential water use to climate and then use this link together with future climate scenarios to project future water demand. Oʻahu is an interesting setting to conduct this study because it has multiple microclimates within a small geographic area, sometimes within a single development. Temperature and rainfall vary by elevation and geographic orientation to mountains and prevailing winds. Average annual rainfall can double or halve over a geographic distance of just 1-2 miles. These microclimates help us to deal with potential omitted variable bias: factors besides climate that influence water use but happen to be geospatially associated with climate.

Typically, to observe enough climate variation to identify its effect on water use, would require comparisons between disparate regions, potentially ones with very different utilities, pricing, demographics, and local economies. These other differences may confound differences in water use stemming from climate. Oʻahu provides an opportunity to apply this strategy more convincingly, since it is a small island with many consumers exposed to a variety of climate conditions, but with many factors largely held constant. The island is approximately 44 miles by 30 miles, with the maximum distance between any two homes being about 37 miles. These consumers all fall under one utility, the Honolulu Board of Water Supply, and thus face the same pricing schedule.[1] For climatic variation, we leverage the many microclimates of the island that result from steep topography and prevailing tradewind patterns. Average annual temperature experienced by households on the island ranges from 20.8°C (69.4°F) to 23.8°C (74.8°F), while household average annual rainfall ranges from 21.0 inches to 144.3 inches, depending on location.

Since we want to determine the effect of climate on water use, a daily or monthly scale may be too short-term to identify the correct effects. Water use may be tied to landscapes that are climate dependent, and may be on fixed irrigation schedules that do not react to weather. Thus, Comparing one household's water use behavior during wet and dry spells may yield results that differ from studying two homes experiencing completely different climate conditions. Meanwhile, seasonal variation in water use and weather may be highly correlated with other factors like work schedules, school schedules, and tourism. Thus, a cross-sectional analysis would be preferable, so long as the groups of homes, the people residing in them, as well as their constraints and circumstances, are sufficiently similar in all other respects. Given the strong spatial

[1] As we discuss later, a small number of homes have their own wastewater systems or belong to a small, private water utility and are thus removed from the analysis.

correlation of both climate and other demographic variables, omitted variables bias and confounding is a serious concern.

To estimate the relationship between climate and water use, we develop a climate measure we call *net landscape water demand* and compare it to billing data for single family homes on O‘ahu. We find water use is highly correlated with climate, even after controlling for household characteristics and location. These results are then applied to downscaled models of CMIP5 RCP 4.5 and RCP 8.5 climate projections. Our results suggest that, by the end of the 21st century, island-wide water use by single family homes will increase between 20% and 37% depending on the model specification, and holding all else constant.

In the next section, we begin by outlining our empirical strategy. Section (2.3) details our historical climate and billing data. Section (2.4) presents future climate scenarios for O‘ahu. It also explains our empirical strategy in more detail, for reasons that are discussed below. Our results are presented in section (2.5), and section (2.6) provides a discussion about potential ways to offset the projected increase in water use. We also discuss the role this study may play in the larger literature that examines optimal watershed management and consumer welfare

2.2 Empirical strategy

Average annual temperature and rainfall are typical measures of climate, but may be relatively poor indicators of economic outcomes. In other contexts, nonlinear temperature effects and complex interactions between rainfall, humidity and temperatures have been shown to be obscured by averages (Schlenker and M. J. Roberts 2009; M. J. Roberts, Schlenker, and Eyer 2013; Auffhammer and Mansur 2014; Lobell et al. 2013). Various measures of weather and climate can also be correlated, which may increase standard errors due to multicollinearity and complicate interpretation of regression coefficients.

Because the most logical link between climate and water demand pertains to landscape irrigation, we draw on basic plant science to develop a new measure that we call net landscape water demand (NLWD), defined as

$$\text{NLWD} = \text{Evapotranspiration} - \text{Rainfall}.$$

Evapotranspiration, the sum of water that is evaporated or transpired through plants, is also measured in average annual inches. Rainfall is average annual rainfall in inches. NLWD is thus the average annual difference between how much water is needed by plants (e.g. a lawn) and available rainfall, measured in inches.[2] Large positive values of NLWD indicate a deficit in available water, while negative values indicate a surplus. Our main specification relating residential water use to this climate indicator will thus be

$$w_i = \alpha_0 + \alpha_1 NLWD_i + X_i\mathbf{A} + u_i, \tag{2.1}$$

where w_i is the average daily water use of household i in gallons, $NLWD_i$ is the household's average annual net landscape water demand, X_i is a vector of location and household characteristic controls, and u_i is the idiosyncratic error term.

Note that unlike the non-linear studies cited above, our model is purely cross-sectional. Although we have a panel of billing data and attempted to create a model that made full use of it, there are two main

[2] For context, an average lawn may require approximately 1-3 inches of water per week, depending on climate, type of grass, and length of grass.(Gross and Swift 2008)

reasons we do not report their results.[3] First, available weather data are poorly measured as compared to climate data. The weather data, particularly rainfall, cannot be well interpolated between the few weather stations, many of which have missing data. Second, a household's response to day-to-day weather may not be indicative of its response to a longer-term climate. For example, landscape plantings and irrigation systems can change with climate but cannot easily change with the weather. Whereas weather may have short-term shocks, the distributions of climate measures remain stable for longer periods of time. We are more concerned with the latter due to its closer relationship to our interest in the effects of climate change. Because the model is cross-sectional, care must be taken to ensure our results are not biased by omitted variables.

To address omitted variables bias, we consider different variations in climate across the island. These mainly pertain to (1) windward (Northeast) or leeward (Southwest) location, and (2) elevation. Locations more windward and of higher elevation tend to be cooler and wetter. Areas closer to the mountains can be much wetter too, even if elevation change is minimal. Climatic differences can be substantial, even over distances as short as a mile or two. While observed demographic variables tend to be associated with climate on a larger scale (windward versus leeward), they have much less and rather different association on a smaller scale (local, watershed-specific differences in elevation and distance to mountains). By estimating models with and without fixed effects (described below), we consider both sources of variation. In each case, we also estimate models with and without explicit controls for other demographics. We also consider how well the NLWD variable predicts water use in comparison with other climate measures.

2.3 Data

2.3.1 Billing, parcel, and home characteristics

Monthly billing data from June 2011 to August 2019 for 140,983 single family homes were obtained from the Honolulu Board of Water Supply. The dataset includes each parcel's unique identifier called a tax map key (TMK), the beginning and end date of each billing period, the number of days in the billing period, location of the parcel in latitude and longitude, and the consumption billed rounded to the nearest 1000 gallons. From this water consumption value, we calculate an average daily use value for each home using the total quantity consumed and the number of days in each billing period. This is done because the lengths of billing periods are not consistent in the data: periods may last from a couple weeks to several months. Median daily use for single family homes is 225.8 gallons per day, with a mean of 272.8 and standard deviation of 196.1. The water use data have a large positive skew as shown in figure (2.1).

Using the provided TMK numbers for each parcel, physical characteristics of each home were obtained from the Honolulu Real Property Assessment Division's public property records search. This provided characteristics such as lot square footage, home square footage, year built, effective year built[4], assessed land and building value, number of bedrooms, and number of full and half bathrooms. A yard size variable for

[3] We attempted panel regressions with a wide range of specifications and found no statistically significant relationship between weather and water demand when using parcel fixed effects. The standard errors, however, were extremely large, unable to rule out very substantial impacts. At the same time, we questioned the quality of our fine-scale weather data interpolation methods as cross-validation indicated poor accuracy. Such error may lead to attenuation bias as well as biased standard errors (Fisher et al. 2012).

[4] Many older homes have been renovated, effectively decreasing the age of the home. To account for this, the "effective" year built is provided by the Honolulu Real Property Assessment Division.

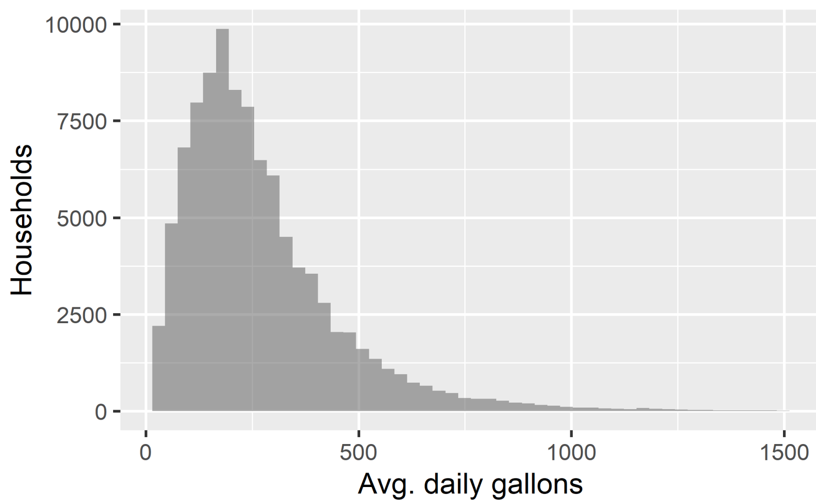


Figure 2.1: Histogram of water use by single family homes on Oʻahu

each parcel was created by dividing the square footage by the number of floors in the home to get a 'home footprint' value, which was then subtracted from lot size. Note that this definition thus includes surfaces such as driveways and patios as part of the yard.

Most homes on Oʻahu receive water service from the Honolulu Board of Water Supply. These residential consumers all face the same pricing structure, except for two groups. The first is a small group of homes that receive separate, private sewer service. Their billing rates are not publicly available so these homes are excluded from the analysis. The second group is homes with on-site disposal systems (OSDS) such as septic tanks and cesspools. These homes pay the same rate for water as the other homes, but they do not pay to receive sewer service which significantly decreases their bill. Because these homes tend to be clustered together in particular areas of the island, there is a concern that they may confound our results. A robustness check is performed in the appendix that excludes homes with OSDS to compare with the results presented below.

The data include many outliers in terms of water use and home characteristics. These may result from a variety of potential causes, such as an entire private community being billed as one unit, significant leaks in the water system, or vacation homes that remain vacant for a significant portion of the year. Cases where a single TMK included many homes were removed manually using the Tax Assessor's database, which includes a satellite image of each TMK. This did not remove all outliers, so the remaining top and bottom 0.1% of households were removed as well to exclude potential vacant homes, homes with leaks, and database errors. Removing these extremely large and extremely small outliers, merging billing and characteristics data, and removing observations with missing data yielded a complete dataset with 98,162 single family homes.

2.3.2 Historical climate data and land divisions

Average historical monthly climate data for the period 1978 to 2005 were obtained from the Rainfall Atlas of Hawaiʻi (T.W. Giambelluca et al. 2013). Variables obtained for this study include average rainfall, temperature, vapor pressure deficit, evapotranspiration, and grass reference evapotranspiration at a 250m resolution for all of Oʻahu. Wind direction data were also obtained from windfinder.com. Vapor pressure

Table 2.1: Summary of home characteristics and climate data. NLWD is net landscape water demand. Mean climate variables are historical averages for the period from 1978 to 2005.

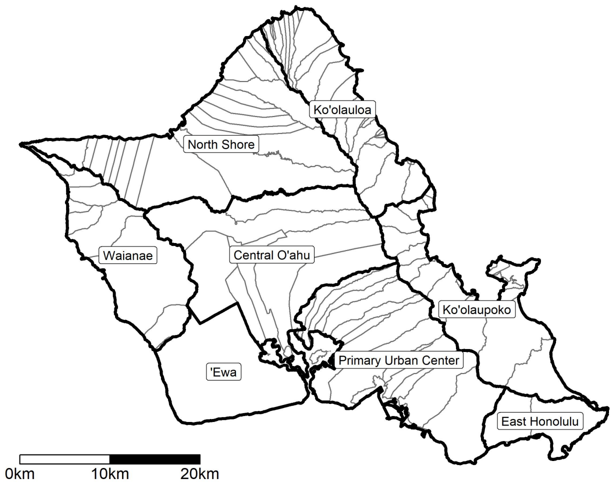
	Median	Mean	SD	Min	Max
Avg. water use (gal/day)	225.8	272.82	196.1	24.3	2386.4
Elevation (m)	35.3	70.1	83.4	0.0	388
Temperature (°C)	23.4	23.2	0.62	20.8	23.8
Rainfall (in/yr)	34.3	38.5	16.6	21.0	144.3
Reference ET (in/yr)	92.9	90.5	10.1	60.7	111.8
NLWD (in/yr)	58.6	52.0	23.1	−63.6	90.2
Home size (sq ft)	1616	1749	705	502	7933
Yard size (sq ft)	4512	4959	2226	0	14,602
Year built	1971	1973	19.7	1899	2015
Effective year built	1975	1977	17.9	1901	2015
Num bedrooms	4.0	3.7	0.92	1.0	6.0
Num bathrooms	2.0	2.1	0.80	1.0	5.0

deficit (VPD), measured in pascals (Pa) or kilopascals (kPa), is the difference between how much moisture is in the air and how much the air can hold when saturated. Evapotranspiration (ET) is the sum of water evaporation and transpiration from plants, and is measured in inches. Grass reference ET is a hypothetical reference value for ET, indicating the potential evapotranspiration if the land were covered with grass. We consider VPD, ET, and reference ET in addition to rainfall and temperature when selecting our models. We also consider our constructed net landscape water demand (NLWD), defined above. Both ET and rainfall are given in inches per year, so NLWD is in inches per year as well. We choose to use reference ET instead of actual ET in constructing NLWD because, as we show and discuss below, it is more highly correlated with household water use than actual ET. Table (2.1) summarizes the billing and physical characteristics of the homes, along with the merged climatic data.

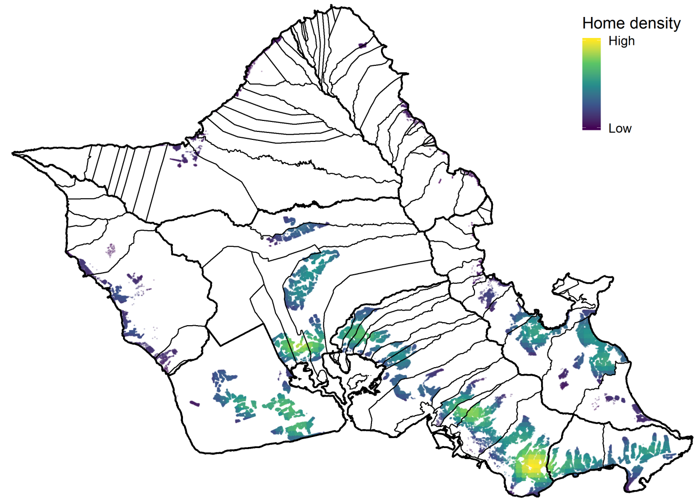
The longitude and latitude provided in the household data were also used to match each parcel to its district, ahupuaʻa, watershed, census tract, and census block. Districts are major land divisions of Oʻahu that correspond to the Honolulu Board of Water Supply's Watershed Management Plan, and which are further divided into ahupuaʻa. Ahupuaʻa are traditional land divisions usually extending from the sea to the mountains, so called because the boundary was marked by a heap (ahu) of stones surmounted by an image of a pig (puaʻa), or because a pig or other tribute was laid on the alter as tax to the chief'.[5] A map of Oʻahu's districts and their ahupuaʻa is shown in figure (2.2a). Due to geography and development patterns, ahupuaʻa span a wide range of microclimates and household characteristics. Thus, we may use models with and without ahupuaʻa fixed effects to study the relationship between water use and climate both within and between these land divisions. Panel (2.2b) shows the location and density of single family homes on the island. All shapefiles for these data were obtained from the State of Hawaiʻi Office of Planning.

The variation in climate on Oʻahu comes from a combination of stark contrasts in elevation over relatively short distances, and the prevailing trade wind pattern. An elevation contour map and distribution of

[5] Pukui/Elbert Hawaiian Dictionary, `http://www2.hawaii.edu/~dhonda/ahupua'a.htm`



(a) Districts and ahupuaʻa



(b) Home location and density

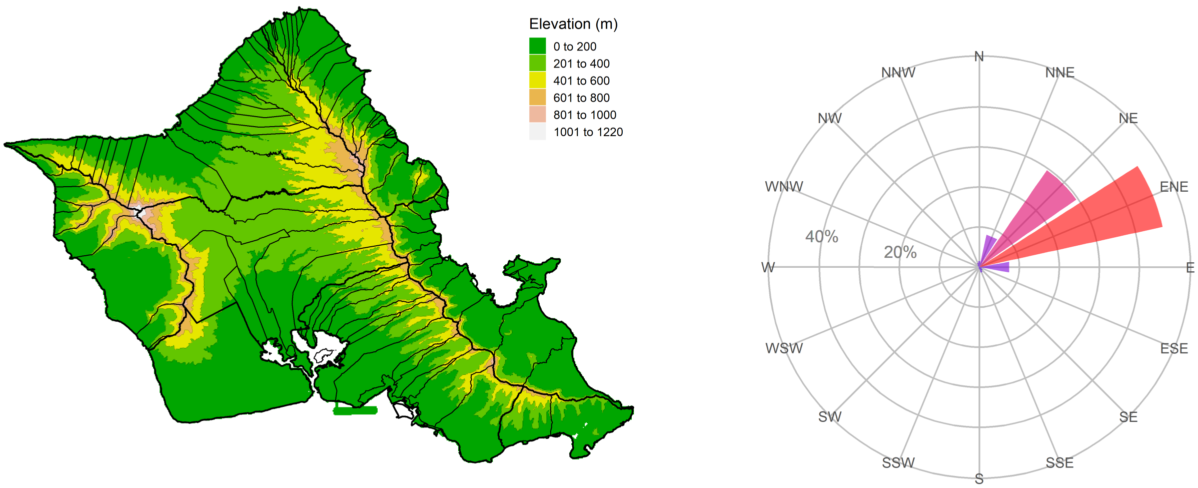
Figure 2.2: Districts, ahupuaʻa, and home locations on Oʻahu

prevailing winds is shown in figure (2.3). This combination of elevation and wind patterns results in the windward, northeast side of the island receiving more rain than the leeward side. Island-wide, annual rainfall averages range from a low of 21 inches in the dry ʻEwa plain in southwest Oʻahu to a high of nearly 280 inches in the Koʻolau mountains running along the northeast portion of the island. Elevation also has a significant effect on average annual temperature, which ranges from nearly 24°C in dry, sunny southwest Oʻahu to 15°C at the highest peaks of the eastern Koʻolau range and western Waiʻanae range. These prevailing rainfall and temperature patterns have a direct effect on our other climate variables VPD and ET, and thus our constructed NLWD parameter. Maps of these climate variables are shown in figure (2.4).

2.4 Future climate projections

2.4.1 Climate scenarios

We use data from two models for our climate change projections. Both models give downscaled projected changes to temperature and rainfall for CMIP5 RCP 4.5 and RCP 8.5. Although we focus on using the deltas associated with the period from 2071 to 2099, we also present results using deltas for the mid-century period from 2040-2070. The first model is a statistically-downscaled rainfall model produced by Timm, Thomas W Giambelluca, and Diaz (2015), which contains projections for both the wet (winter) and dry (summer) seasons. The data use 32 equally-weighted GCMs to which a statistical ensemble method was applied to provide end-of-century deltas, and their errors, downscaled to the same resolution as the Rainfall Atlas climate data described above. We merge the wet and dry season data together to create average annual values. Timm (2017) uses a similar statistical downscaling method to provide future projected temperatures.



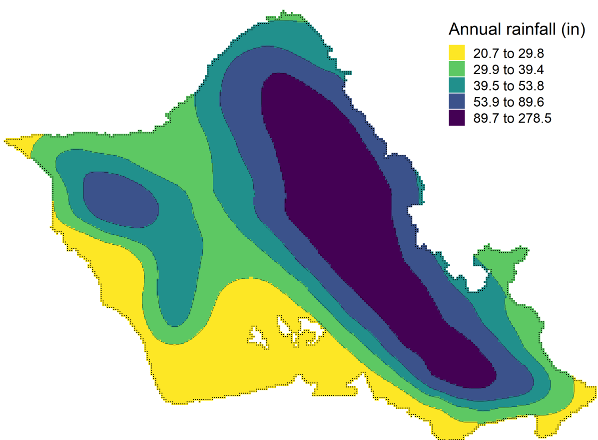
(a) Elevation contour map (b) Annual average wind direction distribution

Figure 2.3: O'ahu elevation and prevailing winds

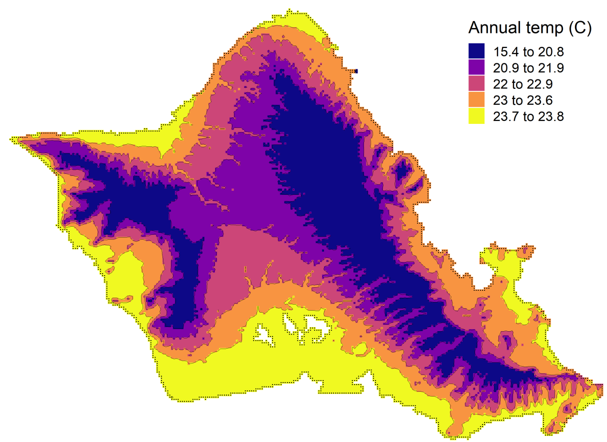
The temperature data use an ensemble of 32 GCMs and includes the mean, standard deviation, and min and max estimates for the ensemble projections. We use the RCP 4.5 and RCP 8.5 averages for the period 2071-2099. The second source of downscaled data comes from a dynamical model from Zhang et al. (2016), which uses an ensemble of 20 GCMs. The resolution is slightly larger than the 250m resolution of the current climate data, so each grid cell in the 250m base data was matched with the closest grid cell in the Zhang et al. data to project future values of temperature and rainfall.

The statistical downscaled data include errors for their estimates, but the dynamical data do not. Following advice given in Varela, Lima-Ribeiro, and Terribile (2015), we use the error terms provided by the statistical downscaled data to make estimates across the various GCMs in the ensemble. This allows us to incorporate uncertainty between the GCMs within our own model. The variation in GCM estimates, even within a given RCP scenario, result from their individual choice of input variables, along with simulation and calibration techniques. Simply using the mean prediction provided by the ensemble would not allow us to estimate a full distribution of potential outcomes in our results.

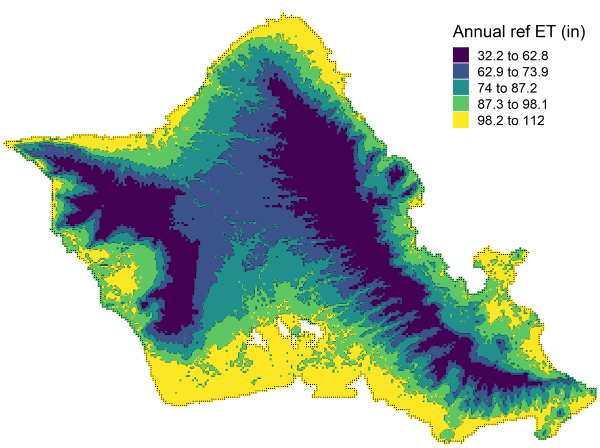
Figure (2.5) shows the current and projected end-of-century average annual temperatures for both RCP scenarios under the dynamical and statistical models. The dynamical model predicts a more extreme increase in temperature than the statistical model, particularly under RCP 4.5, but the models are otherwise similar. Note that the two lightest contours seen in the dynamical RCP 4.5 scenario and in both RCP 8.5 scenarios show regions that may, by the end of the century, experience an average annual temperature that is warmer than the current average temperature of any part of the island.



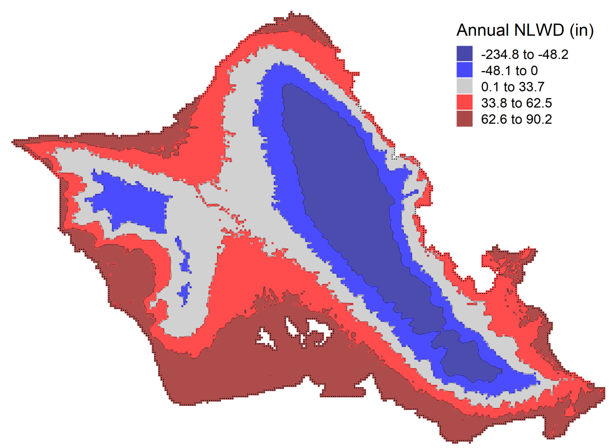
(a) Rainfall



(b) Temperature

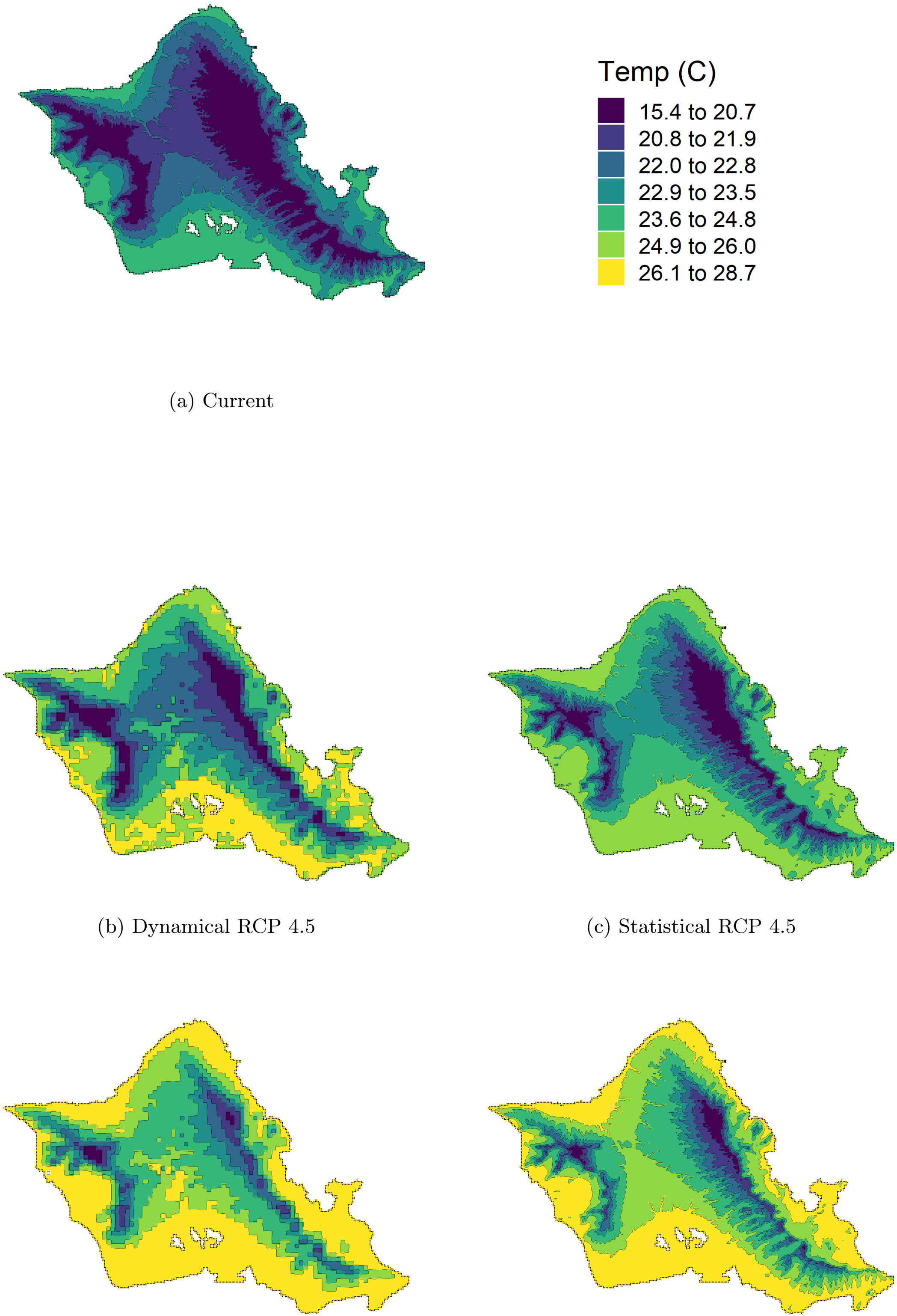


(c) Grass reference evapotranspiration



(d) Net landscape water demand

Figure 2.4: Oʻahu historical average annual climate, 1978 to 2005.



(a) Current

(b) Dynamical RCP 4.5

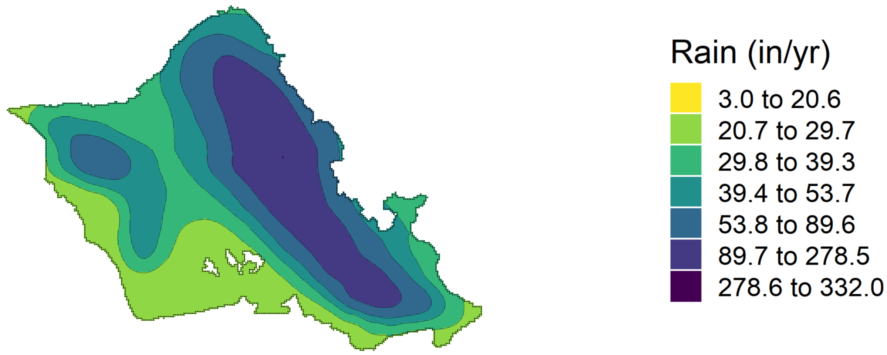
(c) Statistical RCP 4.5

(d) Dynamical RCP 8.5

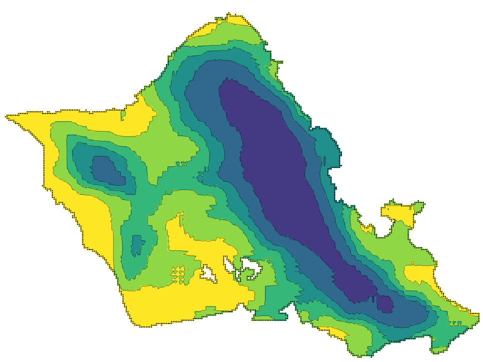
(e) Statistical RCP 8.5

Figure 2.5: Downscaled projected temperature under the statistical and dynamical models. Current climate generated from historical averages for the period 1978 to 2005, and projected future climate for the period 2071-2099.

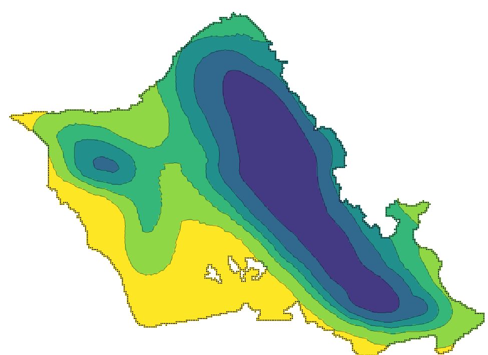
Historical average and projected end-of-century average annual rainfall values for all models are depicted in figure (2.6). Here, the dynamical and statistical models differ slightly in their projections. As in the temperature projection figure, the lightest contour is used to indicate areas of Oʻahu that may experience less rainfall by the end of the century than is currently observed on the island. Additionally, the darkest contour in the dynamical RCP 8.5 model is introduced as it predicts some areas of the island will experience an increase in average annual rainfall. For the statistical model, rainfall in the windward Northeastern portions of the island is predicted to remain relatively stable, but the leeward areas may have significant decreases in rainfall.



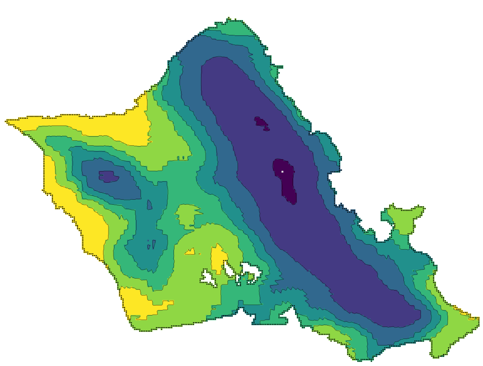
(a) Current



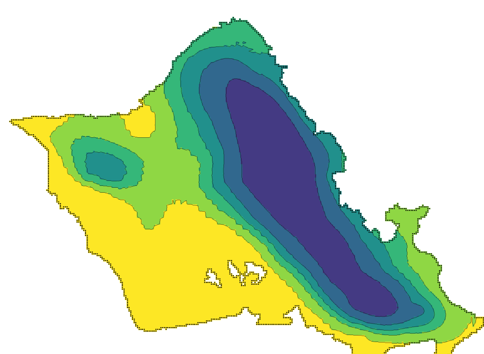
(b) Dynamical RCP 4.5



(c) Statistical RCP 4.5



(d) Dynamical RCP 8.5



(e) Statistical RCP 8.5

Figure 2.6: Downscaled projected rainfall under the statistical and dynamical models. Current climate generated from historical averages for the period 1978 to 2005, and projected future climate for the period 2071-2099.

Table 2.2: Correlations between climate variables and household water use. ET is evapotranspiration.

	Avg. daily gallons	ET (in/yr)	Reference ET (in/yr)	Rainfall (in/yr)	Avg ann temp (C)	NLWD (in/yr)	VPD (kPa)
Avg. daily gallons	1						
ET (in/yr)	0.003	1					
Reference ET (in/yr)	0.15	-0.059	1				
Rainfall (in/yr)	-0.148	0.195	-0.475	1			
Avg ann temp (C)	0.141	-0.2	0.926	-0.573	1		
NLWD (in/yr)	0.171	-0.165	0.775	-0.924	0.814	1	
VPD (kPa)	0.128	-0.179	0.931	-0.438	0.985	0.719	1

2.4.2 NLWD proxy for future climate

The model in equation (2.1) uses net landscape water demand as the explanatory variable, while the climate projection models above provide only temperature and rainfall predictions. To link the climate projections to NLWD we therefore generate a proxy for NLWD using current NLWD, temperature, and rainfall for application with the climate scenarios.

Table (2.2) shows the correlations between all climate variables and household water use. The high correlation between average rainfall and average temperature creates concerns for multicollinearity when modeling the relationship between water use and climate. Moreover, these metrics may not be ideal for predicting water demand. Still, it is useful to consider these standard metrics in comparison to our selected metric, NLWD, to test whether it improves prediction. Looking at the first column of table (2.2), we find that net landscape water demand is most strongly associated with water use. This fact, by itself, helps to support the idea that the link between climate and water use is causal. This inference follows from the fact temperature, rainfall, and evapotranspiration show similar degrees of spatial correlation and association with other home characteristics but do not have

Although NLWD is most highly correlated with household water use, only projected temperature and rainfall are available in the future climate data. To resolve this, a climate proxy can be constructed from temperature and rainfall to simplify the relationship between water use and climate easier. Thus, to create a relationship between the climate projection models and equation (2.1) we generate a proxy for NLWD,

$$NLWD_j = \beta_0 + \beta_1 T_j + \beta_2 R_j + A_j + v_j, \tag{2.2}$$

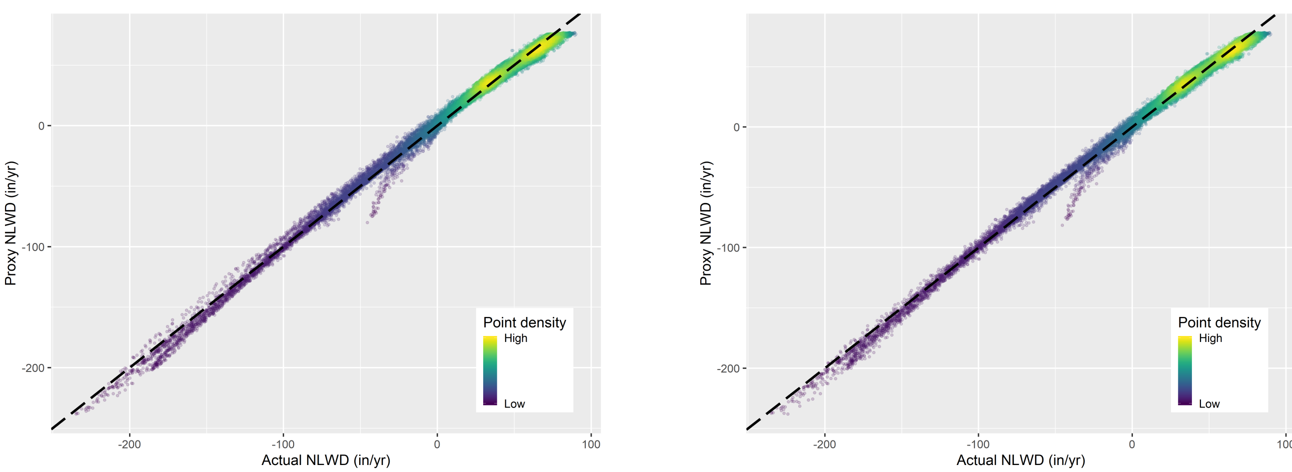
where T_j is average annual temperature for grid cell j, R_j is average annual rainfall, A_j is the ahupuaʻa fixed effect, and v_j is the error term. The fitted NLWD values of this model will be used as the NLWD proxy. Note here that we use the full climate dataset for all of Oʻahu, rather than only the grid cells containing households. This provides us a slightly larger range of temperature, rainfall, and NLWD. Although the explanatory variables T and R are highly correlated ($r = -0.77$) and $NLWD$ is itself constructed using R, we are not overly concerned about multicollinearity or endogeneity in this stage since we are simply trying to construct a proxy for NLWD that will allow us to predict changes in water use under climate change scenarios.

Table (2.3) shows the results for equation (2.2). Note that R^2 is over 0.99 because first, NLWD is itself created using rainfall; and second, reference ET, also used to create NLWD, is very highly correlated with temperature. Adding ahupuaʻa fixed effects in column (4) does little to increase the explanatory power of the specification. The scatterplots in figure (2.7) show the NLWD proxy (calibrated with and without ahupuaʻa

Table 2.3: Calibration of NLWD proxy using equation (2.2).

	Dependent variable:			
	NLWD (in/yr)			
	(1)	(2)	(3)	(4)
Mean temperature (°C)	33.113***		12.210***	12.371***
	(1.977)		(0.362)	(0.415)
Mean rainfall (in/yr)		−1.259***	−0.935***	−0.922***
		(0.037)	(0.021)	(0.023)
Ahupuaʻa FE	No	No	No	**Yes**
Observations	26,289	26,289	26,289	26,289
R^2	0.781	0.951	0.994	0.995
Adjusted R^2	0.781	0.951	0.994	0.995
Residual Std. Error	27.838 (df = 26287)	13.181 (df = 26287)	4.600 (df = 26286)	4.212 (df = 26199)

Notes: *p<0.1; **p<0.05; ***p<0.01. Errors clustered by watershed.



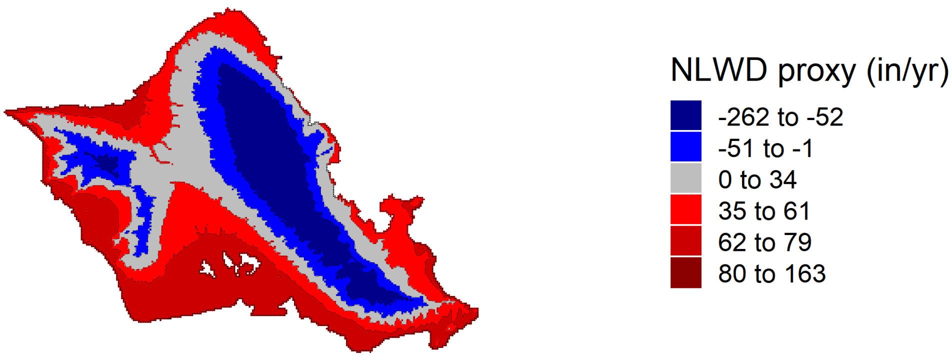
(a) NLWD proxy calibrated with temperature and rainfall.

(b) NLWD proxy calibrated with temperature, rainfall, and ahupuaʻa fixed effects.

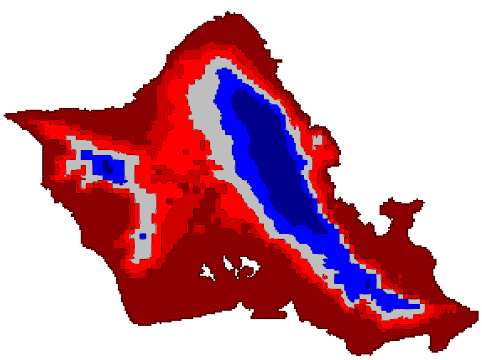
Figure 2.7: Scatterplot of calibrated NLWD proxy and actual NLWD. The left and right panels correspond to columns (3) and (4) in table (2.3), respectively. The "tail" of values with a relatively poor fit centered around Actual NLWD = −25 are grid cells on or near Mount Kaʻala. No homes are located in these cells. The dashed line is the 45° line.

fixed effects) against the original NLWD value. The data points where NLWD proxy is over-predicted (that is, NLWD proxy is more negative than actual NLWD) occur exclusively on or near the summit of Kaʻala, the highest point of Oʻahu. On the map in figure (2.3a), this is the high peak on the northern tip of the western Waiʻanae mountain range. No homes are located in this area.

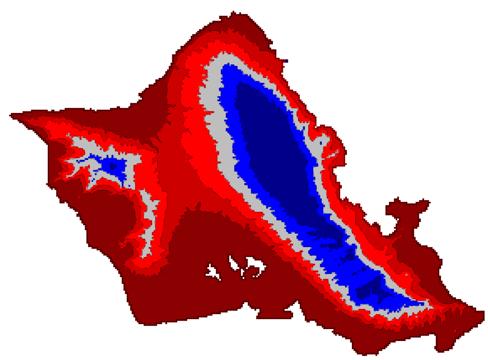
Using the results of model (4) in table (2.3) and the downscaled climate projection data, we calculate projected end-of-century NLWD values under RCP 4.5 and RCP 8.5. Maps of these changes are shown in figure (2.8). The darkest red contour indicates areas of Oʻahu that may experience NLWD that is larger than any current NLWD. Projections are similar between statistical and dynamical models, with statistical RCP 8.5 projecting the largest changes in NLWD.



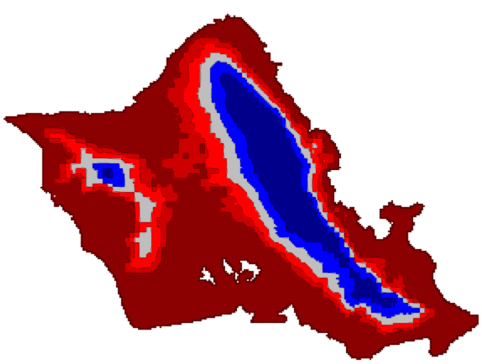
(a) Current



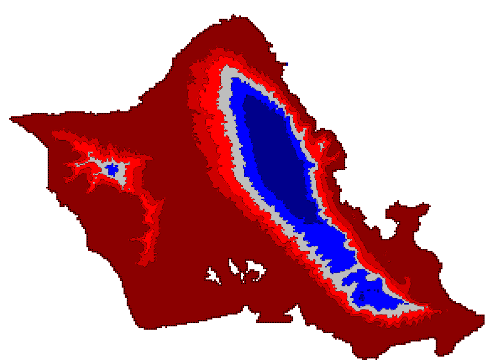
(b) Dynamical RCP 4.5



(c) Statistical RCP 4.5



(d) Dynamical RCP 8.5



(e) Statistical RCP 8.5

Figure 2.8: Projected net landscape water demand proxy for the period 2071 to 2099 under the statistical and dynamical models.

Table 2.4: Results for the model in equation (2.3). NLWD cal. with ahupua'a FE indicates the proxy was calibrated with ahupua'a fixed effects in addition to temperature and rainfall. Home characteristic controls include yard size, home size, and effective home age.

	Dependent variable:					
	Average daily gallons					
	(1)	(2)	(3)	(4)	(5)	(6)
NLWD proxy (in/yr)	1.5137***	1.5150***	1.9977***	1.9844***	1.7930***	1.8024***
	(0.2067)	(0.1941)	(0.2687)	(0.2544)	(0.0497)	(0.0486)
NLWD cal. w/ ahupua'a FE	No	**Yes**	No	**Yes**	No	**Yes**
Home characteristics	No	No	**Yes**	**Yes**	**Yes**	**Yes**
Ahupua'a FE	No	No	No	No	**Yes**	**Yes**
Observations	98,162	98,162	98,162	98,162	98,162	98,162
R^2	0.0260	0.0268	0.0950	0.0957	0.1174	0.1174
Adjusted R^2	0.0259	0.0268	0.0950	0.0956	0.1168	0.1168
Note:						*p<0.1; **p<0.05; ***p<0.01
						Errors clustered by watershed

2.5 Results

2.5.1 Water use and current climate

We modify the main specification to account for the fact we are now using a proxy for NLWD instead of NLWD itself. If we denote the NLWD proxy as $\widehat{NLWD}$, equation (2.1) becomes

$$w_i = \gamma_0 + \gamma_1 \widehat{NLWD}_i + X_i \Gamma + u_i. \tag{2.3}$$

Table (2.4) summarizes the results of this model. Columns (2), (4), and (6) use the same specifications as columns (1), (3), and (5), respectively, except the proxy is calibrated using ahupua'a fixed effects in addition to temperature and rainfall. Home characteristics, included in models (3) through (6), include home size, yard size, and effective home age. Other characteristics such as number of bedrooms and bathrooms are excluded because they are highly correlated with home square footage. When ahupua'a fixed effects are included in the models, as in specifications (5) and (6), the standard error of the coefficient drops significantly, and the size of the coefficient decreases relative to specifications (3) and (4). However, the effect size is still larger than those in specifications (1) and (2), where no controls for characteristics or location are used.

2.5.2 Water use and future climate

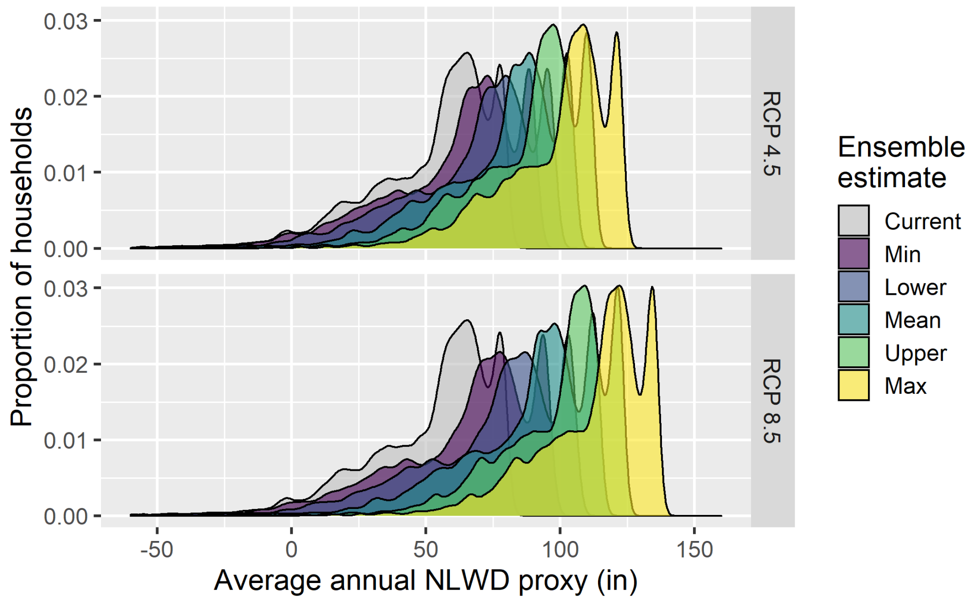
Table (2.5) shows the results obtained from combining our projections for future NLWD proxy values and its relationship with household water use. Specifically, we apply the coefficient from table (2.4) column (6), 1.8024, to estimate water use for each household using the projected values of the NLWD proxy. The values in the table provide the aggregate island-wide projected increase in SFD water use for the period 2071 – 2099, with the 2011 – 2019 billing data being the baseline. The changes in NLWD used for these calculations are based off the indicated climate scenarios and their associated uncertainties, as summarized in table (B.6)

Table 2.5: Percent change in island-wide water use, corresponding to the uncertainty summarized in table (B.6). Percent change indicates percent change in water use for single family homes from historical 2011 – 2019 averages.

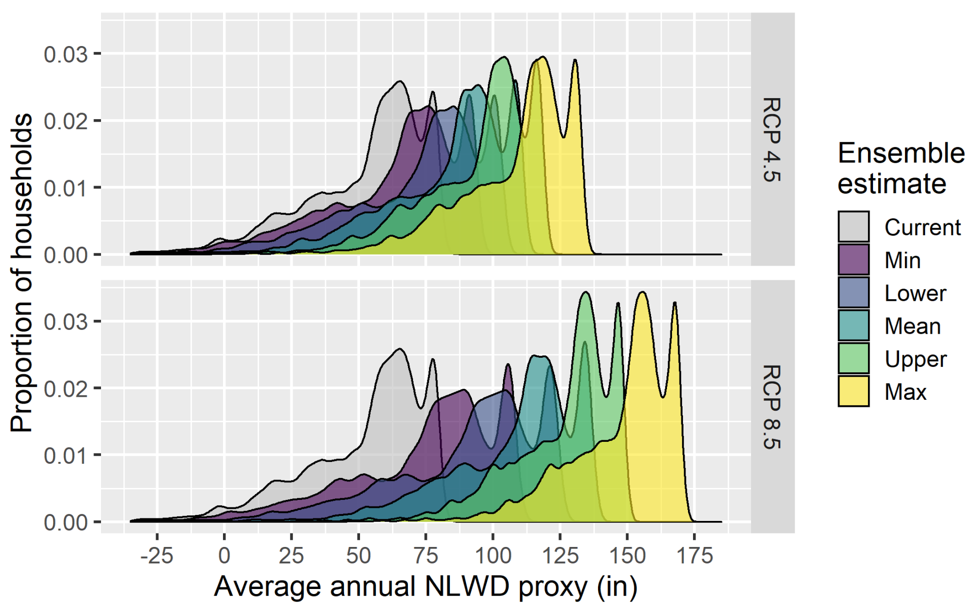
Model	Scenario	Period	Percent increase aggregate SFD water use				
			Min	Lower	Mean	Upper	Max
Statistical	RCP 4.5	2040 – 2070	4.9	9.5	16.7	24.0	31.3
	RCP 4.5	2071 – 2099	6.6	12.8	20.2	27.6	37.1
	RCP 8.5	2040 – 2070	6.7	13.0	24.4	35.7	44.3
	RCP 8.5	2071 – 2099	14.1	24.4	36.7	48.9	62.9
Dynamical	RCP 4.5	2071 – 2099			20.4		
	RCP 8.5	2071 – 2099			29.9		

of the appendix. It is important to note that there is significant uncertainty about future climate and associated water use not only between scenarios (i.e. between RCP 4.5 and RCP 8.5), but also *within* a given scenario. Indeed, the uncertainty of the estimates within a scenario may be just as large as, if not larger than, between scenarios. The statistically-downscaled rainfall data from Timm, Thomas W Giambelluca, and Diaz (2015) contained a variance value for each grid cell estimate, and the downscaled temperature data from Timm (2017) contained the minimum, lower (-2 standard deviations), upper ($+2$ standard deviations) and maximum value for each grid cell estimate, in addition to the means. Since the rainfall data do not contain the minimum and maximum values projected by the ensemble, the minimum and maximum values of the NLWD proxy and change in water use are estimated using the lower and upper values of rainfall and the min and max values of temperature. The dynamical data did not contain errors for their estimates, so only the means are reported. Distributions of the mean NLWD proxy and mean water use for the scenarios are shown in figures (2.9) and (2.10), respectively.

Mean estimates for future water use indicate about a 20% increase under RCP 4.5 for both the statistical and dynamical models. RCP 8.5 under the dynamical model estimates an increase of about 30%, but the statistical model implies an increase of about 37%. However, these means hide a wide range of potential outcomes if we investigate the errors within the statistical downscaled ensemble. The range between the min and max estimates for RCP 4.5 is about 30% and about 50% for RCP 8.5. These ranges are greater than the difference of the mean estimates between RCP 4.5 and RCP 8.5, which is only about 17%. This great degree of uncertainty, deriving from different assumptions and techniques in the underlying GCMs, is important to acknowledge and will require utilities and policymakers to prepare for a wide array of contingencies.

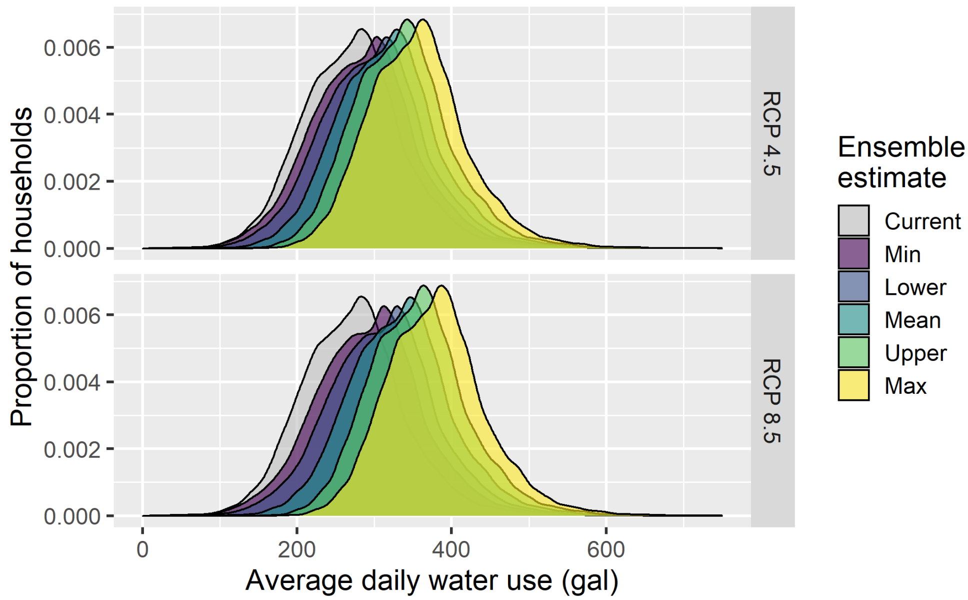


(a) NLWD proxy, average 2040 – 2070

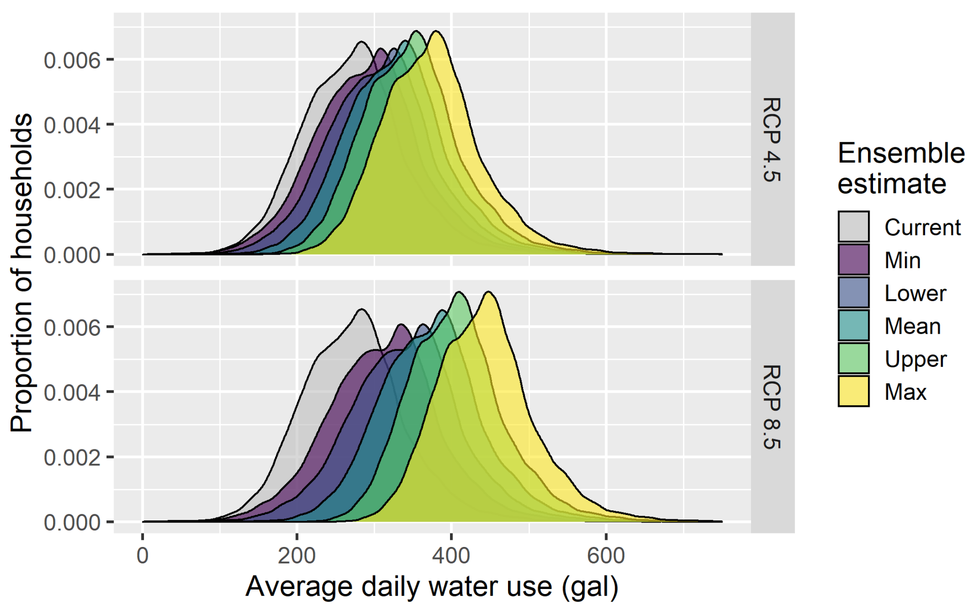


(b) NLWD proxy, average 2071 – 2099

Figure 2.9: Projected average household exposure to net landscape water demand proxy under the statistical downscaled model for periods 2040 – 2070 and 2071 – 2099. Note the large degree of uncertainty between the GCMs within a given RCP ensembles.



(a) Household water use, average 2040 – 2070



(b) Household water use, average 2071 – 2099

Figure 2.10: Projected average household water use under the statistical downscaled model for periods 2040 – 2070 and 2071 – 2099. Note the large degree of uncertainty between the GCMs within a given RCP ensembles.

2.6 Discussion

While many studies have considered the influence of weather and climate on residential water use, little attention has been paid to how this link may factor into water use under a changing climate. Climate variables are typically included as controls rather than as variables of interest. Most of the focus to date has been, and continues to be, how climate change might affect the future availability of water. While topics like the effect climate change will have on watersheds and aquifers are important, it is only half the story. This is particularly true for regions such as the American southwest and Hawai‘i, where water supply and demand are precariously balanced. Fortunately interest in topics pertaining to the effects on demand is becoming more prevalent, including trans-disciplinary research that investigates the relationships between policy, science, and practice (Elshall et al. 2020). Polebitski, Palmer, and Waddell (2010) use a panel of household data in the Seattle-Tacoma region and find water use may increase by about 10% by 2090. This varies significantly from our findings of an overall increase of at least 20%. Reasons for these differences may lie in the fact that this study uses older climate projection data (CMIP3 versus our use of CMIP5), and their use of monthly panel data for identification compared to our cross-sectional analysis. Another study (Lott et al. 2014) suggests residential water use may increase by 5% to 41% for consumers in the Reno, Nevada metropolitan area, again using panel data. As previously discussed, our choice of a cross-sectional model comes from both a lack of quality weather data, and our belief that it is more difficult to draw conclusions about how consumers may respond to changes in long-term climate using short-term weather. Day-to-day or month-to-month weather anomalies may not affect consumers' behavior in the same way as climate. For example, homes accustomed to a cool, wet climate may only sparingly irrigate their lawns with manual sprinklers if they experience an anomalous dry, warm month, but homes exposed to a dry, warm climate may install automatic sprinkler systems. Using cross-sectional data allows us to identify on climate rather than weather, and predict how a changing climate might influence long-term consumer behavior. Hawaii's microclimates provide a compelling natural experiment in which we can compare markedly different climates while holding other factors constant. Our study has also helped to highlight the uncertainty between RCP scenarios and, especially, uncertainty *within* scenarios. In many cases, the error within a given scenario is larger than the difference between the means of two different scenarios. Policymakers and utilities will thus have to prepare for a wide range of possibilities.

A major aspect to long-term behavior that this study only partially addresses is *adaptation* to climate. The cross-sectional differences can account for many kinds of adaptation, similar to arguments made by Mendelsohn, Nordhaus, and D. Shaw (1994) and Schlenker, Hanemann, and Fisher (2006), although we believe we have developed a more convincing argument of a causal link that is not confounded by omitted variables. If, however, aggregate water use were to increase as much as we project, and further water availability were to decline, the island and State would presumably take actions to promote more sustainable use and begin considering alternative sources of water like desalination. Fortunately, a variety of strategies may be implemented to offset the effects of climate change on water use. Ozan and Alsharif (2013) identified four main types of policies with the aim of reducing residential water use: rationing, usage restrictions, pricing, and technology. Implementation of these price- and non-price-based policies have been met with varying degrees of success throughout the nation. For example, in their own article, Ozan and Alsharif study the effects of fining homeowners in Tampa, Florida for irrigating during restriction periods caused by droughts. Their results suggest that not only were the programs not effective, but all communities in the study *increased* water use after the introduction of the policies. They suggest this may be because many of the homes in the study must comply with HOA rules which require lawns to be maintained and do not take irrigation restrictions into consideration. However, there is a large literature suggesting that, properly implemented, many other conservation initiatives have been effective at reducing residential water use (Michelsen, McGuckin, and Stumpf 1999; Wang et al. 1999; Renwick and Green 2000; Kenney et al. 2008; Lee, Tansel, and Balbin 2011; Giacomoni and Berglund 2015).

For price controls in particular, care must be taken by policymakers in constructing the regulations in order for them to have the intended effects. Adjusting prices to control water use not only brings forward concerns about affordability, equity, and "fairness" (Salman, Al-Karablieh, and Haddadin 2008; Jorgensen, Graymore, and O'Toole 2009; Pinto and Marques 2015), but how salient the pricing system is to consumers and how they respond to prices must be properly understood. Many utilities use a block pricing structure, but it is unclear whether consumers respond to the marginal or average price. While traditional economic theory would expect rational consumers to respond to marginal price, and there is evidence to suggest this is the case for some utilities (Howe and Linaweaver Jr 1967; Nataraj and Hanemann 2011), many other studies suggest consumers instead respond to the average price of utilities (Shin 1985; Worthington, Higgs, and Hoffmann 2009; Ito 2014; Wichman 2014). Residential price elasticity of water demand also tends to be highly inelastic (S. M. Olmstead, Hanemann, and R. N. Stavins 2007; S. M. Olmstead and R. N. Stavins 2009; Mansur and S. M. Olmstead 2012; Lott et al. 2014; Klaiber et al. 2014; Ghavidelfar, Shamseldin, and Melville 2016), suggesting that a large increase in price would be necessary to produce even a modest reduction in water consumption. If the way consumers respond to prices is poorly understood, adjusting block cutoffs or changing prices could have unintended consequences on consumer welfare.

Consumer attitude toward conservation also plays a significant role in the effective reduction in residential water use (Fielding et al. 2012). In fact, a "conservation culture" may confound the results of some studies, since those who voluntarily participate in conservation initiatives may already do so for environmental rather than economic reasons (Cameron and Wright 1990). Education programs can thus play an important role in influencing consumer behavior (Syme et al. 2004; Fielding et al. 2012). These programs can bring to light issues of water conservation that were otherwise unknown to consumers. Water use behaviors, and residential use of utilities in general, can also be influenced by social norms and households' beliefs about how much their neighbors consume (Jorgensen, Graymore, and O'Toole 2009; Allcott 2011; Dolan and Metcalfe 2015; Otaki, Ueda, and Sakura 2017). Encouraging the use of xeriscaping (Huang 2008), water reclamation for irrigating lawns (Campbell and C. A. Scott 2011), and the use of rain barrels (Shuster et al. 2013) are still more examples of effective methods of water conservation. Taken together, these factors suggest a well-informed, multi-faceted approach could be used to efficiently implement water conservation measures (Ebbs et al. 2018). A combination of informed pricing schedules, education programs, technology, fixture retrofitting programs, and command-and-control measures like irrigation restrictions may all be part of a comprehensive water management solution.

Finally, advances in technology, particularly the falling costs of renewable energy and energy storage, may help offset the impact water conservation strategies have on consumer surplus. If we assume for a moment that demand and extraction costs are held constant, basic resource economics theory tells us that, often, a steady decrease in head level until we reach maximum sustainable yield is most efficient. That is, barring other ecological and cultural concerns, a decrease in aquifer head level is not necessarily problematic in itself. Indeed, maintaining a high head level may reduce potential extraction due to discharge into the ocean

(J. A. Miller et al. 1997). Once the head level has been reduced and the backstop is reached, any additional demand will have to be met with desalination or other methods like recycling. However, this problem is highly dynamic and the welfare-maximizing combination of extraction, conservation, and transition to alternative sources of fresh water is complex and time-dependent. If demand for water on Oʻahu continues to increase over time due to increasing population and climate change, and extraction costs continue to rise as well, the welfare-maximizing path to this point becomes less clear. J. A. Roumasset and C. A. Wada (2010) outline the various extraction pathways that are both sustainable and welfare-maximizing. Studies such as ours will be important considerations when policymakers implement these types of extraction pathway models, where it is important to understand how water use may change over time due to a changing climate. Implementation of desalination and its effect on the costs for consumers over time due to changing energy costs must also be considered in the welfare analysis (J. Roumasset and C. A. Wada 2014). Conservation strategies will play a role during this transition and must be enacted carefully for the reasons described above, including how they are timed with other factors like climate change, changes to demand, and the source of the water (J. Roumasset and C. A. Wada 2015). Therefore, our study provides only one small component to a long-run solution that must carefully balance many aspects of watershed management while remaining efficient and maximizing welfare now, in the short term, and in the steady state.

Chapter 3

Tourism and water scarcity: The impact of hotels and vacation rentals on water resources

3.1 Introduction

Apart from the current COVID-19 pandemic, global tourism has experienced a strong, sustained growth in recent years, and this growth is expected to continue into the future (UNWTO 2020). While increased tourism generates many economic benefits, particularly for developing countries that rely heavily on tourism (Beyer et al. 2017), it also has the potential to strain the nations' resources, including its fresh water resources. Gössling et al. (2012) find that tourism increases global water use, but overall water consumption from activities related to tourism comprise far less than 1% of worldwide water use, and this will continue to be the case even after considering the projected growth in global tourism. They emphasize, however, that the concentration of tourist activity in particular locations and times may still cause regional water sustainability issues. Water resources may already be strained in regions that are popular tourist destinations, such as dry, warm climates and islands. A study performed in Zanzibar, Tanzania finds this to be the case, where signs of over-use like saltwater intrusion into the island's aquifers, deteriorating water quality, and the lowering of the groundwater table are becoming more apparent (Gössling 2001). The Indonesian island of Bali is facing similar water sustainability concerns (Sudiajeng et al. 2017).

In many cases, taken by itself, simply observing a decline in aquifer head levels should not be cause for concern. Although a decline in head level indicates withdrawal exceeds the current sustainable yield, the *maximum* sustainable yield[1] will often occur when the head level is reduced to a point that water quality issues like saltwater intrusion become a concern. Worth noting is that decreasing head level to a minimal level that meets water quality standards is often optimal, as discharge of fresh water from the aquifer to the ocean is minimized (J. A. Miller et al. 1997).[2] The dynamic problem of reaching the head level that coincides with maximum sustainable yield while also maximizing consumer welfare is complex (J. A. Roumasset and

[1]Maximum sustainable yield as defined in (J. A. Roumasset and C. A. Wada 2010).

[2]Reducing head levels to minimize discharge may have other adverse ecological effects not considered here, such as decreased freshwater springs and compositional changes to near-shore brackish water ecosystems.

C. A. Wada 2010). This complexity may be increased when we introduce tourism, since tourists often pay a flat rate for their accommodations rather than directly pay for utilities like energy and water. In any case, policies aimed at promoting the conservation of fresh water resources must also include careful consideration for the direct and indirect effects such policies may have on consumer welfare.

Issues similar to those faced on Zanzibar and Bali are beginning to surface on the study site of this paper, the Hawaiian island of O‘ahu, yet another location where tourism plays a significant economic role. Unlike the locations considered in other studies of small, tourism-heavy islands, O‘ahu is highly developed, with institutions and an economy that may vary substantially from vacation destinations on islands with developing economies. One major difference that can be readily observed is the water consumption of tourists relative to residents between a developed island like O‘ahu and developing islands. On O‘ahu, as we will see, the water use of an average hotel room is on par with the water use of an average apartment or condominium unit. This is typical of industrialized countries, but in developing countries water use by tourism typically far outpaces water use by locals (Becken 2014; Charara et al. 2011). However, O‘ahu shares many relevant similarities with other small islands with a strong economic dependency on tourism: as with the other locations, the main current source of fresh water for O‘ahu is its aquifers that are replenished by rainfall. The island's topography and tradewind patterns provide fairly consistent rainfall to replenish large freshwater aquifers within the porous volcanic rock. However, uncertainty surrounding the future of tradewind patterns due to climate change is beginning to raise concerns about water resource sustainability. Already, there is evidence that available freshwater resources on O‘ahu have been diminishing over time (Bassiouni and Oki 2013). Additionally, some climate projections indicate an overall reduction in rainfall (Timm, Thomas W Giambelluca, and Diaz 2015) and increase in temperature (Timm 2017) in the future[3], and many previous and ongoing studies are exploring the implications for groundwater recharge (J. A. Roumasset and C. A. Wada 2010; Burnett and C. A. Wada 2014; A. El-Kadi 2014; J. Roumasset and C. A. Wada 2015; Bateni 2016; Leta, A. I. El-Kadi, and Dulai 2017; Tsang and Evensen 2017; C. A. Wada et al. 2017). The combination of great uncertainty surrounding the current and future status of the aquifer, combined with continued population growth, increasing tourism, and urban expansion into warmer, drier areas of the island introduces the potential for creating an unsustainable pressure on the island's aquifers.

Our paper focuses on water consumption in two main accommodations for tourists visiting the island: traditional hotels and resorts, and transient vacation rentals like Airbnb, VRBO, and Home Away. Hotels and resorts have long been fixtures on the island, but vacation rentals offered by individual homeowners have recently become extremely popular. An estimated 8000 to 10,000 short-term units are being offered online at any given time (UHERO 2019), making such units an important consideration. Using a panel of approximately 7 years of billing data and information gathered about hotels and Airbnbs, we analyze the relationship between water use and tourism on O‘ahu. To our knowledge, this is the first analysis that separately considers these two forms of visitor accommodations. We find a weak positive relationship between hotel occupancy and hotel water use, with a 1-percentage-point increase in hotel occupancy being associated with a 0.4 – 0.7% increase in hotel water use. In the case of transient vacation rentals like Airbnbs, we find no statistically or economically significant relationship between water use and the number of vacation rental reservations. Potential reasons for weak results, including data limitations, are considered. We conclude with a discussion of implications for the future of tourism growth and related water management strategies.

[3]It's worth mentioning that other studies suggest some areas of Hawai‘i may expereince an increase in rainfall. For example, see Zhang et al. (2016).

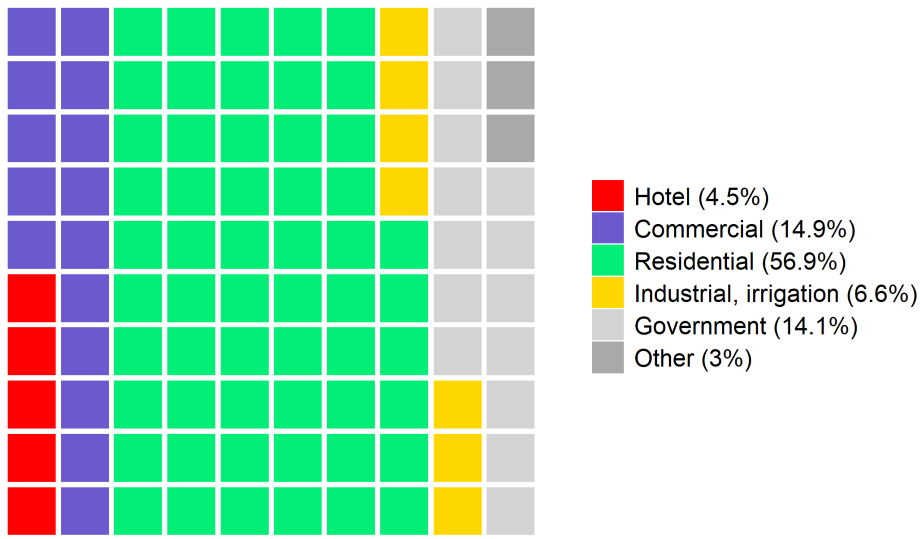


Figure 3.1: O'ahu water use by sector. One box approximately equals 1% of total water consumption over the 7 years of billing data.

3.2 Data

Billing data for each tax map key (TMK), a unique identifier assigned to each individual parcel of land, were obtained from the Honolulu Board of Water Supply (BWS) for the period from January 2013 to August 2019. The top and bottom 0.5% of outliers are removed for the analysis. The distribution of overall water use on O'ahu is shown in figure (3.1). The residential sector is the largest consumer of water at 56%, while hotels are one of the smallest at less than 5%. Although the billing periods are typically roughly four weeks in length, they are not aligned between TMKs or with the beginning and end of each month. To overcome this, we instead rely on the average daily consumption calculated from the total usage and number of days in the individual billing periods.

Using the TMK identifiers provided by the BWS billing data, we then scraped information about location and number of residential units for each building from the Honolulu Real Property Assessment Division database. High-rises and low-rises that do not have the number of units publicly available were removed from the data.[4] SFDs are counted as single units, low-rise buildings have a mean of 73 units, and high-rises have a mean of 188 units. The number of rooms for each hotel was matched manually by hotel name using data from the Hawaii Tourism Authority. Hotels have a mean of 370 rooms. With these numbers, we estimate hotels use about 145 gallons per room per day. This is compared to 181 gallons per unit per day for high-rise residential, 176 gallons per day for low-rise residential, and 293 gallons per day for SFDs. After cleaning water use outliers and TMKs with missing units information, the data contained a panel of 140,708 single family dwellings (SFD), 754 low-rise residential buildings, 159 high-rise residential buildings, and 66 hotels. Table (3.1) summarize the number of units by TMK type, along with average daily per-unit water use.

[4]These were typically parcels that were wholly owned by an individual or company so records were not available for the individual unit owners, which was important for our scraping process.

Table 3.1: Summary of number of units and per-unit water use by TMK type. Top and bottom 0.5% of outliers (by type) are omitted from the data.

TMK type	N	Number of units per TMK					Daily per-unit water use (gallons)				
		Median	Mean	SD	Min	Max	Median	Mean	SD	Min	Max
SFD	142,130	1	1	0	1	1	230	293	260	0.1	31,049
Low-rise	762	48	73	83	2	968	138	176	198	0.1	6434
High-rise	161	84	150	188	12	1404	137	181	221	0.1	2416
Hotel	68	218	370	450	14	2860	125	145	142	0.2	1503

Monthly island-wide tourism data is available from the Hawaii Tourism Authority. From this we obtained monthly visitors and aggregate hotel occupancy rates. Additionally, since there is evidence that water use for irrigation and other purposes is influenced by temperature and rainfall (Gato, Jayasuriya, and P. Roberts 2007; Kenney et al. 2008; Mieno and Braden 2011; Ozan and Alsharif 2013; Ouyang et al. 2014; Ghimire et al. 2015), a time series of weather data including average monthly temperature and cumulative monthly rainfall for the Honolulu airport was downloaded from NOAA are included as controls. Many of these previous studies focus on the residential sector, but we include the weather controls in our analysis of hotels as well, since hotel water use can conceivably respond to weather for similar reasons (irrigation, etc.). Figure (3.2) shows the aggregate time series of hotel water use, tourism count, hotel occupancy, monthly temperature, and monthly rainfall. We see there is generally one- or two-peak seasonality in all time series. Tourist count peaks twice per year, once in the summer and once in the winter, which is also reflected in hotel occupancy. However, note that hotel occupancy tends to remain much more constant than tourist count, with occupancy only varying by about 10 percentage points between peak season and the off-season. Average temperature peaks in the summer, while rainfall tends to peak more during the winter months.

One important observation that led us to also include an analysis of transient vacation rentals (e.g., Airbnb, VRBO, etc) is the lack of a winter peak in hotel water use despite an increase in tourism during these times. We instead see only one peak per year coinciding with summer. This may be expected, since total occupancy in hotels remains rather stable relative to the seasonality we see in overall tourist count. Although occupancy can be seen to fluctuate with tourism count, it tends to stay above 80%, rarely going above 88%. This leads to the hypothesis that the resulting "overflow" of tourists arriving on the island is then using other accommodations like Airbnb.

Data for 14,924 Airbnbs were scraped approximately monthly for the period from October 2018 to March 2020 by Inside Airbnb.[5] The data contain information about the Airbnb, including location, type of accommodation (i.e. apartment, room in house, etc.), price per night, minimum nights required for a reservation, and future reservation status. The future reservation status for a particular Airbnb on a particular night is given every time the data are scraped, so the status closest to the date in question is used as the best estimate for the true occupancy status.[6] A larger source of uncertainty comes from the inability to pinpoint the vast majority of Airbnbs to particular residential TMKs. Only about 1500 Airbnbs provided the exact location. For the rest, the coordinates in the data only provide an approximate location to preserve the confidentiality of the host until a booking is confirmed by the customer. The exact method Airbnb uses

[5] `http://insideairbnb.com/`

[6] For example, suppose datasets scraped on two separate dates, October 15, 2018 and November 15, 2018, give the status of a particular Airbnb on December 3, 2018. In this case we would use the December 3 reservation status from the November scrape since it is the most up-to-date information available.

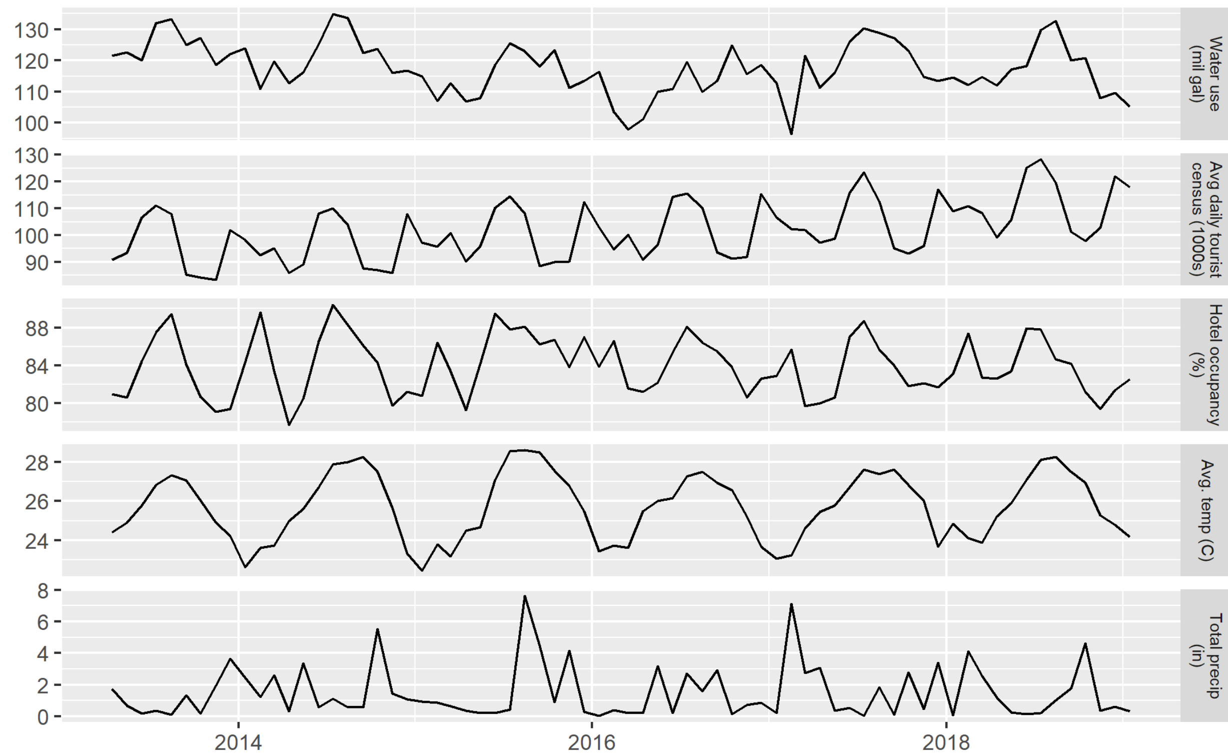


Figure 3.2: Aggregate monthly time series of monthly hotel water use, average daily tourism count, hotel occupancy, average temperature, and total monthly rainfall.

to display locations is not known but, using the listings on the Airbnb website, we find the coordinates in the data give the center of a circle with radius of approximately 500m. Thus, the error in the coordinates provided for a given Airbnb can be at most 500m. To overcome this locational uncertainty we aggregate the data to a grid, which is described in more detail in the next section.

The highest density of Airbnbs is in the Waikiki area, as shown in figure (3.3), but units exist in all areas of Oʻahu. The units in Waikiki remain occupied fairly steadily throughout the year. However, during peak seasons (summer months and mid-winter) the overflow of tourists spread into units located in other areas of the island. A time series of residential water use and Airbnb occupancy is shown in figure (3.4). Here, we see a summer peak in water use, while Airbnb occupancy experiences peaks in both the summer and winter. Note that only the final year of the Airbnb occupancy data is actual data: the time series until October 2018 is estimated using a model discussed in the next section. Appendix figures (C.1) and (C.2) show average monthly occupation, where the spatial aspect of the seasonal fluctuations can be more clearly seen.

3.3 Empirical strategy

3.3.1 Tourism count and hotel water use

We perform two separate analyses in studying the effect tourism has on water use on Oʻahu. In the first, we attempt to determine the relationship between tourism count and water use in hotels. In this portion of the analysis, we examine how water use in individual hotels is correlated with overall tourism levels

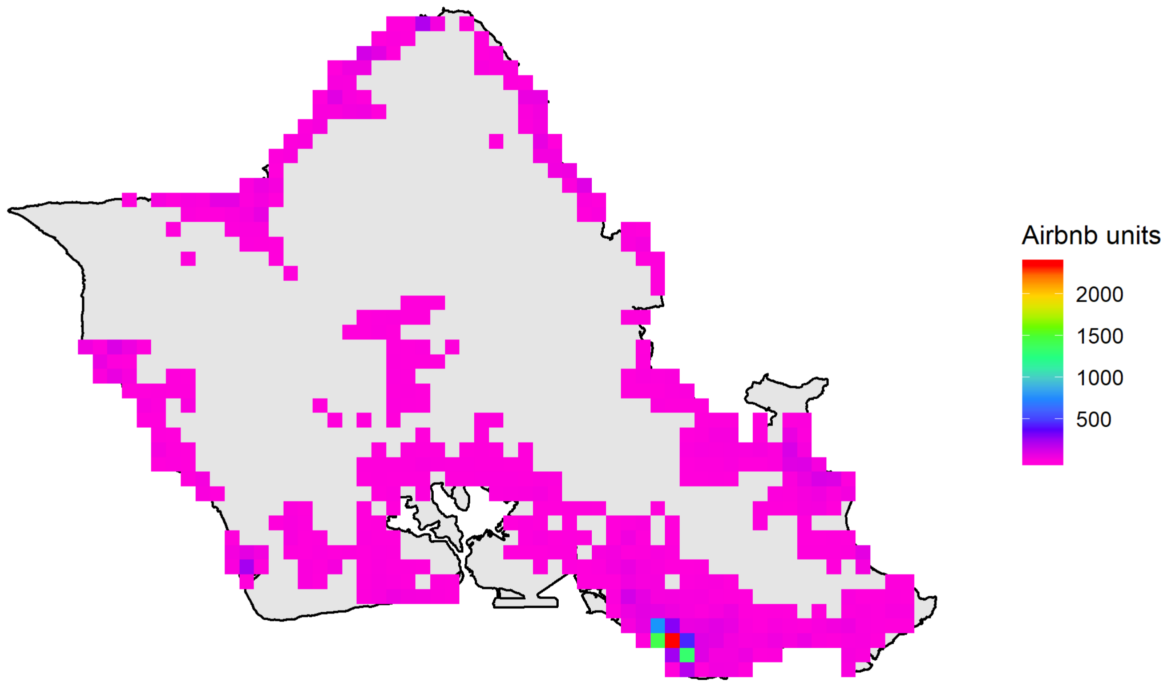


Figure 3.3: Airbnb density map. The majority of Airbnb units are in Waikiki, the center for tourism on the southern shore of the island.

and hotel occupancy rates. Ideally, we would match the billing data for the hotels with individual hotel occupancy to more precisely measure the relationship between a hotel's water use and its occupancy but, unfortunately, such fine-scale hotel occupancy data are not available. We thus rely on aggregate, island-wide hotel occupancy in the form of a monthly time series as a second best alternative. The main concern with this approach is that hotels are not necessarily perfectly competitive, so the assumption that the aggregate hotel occupancy may be applied individually to each hotel may be weak. We use the full panel data with individual TMKs in our analysis of hotel water use. The basic model takes the form

$$\log w_{it} = \alpha_0 + \alpha_1 V_t + \alpha_2 \log T_t + \alpha_3 \log R_t + H_i + \varepsilon_{it}, \tag{3.1}$$

where w is the water use of hotel i in month t, V is the total number of visitors to O'ahu in the given month, T is the average temperature in degrees Celsius, R is the total rainfall in inches, H is the hotel-specific fixed effect, and ε is the idiosyncratic error term. We use two measures of V in our analysis: the first is a log-transformed total monthly census of tourists who visited the island, and the other is the monthly percent of all hotel rooms occupied.

3.3.2 Airbnb occupancy and residential water use

In the second part of our analysis, we examine the relationship between Airbnb occupancy and residential water use. To match the water use of individual TMKs with the imprecise location of the Airbnbs, we

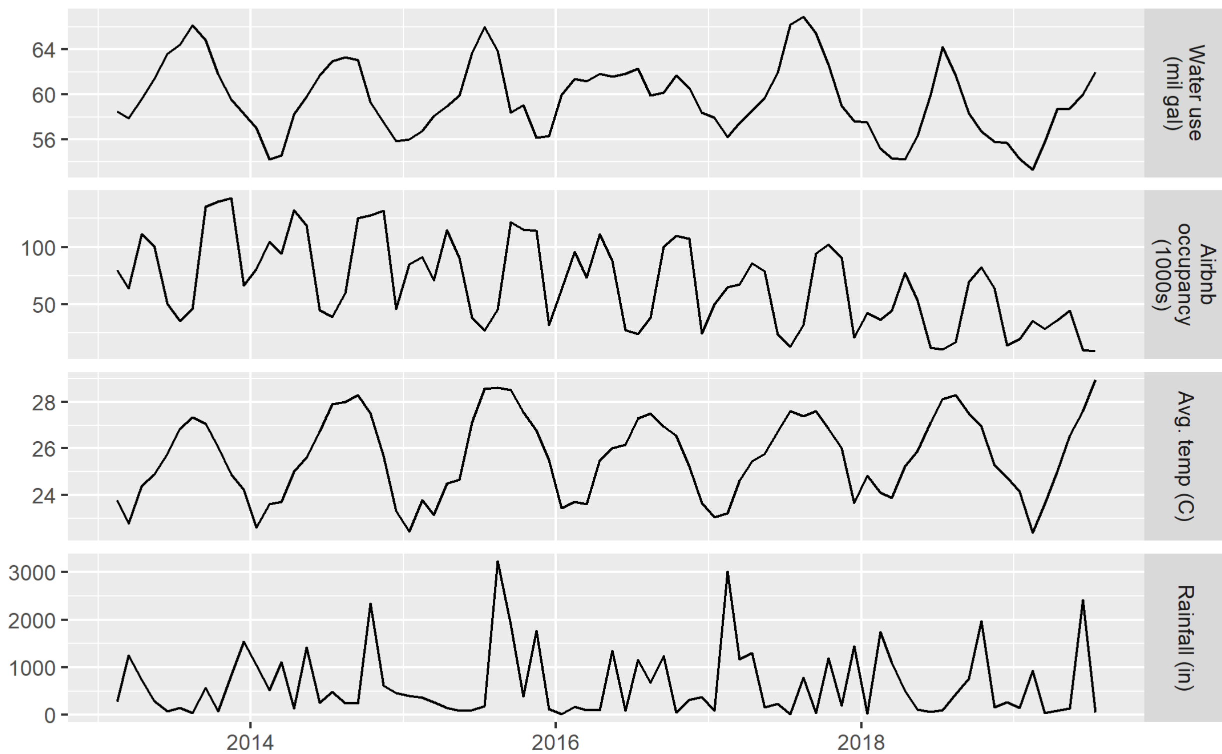


Figure 3.4: Aggregate monthly time series of residential water use, Airbnb occupancy, and weather variables. For Airbnb occupancy, only October 2018 to March 2020 plots actual occupancy. The remaining occupancy data are estimated using fitted values, as discussed in section (3.3).

aggregate both datasets to a custom grid laid across O‘ahu. The grid was laid across the extent of all residential units on the island with a resolution of 1 km by 1 km. This resolution was chosen as a compromise between ensuring the grid cells were large enough to minimize Airbnb units from being assigned to the incorrect grid cell, while also not making the resolution too coarse and limiting the number of observations. In appendix section (C.2), we perform a robustness check by increasing the size of the grid cell to 2 km by 2 km. No significant differences in the results are seen between the two choices of grid resolution. Figure (3.5) shows O‘ahu and its residential units overlaid with the grid. All data were then aggregated to the grid level, where we calculate total number of residential units, number of Airbnbs, Airbnb density relative to total residential units, total water use, and water use per residential unit for each grid cell.

Only about one year of Airbnb occupancy data were available, so we develop a model to estimate occupancy at the grid level for other periods where the occupancy data is missing but we have aggregate tourism counts and water use billing data. We estimate Airbnb occupancy data with

$$b_{it} = \beta_0 + \beta_1 V_t + G_i + \epsilon_{it}, \tag{3.2}$$

where b is the number of Airbnb occupancy nights in grid i and month t. An Airbnb occupancy night is defined as one Airbnb being occupied for one night in a given month. So, for example, if 10 Airbnbs in a grid cell are each occupied for 10 nights in a given month, $b = 10 \times 10 = 100$ occupancy nights for that grid cell. The other terms in the model include V, the aggregate tourist count from above; G, the grid cell fixed effect; and ϵ, the error term.

We then model water use within grid cells as a function of Airbnb occupancy with the equation

$$\log PUW_{it} = \gamma_0 + \gamma_1 \log b_{it} + \log T_t + \log R_t + G_i + \zeta_{it}, \tag{3.3}$$

where PUW is the per-unit water use in grid cell i and month t, b is the grid-level Airbnb occupancy, G is the grid cell fixed effect, and ζ is the error term. We present the results of this model in two forms: (1) using the one year of actual Airbnb occupancy for b and (2) using actual occupancy for b, and filling those that are missing with values predicted using the model in equation (3.2).

A separate model was developed to examine the relationship between TMK water use and Airbnb occupancy for the cases where an exact match between TMK and Airbnb could be made. For this model, we could simply regress TMK water use onto Airbnb occupancy. This method, however, would not control for weather and other unobserved factors. Instead of including various control variables directly, we match each Airbnb whose exact location is known to the nearest five neighbors without Airbnbs. For each Airbnb and a given month t, we then define the water use ratio of Airbnb i's water use to its neighbors' water use as

$$WR_{it} = \frac{w_{it}}{n_{it}},$$

where w_{it} is the water use of the home with the Airbnb, and n_{it} is the mean water use of the nearest five neighbors without Airbnbs.[7] This helps to control for weather, home characteristics, and unobserved

[7]Ideally, we would have only used neighbors without Airbnbs that were directly adjacent to the TMK with the Airbnb. However, due to errors in the shapefile provided to us in the data, matching by adjacency was not possible and so distance was used as a second-best.

Figure 3.5: Grid used to aggregate residential TMK data with Airbnb data. This was used since only the general vicinity of the Airbnb is available. The grid contains cells that are approximately 1 km by 1 km, and covers the extent of all residential units on O'ahu, including single family dwellings (SFDs), low-rise residential, high-rise residential, and mixed residential. Included also in the figure are the locations of hotels. While SFDs are spread across the island, high-density residential units are concentrated in the urban center and hotels are located almost exclusively in Waikiki on the south shore of the island. Notable exceptions are the Turtle Bay Resort on the northernmost point of the island, and Ko Olina and Aulani resorts on the western side of the island.

variables. The model is then

$$WR_{it} = \delta_0 + \delta_1 O_{it} + B_i + u_{it}, \tag{3.4}$$

where O_{it} is the Airbnb occupancy of the TMK in month t, B_i is the Airbnb fixed effect, and u_{it} is the error term. The fixed effect requires some explanation. Note that it is still not known whether the Airbnb comprises the entire TMK. A given TMK may thus house permanent residents that rent out a room or additional unit on their property or, alternatively, the entire TMK may be dedicated to the Airbnb. If there are no permanent residents water use will be substantially lower than the surrounding neighbors when the Airbnb is not occupied, and if there are permanent residents the water use may exceed the neighbors when the Airbnb is occupied. Since this distinction cannot be made in our data, the fixed effect will allow us to consider only the fluctuation of water use relative to a TMK-level average, rather than the levels themselves.

3.4 Results

3.4.1 Tourism count and hotel water use

Table (3.2) shows the results of regressing monthly hotel water use on monthly aggregate tourism measures from equation (3.1). In columns (1) to (3), log water use is regressed on aggregate tourist count. In all models, there is no significant correlation between water use in hotels and the number of tourists on the island. However, water use has a strong positive correlation with temperature. The lack of a relationship between hotel water use and tourism levels, and the positive relationship between water use and temperature, are seen in the aggregate time series data above in figure (3.2). Water use is seen to fluctuate seasonally with temperature, but there is no increase in water use during the annual peak in winter tourism. Reassuringly, there is some evidence that water use is associated with hotel occupancy, as seen in columns (4) to (6). In these models, a 1 percentage point increase in hotel occupancy is associated with a $0.40 - 0.70\%$ increase in hotel water use. This relationship is likely weak because, again, we have only aggregate hotel occupancy rather than the occupancy of individual hotels. In all models, the TMK fixed effects are responsible for almost all the models' explanatory power, with R^2 and residual standard error changing very minimally when the tourism and climate measures are included.

3.4.2 Airbnb occupancy and residential water use

In table (3.3) we present the results of the model in equation (3.3). Columns (1) to (3) regress average daily water use at the grid cell level onto actual Airbnb occupancy, and columns (4) to (6) regress average daily water use onto all observations, where missing Airbnb occupancy is filled with fitted values predicted by equation (3.2).[8] Even though all coefficients of interest are significant at the 1% level, their economic significance is minimal. The coefficients suggest that a 1% increase in Airbnb occupancy within a grid cell is associated with a 0.03% to 0.06% *decrease* in per-residence water use within the grid cell. We discuss potential reasons Airbnb occupancy may not have an effect on residential water use when measured at the grid cell level in the next section. The grid cell fixed effects introduced in columns (3) and (6) explain almost all variation in the data. When we regress water use on fixed effects only, excluding Airbnb occupancy and

[8]The results of the regression from equation (3.2) are provided in table (C.1) of the appendix.

Table 3.2: Regression of monthly hotel water use on monthly aggregate tourism measures. Columns 1-3 regress water use on aggregate tourist count, and columns 4-6 regress water use on aggregate hotel occupancy. Errors clustered by month and TMK.

	Dependent variable:					
	Log total water use (gal)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log tourism count (1000s)	0.006	0.062	0.036			
	(0.039)	(0.169)	(0.169)			
Hotel occupancy (%)				0.007***	0.007*	0.004
				(0.003)	(0.004)	(0.005)
Log temp (C)			0.459***			0.397**
			(0.150)			(0.186)
Log rain (in.)			0.001			0.001
			(0.005)			(0.005)
Constant	13.265***			12.686***		
	(0.009)			(0.00004)		
TMK FE	No	**Yes**	**Yes**	No	**Yes**	**Yes**
Observations	5,175	5,175	5,175	5,175	5,175	5,175
R^2	0.00000	0.873	0.873	0.0002	0.873	0.873
Adjusted R^2	−0.0002	0.871	0.871	−0.00001	0.871	0.871
Residual Std. Error	1.645	0.591	0.590	1.644	0.590	0.590
Deg. freedom	5173	5100	5098	5173	5100	5098
Note:				*p<0.1; **p<0.05; ***p<0.01		
				Errors clustered by billing period and TMK		

Table 3.3: Total water use per unit regressed on Airbnb occupancy at the grid cell level. Columns 1-3 use only observations for which we have Airbnb occupancy data. Columns 4-6 use all data, where missing Airbnb occupancy is filled using predicted values generated by the model in equation (3.2). Errors clustered by grid cell.

	Dependent variable:					
	Log daily gallons per unit					
	(1)	(2)	(3)	(4)	(5)	(6)
Log actual	-0.039^{***}	-0.053^{***}	0.021^{**}			
Airbnb occupancy days	(0.011)	(0.011)	(0.009)			
Log predicted				-0.030^{***}	-0.029^{***}	0.008^{***}
Airbnb occupancy days				(0.003)	(0.003)	(0.002)
Log avg temp (C)		-0.346^{*}	-0.419^{***}		0.803^{***}	0.841^{***}
		(0.204)	(0.130)		(0.047)	(0.022)
Log total rainfall (in)		0.051^{***}	0.022^{***}		-0.020^{***}	-0.024^{***}
		(0.010)	(0.007)		(0.002)	(0.001)
Constant	5.582^{***}	6.770^{***}		5.724^{***}	3.121^{***}	
	(0.041)	(0.662)		(0.014)	(0.152)	
Grid FE	No	No	**Yes**	No	No	**Yes**
Observations	1,675	1,675	1,675	26,528	26,528	26,528
R^2	0.008	0.022	0.997	0.004	0.017	0.998
Adjusted R^2	0.007	0.020	0.996	0.004	0.017	0.998
Residual Std. Error	0.604	0.600	0.353	0.516	0.512	0.244
F Statistic	12.754^{***}	12.525^{***}	973.242^{***}	109.729^{***}	155.222^{***}	$32{,}820.490^{***}$
Deg. freedom	1673	1671	1261	26526	26524	26104
Note:						*p<0.1; **p<0.05; ***p<0.01

controls for weather, R^2 remains greater than 0.99. Also note that the coefficients on the weather variables have unexpected signs in columns (2) and (3) where we use the limited dataset with no missing Airbnb occupancy, but using the full dataset yields expected signs. In appendix section (C.3), we perform the same regression analysis on the levels data, as grid cells with relatively few residential units will have low water use and may become outliers when log-transformed. This model yields results that are similarly economically insignificant.

Finally, we present the results of equation (3.4) in table (3.4). The coefficient on the water use ratio is not statistically different from 0, but the size of the error is very large so it is difficult to rule out potentially-significant effects. Again it is likely that we do not have data for enough homes over a sufficiently long period of time to be able to extract an effect from the noise.

Table 3.4: Water use ratio regressed onto Airbnb occupancy for those houses where an exact match between TMK and Airbnb could be made. The water use ratio is the ratio between the water use of the home with the Airbnb and its nearest 5 neighbors without Airbnbs. Errors clustered by TMK. TMK fixed effects are included but not reported.

	Dependent variable:
	Water use ratio
Airbnb occupancy days	-0.001
	(0.009)
Observations	2,513
R^2	0.182
Adjusted R^2	0.097
Residual Std. Error	1.951 (df = 2276)
Note:	*p<0.1; **p<0.05; ***p<0.01

3.5 Discussion

Resource strain in popular tourist destinations is becoming an increasingly popular topic among both policymakers and academics. While the growth of tourism sectors may provide many economic benefits, particularly for historically undeveloped regions, it also poses unique challenges. Regions that were once capable of supporting their own populations are now beginning to show concern over resource sustainability as their tourism sectors experience growth. Although highly developed, our study site, Oʻahu, is a small, isolated island. Its limited land and resources, and heavy reliance on tourism, help to showcase these water management concerns. Our focus was on water use, but this concept could be extended to energy, land use, and other sustainability issues. On Oʻahu, freshwater is sourced from aquifers that are replenished by rainfall driven by tradewind patterns. However, due to climate change, there is uncertainty surrounding the future of the tradewinds and the corresponding precipitation patterns. This, combined with a growing population, tourism, and the potential for a drier, warmer climate, exacerbates concerns about the sustainability of the island's water resources.

There are two broad tourism accommodation sectors we considered: hotels, and transient vacation rentals (specifically in this study, Airbnb units located in residential buildings). Our strongest results suggest a 1% increase in hotel occupancy is associated with about a $0.4 - 0.7\%$ increase in hotel water use. These results were weak, however, likely because we only had data for aggregate hotel occupancy, rather than the occupancy of individual hotels. Also worth noting is that hotels consume relatively little water when compared to the residential sector. Even if increased tourism results in higher hotel occupancy, their current consumption is only about 4.5% of the island-wide total, or about 4.7 million gallons per day (MGD). The combined residential sector, which includes SFDs, high-rises, low-rises, and mixed residential, comprise nearly 57% of all water consumption at about 62 MGD.

The numerous transient vacation rentals on the island are spread among the low- and high-rise residential units, and the single family homes. Our analysis indicated no strong relationship between Airbnb occupancy and residential water use, which may be due to several reasons. First, since the exact location of the Airbnbs was not provided, we were unable to match the units with particular TMK billing data. This led to our use of an aggregation technique that may not allow us to precisely estimate the effects. Since the data were aggregated to a grid, and we rely heavily on variation in Airbnb occupancy between the on- and off-seasons, it may be that residents of the grid cell leaving for vacation (and thus using less water) may offset the increase in water use brought by increased tourist levels in the grid cell. Further, many Airbnb units are part of TMKs that also include permanent residents. For instance, an Airbnb unit may exist in an apartment building where the majority of units are not Airbnbs or, in the case of SFDs, an add-on unit or separate structure may be used for the Airbnb while the main home on the lot is occupied by the homeowner. In these cases, the marginal water use may be quite small, especially in scenarios where the guest renting the Airbnb does not stay long enough to do laundry and spends most of their time on other activities around the island. Whatever water they use while in the Airbnb (shower, toilet, etc.) may be relatively small compared to the consistent water use of permanent residents (irrigation, kitchen, laundry, bathroom, etc.). On Oʻahu, the relevance of Airbnbs to water use may diminish as a new ordinance passed by the local government takes effect that severely limits short-term rentals.[9] As many as 4000 – 6000 Airbnb units on the island are now considered illegal, and only a limited number of permits that come with additional restrictions will be provided for those who wish to retain their listing on the website. This may provide the opportunity for more work to be done on this topic as more data becomes available: the drastic change in the number of Airbnbs may allow for a more apparent effect on water use to be observed. Based on results from Gabarda-Mallorquí, Garcia, and Ribas (2017), who suggest hotel water use benefits from economies of scale, we may expect a decrease in per-capita water use among tourists as more stay in hotels rather than low-density individual transient vacation rentals.

An important factor we did not explore in this study is the use of water by tourists outside of their accommodations. Certainly, restaurants and other commercial properties use more water with increased patronage, which is likely tied closely to tourism numbers. This is especially true in locations like Hawaiʻi where visitors make up a significant portion of the overall population. We discuss a potential strategy for studying this in more detail below.

Looking more broadly at the future of water resource management in the context of tourism, particularly on small islands with limited resources, technological advances may help to overcome many of the difficulties surrounding water resource management. Although the islands' aquifers are limited, and climate change brings the potential for aquifer recharge to reduce the availability of freshwater even further, desalination is becoming an increasingly viable alternative. With the steadily decreasing costs of photovoltaics (Branker, Pathak, and Pearce 2011; Trancik 2015) and energy storage (Ralon et al. 2017; Gardner et al. 2016), obtaining freshwater from surrounding seas is becoming more affordable. The more-widespread use of desalination plants may then be able to satisfy the excess demand for freshwater that is not available from the aquifers.

Another strategy available to control the use of water by tourism sectors is increasing the water use efficiency of hotels and resorts. Hotels may invest in water-efficient fixtures; indeed, many have done this as part of more comprehensive sustainability plans that not only help hotels reduce their own costs, but have the extra benefit of attracting customer loyalty from those who value such initiatives (Ruiz-Rosa, García-Rodríguez, and Santamarta-Cerezal 2017). Another study (Tiefenbeck et al. 2019) shows that hotel guests respond to real-time feedback on their energy use, even though they have no financial incentive to conserve power. Further research may be able to determine whether such an effect can be found with guests' water

[9] `http://www4.honolulu.gov/docushare/dsweb/Get/Document-238476/DOC%20(37).pdf`

use. Other market-based strategies include the introduction of tradeable permits to help increase water use allocative efficiency while improving the management of water resources (Cashman and Moore 2012).

A recent event that may provide an excellent natural experiment is the near-complete shutdown of tourism on Oʻahu due to COVID-19. All hotels were closed in late March 2020 and will remain closed at least through May 2020, and all arrivals to the island must undergo a two-week quarantine before being allowed to appear in public. As a result, many other businesses driven by tourism and considered non-essential also closed. This sudden, immediate reduction in tourism will undoubtedly have a large effect on the island, including the relationship with water use studied here. Such a stark change in tourism may produce a stronger statistical signal that can be measured more precisely which our current study is unable to detect due to the various sources of uncertainty and lack of data described above. One more limitation of this study is that it considers only direct water use by visitors in hotels and vacation rentals. A study by Hadjikakou, Chenoweth, and G. Miller (2013) finds that indirect water use by tourists, particularly that used in the production of food consumed by tourists, far exceeds direct water use in, for example, hotel rooms and pools. This may be a concern in other locations where the food consumed by tourists is produced locally but this is not the case in Hawaiʻi, which imports approximately 92% of its food (Kent 2016). However, effects like this can be tested with billing data: the state of Hawaiʻi will reopen its commercial venues before allowing the return of normal tourism. This will hopefully give us the opportunity to separately identify water use from local residents and, once tourism returns, water use from visitors.

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Appendix A

Chapter One Appendix

A.1 Full regression tables

Table (A.1) shows the full regression results summarized in table (1.3). The coefficient estimates, for the most part, have the expected signs. Perhaps most surprising is the lack of effect of yard size, which is thought to be one of the larger sources of discretionary water use.

A.2 Neighbor matching robustness to tie-breaking characteristic

In the neighbor matching method, the yard size was used to break ties whenever a home with a cesspool had more than one neighbor with a sewer connection. We test the robustness of the resulting OSDS coefficient estimates to those derived by tie-breaking with other characteristics. This is shown in table (A.2). The columns marked (6) through (8) correspond to the regression models from table (1.3). Only the coefficient estimates for OSDS are shown. The best characteristic to break ties was determined using t-statistics of the resulting pairs' characteristic matches. Overall, the characteristic that yielded the lowest mean t-statistic was used to break ties. Note that, while the sign and magnitude vary slightly from model to model, the estimates remain insignificant at the 10% level. All R^2 and adjusted R^2 values remained largely unchanged compared to those presented in table (1.3).

Table A.1: Full results of regression summary shown in table (1.3).

	Dependent variable:							
	Log mean daily water use (gal)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OSDS	0.214***	0.230***	0.071**	0.021	0.045	0.041	0.059	0.040
	(0.046)	(0.025)	(0.029)	(0.036)	(0.045)	(0.060)	(0.051)	(0.074)
Net val ($100,000)		0.019***	0.023***		0.021***		0.018***	0.046***
		(0.001)	(0.002)		(0.002)		(0.005)	(0.013)
Home size (1000s sq ft)		0.101***	0.101***		0.079***		0.098**	−0.018
		(0.007)	(0.006)		(0.018)		(0.042)	(0.108)
Yard size (1000s sq ft)		0.001	0.0003		0.001		0.030***	−0.010
		(0.0005)	(0.0003)		(0.001)		(0.007)	(0.022)
Eff. home age (decades)		−0.015***	0.013***		−0.008		0.019	0.057*
		(0.004)	(0.003)		(0.005)		(0.016)	(0.035)
Median HH income ($10,000)		0.001			−0.001		−0.007	
		(0.003)			(0.003)		(0.011)	
Avg. ann temp (C)		0.066***			0.210***		0.250***	
		(0.018)			(0.058)		(0.082)	
Avg ann rain (in)		−0.008***			−0.005**		−0.008***	
		(0.001)			(0.002)		(0.002)	
Num beds		0.064***	0.056***		0.059**		0.024	0.036
		(0.005)	(0.003)		(0.026)		(0.022)	(0.054)
Num baths		0.052***	0.062***		0.030		0.085**	0.111
		(0.005)	(0.004)		(0.029)		(0.040)	(0.095)
Data	All	All	All	All	All	Neighbors	Neighbors	Neighbors
Model	OLS	OLS	OLS	PS wtd. GLM	PS wtd. GLM	OLS	OLS	OLS
Census tract dummy	No	No	**Yes**	No	No	No	No	No
Neighbor pair dummy	No	No	No	No	No	No	No	**Yes**
Observations	109,875	109,875	109,875	109,875	109,875	559	559	559
R^2	0.005	0.214	0.274	0.000	0.237	0.001	0.373	0.812
Adjusted R^2	0.005	0.214	0.270	0.000	0.237	−0.001	0.362	0.414
Note:								*p<0.1; **p<0.05; ***p<0.01
								Robust standard errors clustered by census tract except model (8)
								Observations limited to complete cases

Table A.2: Robustness of OSDS coefficient estimates with different characteristics used for neighbor tie-breaking. The best matching variable, yard size, was chosen based on its ability to create the most balanced matches. Rows ordered according to matching effectiveness (best at the top). Matching effectiveness based on mean t-statistics of differences between matched pairs. Mean D-statistics are also reported. None of the coefficient estimates are significant at the 10% level.

Neighbor tie-breaker variable	Model OSDS coefficient estimate			Mean t-statistic	Mean D-statistic
	(6)	(7)	(8)		
Yard size (table (1.3))	0.041	0.059	0.040	−0.33	0.059
Home size	0.028	0.046	0.039	−0.42	0.048
Effective home age	−0.011	0.042	0.013	−0.51	0.067
Net value	0.010	0.007	−0.051	−0.80	0.047

Appendix B

Chapter Two Appendix

B.1 Functional form selection

We use a simple linear model for our main specification for its ease of interpretation and implementation in the climate change scenarios. Additionally, we chose to consolidate our climate variables into a single measure, the net landscape water demand proxy. To see whether this specification appropriately fits the data, we test this model against a number of more complex models using out-of-sample predictions. Out-of-sample predictions are obtained by omitting one watershed at a time from estimation and using the fitted model to predict water demand in the omitted watershed. We compare out-of-sample prediction of the linear NLWD proxy model against restricted cubic spline models using a variety of climate measures as alternative explanatory variables. The results of the cross-validation process are shown in table (B.1), which shows the correlation between the fitted and actual values for the out-of-sample data. For any choice of climate variable, we see the restricted cubic spline models do not significantly increase predictive power. Further, NLWD and its proxy perform better than reference grass evapotranspiration (ET) and its proxy. The temperature and rainfall combination performed the worst. We are therefore comfortable using the simpler linear model that uses the NLWD proxy.

B.2 Exclusion of homes with OSDS

Whether or not the home has an on-site disposal system (OSDS) such as a cesspool or septic tank was obtained from the Hawaiʻi State Department of Health. There were 40,037 such homes in our data. These homes are important to consider because these consumers face a different billing rate than homes with sewer connections. Homes with OSDS pay only for water, while those with sewer connections pay for both water and sewer. The sewer connection includes an additional large monthly fixed fee and approximately doubles their volumetric charge. Homes with sewer connections thus pay about three times the amount that homes with OSDS pay for the same quantity of water, on average. Figure (B.1) shows the locations of homes with OSDS. These homes may confound our results, especially since they tend to be grouped together and our identification strategy relies on spatial variation. Another small group of homes on a private sewer service were excluded altogether from our analysis.

First, note that whether or not the homes have an OSDS is not highly correlated with climate. The

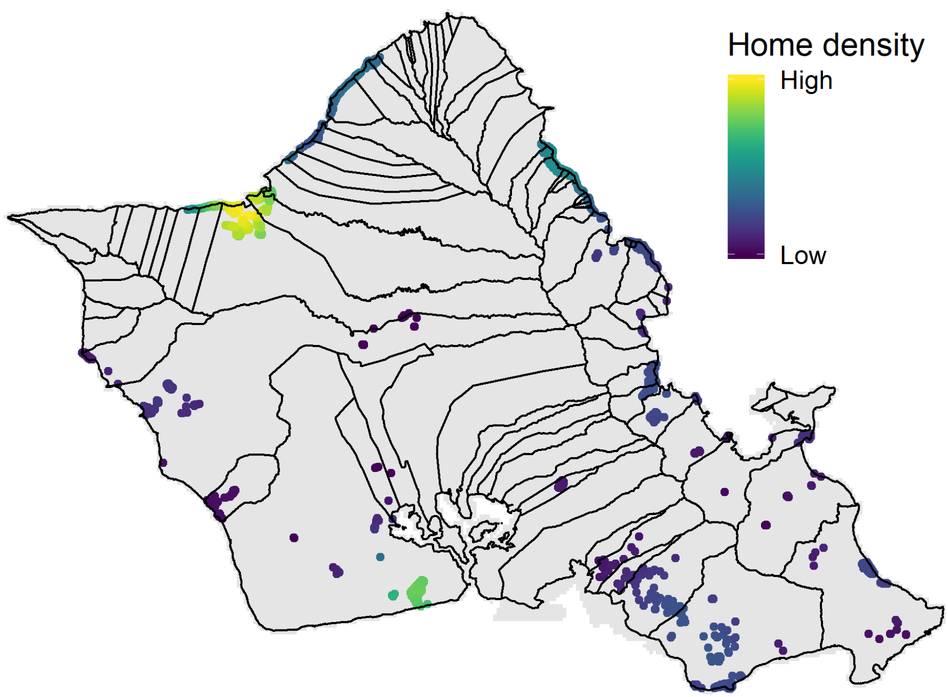

Figure B.1: Location of homes with OSDS. Point color indicates the density of the homes.

Table B.1: Correlation table of out-of-sample predictions at the ahupuaʻa level. RCS is a restricted cubic spline model with the indicated number of evenly-spaced knots. FE indicates the corresponding proxy was calibrated with ahupuaʻa fixed effects in addition to temperature and rainfall. ET is reference grass evapotranspiration.

Model	Temp and rain	ET	ET proxy	ET proxy w/ FE	NLWD	NLWD proxy	NLWD proxy w/ FE
Linear	0.126	0.134	0.113	0.130	0.162	0.151	0.159
RCS 3 knots	0.139	0.134	0.133	0.127	0.169	0.163	0.165
RCS 4 knots	0.147	0.119	0.145	0.120	0.168	0.160	0.162
RCS 5 knots	0.144	0.111	0.142	0.112	0.167	0.160	0.162

Table B.2: Reproduction of table (2.4) for homes without OSDS.

	Dependent variable:					
	Average daily gallons					
	(1)	(2)	(3)	(4)	(5)	(6)
NLWD proxy (in/yr)	1.4585***	1.4618***	1.9283***	1.9160***	1.7693***	1.7790***
	(0.2130)	(0.2030)	(0.2674)	(0.2539)	(0.0854)	(0.0837)
NLWD cal. w/ ahupuaʻa FE	No	**Yes**	No	**Yes**	No	**Yes**
Home characteristics	No	No	**Yes**	**Yes**	**Yes**	**Yes**
Ahupuaʻa FE	No	No	No	No	**Yes**	**Yes**
Observations	94,125	94,125	94,125	94,125	94,125	94,125
R^2	0.0248	0.0256	0.0927	0.0933	0.1139	0.1139
Adjusted R^2	0.0248	0.0256	0.0926	0.0933	0.1135	0.1135
Note:						*p<0.1; **p<0.05; ***p<0.01 Errors clustered by watershed

correlation is highest for average temperature at $r = 0.11$. This is followed by our proxy for average NLWD at 0.03 and average rainfall at 0.02. Although these correlations are relatively small, we still exclude homes with OSDS as a robustness check due to the significant difference in prices paid. Table (B.2) is a recreation of the results presented in table (2.4), except homes with OSDS are excluded. These models are consistent with our main results, with no significant change in the magnitude or statistical significance of the coefficients.

B.3 NWLD and NLWD proxy comparison

Whether or not the models resulting from equations (2.1) and (2.3) yield similar results is important to consider. If the proxy is calibrated well, it should have a similar effect on water use as actual NLWD: their coefficients should be statistically equivalent. Table (B.3) compares the coefficients of table (2.4) to the coefficients of the same models, but run with actual NLWD instead of the proxy. All proxy coefficients are larger than actual NLWD coefficients. The Z-scores[1] are provided for each model, which indicates the significance of the difference between the coefficients generated with NLWD proxy and the coefficients generated with NLWD. In all specifications, the coefficient on NLWD proxy is slightly larger than the corresponding NLWD coefficient by about 5 to 10%.

[1] We calculate Z-scores to compare coefficients of two different models following Clogg, Petkova, and Haritou (1995). A Z-score of 1 indicates the difference between the estimates is 1 standard deviation.

Table B.3: Comparison of coefficients of NLWD and NLWD proxy when regressed with water use. Columns correspond to models in table (2.4), with the top row repeating the NLWD proxy coefficient modeled with and without ahupuaʻa fixed effects. The second row shows the coefficient of water use regressed onto NLWD (rather than its proxy) in the same model.

	(1)	(2)	(3)	(4)	(5)	(6)
NLWD proxy	1.5137***	1.5150***	1.9977***	1.9844***	1.7930***	1.8024***
	(0.2067)	(0.1941)	(0.2687)	(0.2544)	(0.0497)	(0.0486)
NLWD	1.4422***		1.8257***		1.6471***	
	(0.2127)		(0.1975)		(0.0773)	
Z-score	0.24	0.25	0.52	0.49	1.59	1.70
Note:					*p<0.1; **p<0.05; ***p<0.01	
					Errors clustered by watershed	

B.4 Ahupuaʻa-level regressions

In our main specification, equation (2.3), we include ahupuaʻa as fixed effects. Here, we run the same model at the ahupuaʻa level to examine the relationship between our NLWD proxy and household water use within the ahupuaʻa. This is shown in figure (B.2). In the figure, each regression line corresponds to one ahupuaʻa. The density of each line indicates the standard error of the corresponding coefficient, with smaller errors being indicated by darker lines. The colored line indicates the inverse standard error-weighted average of all ahupuaʻa coefficients. The slope of the weighted average line is 1.78 which is comparable to the corresponding coefficient from table (2.4) specification (6), 1.80.

Notice that, while most ahupuaʻa show the expected positive relationship between NLWD proxy and water use, a few ahupuaʻa show a negative relationship. These ahupuaʻa are located exclusively on the north shore of Oʻahu. As is seen in figure (2.2b), homes in these locations are exclusively on or very near the coastline. Thus, they also lack meaningful variation in climate which makes estimating the relationship difficult. This is indicated by the relatively transparent lines implying large standard errors of the estimates.

B.5 Dependent variable placebo tests

Table (B.4) provides the results of out-of-sample placebo tests run at the watershed level. Each row represents the dependent variable of the regression, with the final row, water use, being the variable of interest in the regressions used in our main results. The other rows with home characteristics indicate the placebos. Each row's independent variable was regressed against the household fixed effects, with and without the inclusion of the climate control variable(s) indicated by the columns. Out-of-sample predictions at the watershed level were estimated for each placebo. The values in the table represent the percent change in root mean square error of the placebo estimates after adding the climate variables to the model. In each case, RMSE is reduced the most for water use, indicating there is evidence that the relationship between climate and water use is causal. However, the percent change in RMSE for water use is in some cases modest when compared to the placebos. To check whether the out-of-sample placebo predictions are appropriate, table (B.5) summarizes

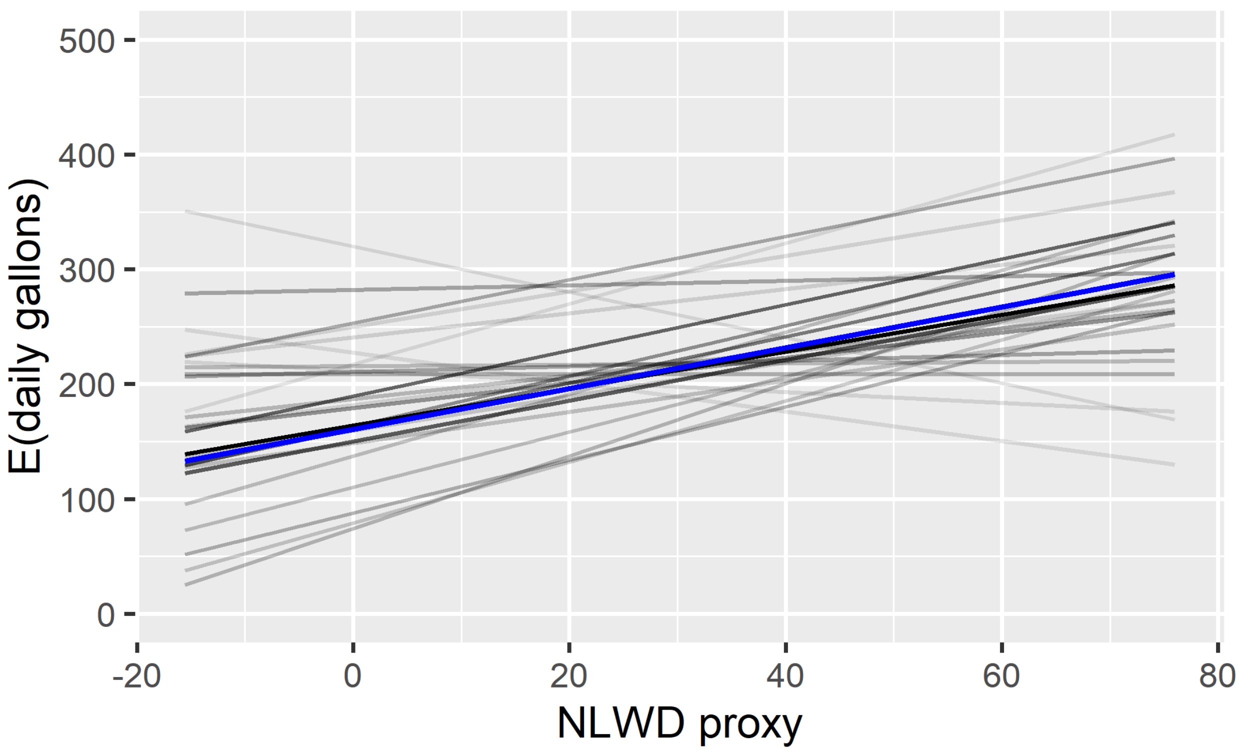

Figure B.2: Regressions by ahupuaʻa. The model from equation (2.3) was run on individual ahupuaʻa and plotted here. Each regression line represents one ahupuaʻa. Line shading represents the standard error of the corresponding coefficient, with darker lines indicating a smaller standard error. The blue line is the weighted average of all regression lines, and has a slope of 1.78. Compare this to the corresponding coefficient in table (2.4) specification (6), which has a value of 1.80.

the placebo home characteristics by watershed. Ideally, households should share similar characteristics, or at least have approximately the same range of values, between watersheds for the out-of-sample predictions to be accurate.

Table B.4: Placebo tests: percent change in RMSE after adding indicated climate variable as a control for out-of-sample predictions at the watershed district level.

Dependent variable	Temp and rain	ET	ET proxy	ET proxy w/ FE	NLWD	NLWD proxy	NLWD proxy w/ FE
Year built	0.64	−0.13	−0.09	−0.08	1.31	1.77	1.73
Effective year built	−1.28	−1.49	−1.13	−1.29	−1.49	−1.25	−1.34
Home size	−2.12	−1.39	−1.16	−0.87	−2.05	−2.12	−2.12
Yard size	5.70	2.91	3.97	4.12	2.76	3.09	2.96
Water use	−4.04	−3.62	−3.62	−3.70	−3.92	−3.61	−3.66

Table B.5: Mean and median values of dependent variables by watershed region. These are the household characteristics used for the placebo tests in table (B.4)

Dependent variable	Regional mean (median) value							
	Central Oʻahu	East Honolulu	ʻEwa	Koʻolauloa	Koʻolaupoko	North Shore	Primary Urban Center	Waiʻanae
Year built	1981 (1984)	1972 (1970)	1992 (1995)	1974 (1979)	1968 (1964)	1968 (1967)	1963 (1962)	1980 (1979)
Effective year built	1983 (1985)	1977 (1975)	1993 (1995)	1978 (1982)	1973 (1970)	1976 (1976)	1968 (1968)	1981 (1980)
Home size (1000s sq ft)	1.653 (1.576)	2.078 (1.904)	1.619 (1.532)	1.413 (1.194)	1.807 (1.687)	1.502 (1.344)	1.812 (1.669)	1.293 (1.176)
Yard size (1000s sq ft)	4.280 (3.982)	5.976 (5.670)	3.628 (3.357)	5.655 (4.669)	6.268 (6.012)	5.626 (5.283)	4.976 (4.546)	4.669 (4.040)

B.6 Climate model uncertainty

Table (B.6) provides a summary of the uncertainty associated with the statistically-downscaled RCP 4.5 and RCP 8.5 data. Columns within a climate variable provide a summary of the island-wide statistics. For the statistical downscaled ensemble, rows indicate the minimum, lower (-2 standard deviations), mean, upper ($+2$ standard deviations), and maximum estimated values obtained from the ensemble for the given statistic. No minimum or maximum values were provided for rainfall, so the minimum and maximum NLWD values were calculated using the minimum and maximum of temperature, and the lower and upper values of rainfall. No form of estimate error was provided with the dynamical downscaled data. Note that the difference between the min and the max for a given climate variable is typically larger than the difference of means between RCP 4.5 and RCP 8.5, which showcases the great degree of uncertainty between GCMs within an ensemble. Also apparent is the uncertainty surrounding future rainfall, with means and standard deviations typically having a larger variation than that of temperature.

Table B.6: Historical (1978 – 2005) and future estimated values (2071 – 2099) for rainfall, temperature, and NLWD. Columns within a climate variable provide a summary of the island-wide statistics. For the statistical downscaled ensemble, rows indicate the minimum, lower (−2 standard deviations), mean, upper (+2 standard deviations), and maximum estimated values obtained from the ensemble for the given statistic. No minimum or maximum values were provided for rainfall, so the minimum and maximum NLWD values were calculated using the minimum and maximum of temperature, and the lower and upper values of rainfall. No form of estimate error was provided with the dynamical downscaled data.

			Mean annual rainfall (in/yr)					Mean annual temperature (C)					Mean annual NLWD proxy (in/yr)				
			Median	Mean	SD	Min	Max	Median	Mean	SD	Min	Max	Median	Mean	SD	Min	Max
Historical average			34.3	38.5	16.6	21.0	144.3	23.4	23.2	0.62	20.8	23.8	58.5	52.0	22.9	−66.3	79.7
Statistical	RCP 4.5	Min						24.1	23.9	0.63	21.5	24.5	69.2	620.	26.5	−82.8	94.5
		Lower	34.3	38.9	20.8	15.3	172.2	24.8	24.5	0.62	22.2	25.2	78.6	71.4	26.5	−73.3	103.9
		Mean	27.1	31.0	17.6	10.9	144.3	25.0	24.8	0.62	22.4	25.4	89.0	82.6	23.5	−44.3	111.6
		Upper	19.9	23.1	14.3	6.4	116.9	25.2	25.0	0.62	22.7	25.7	99.7	93.8	20.6	−15.2	119.5
		Max						26.2	26.0	0.62	23.4	26.7	114.0	108.1	20.6	−0.8	133.9
	RCP 8.5	Min						25.0	24.8	0.63	22.4	25.4	80.8	73.3	29.5	−90.2	109.7
		Lower	36.0	40.7	24.1	11.0	193.5	26.1	25.9	0.62	23.5	26.5	96.4	88.9	29.4	−74.5	125.3
		Mean	23.7	27.0	18.5	3.2	144.8	26.5	26.2	0.62	23.4	26.9	114.0	107.6	24.1	−24.2	138.2
		Upper	11.4	13.5	12.8	0.0	97.6	26.8	26.6	0.62	24.3	27.3	131.7	126.0	18.9	26.1	149.8
		Max						28.3	28.1	0.62	25.8	28.7	152.8	147.2	18.8	47.3	171.0
Dynamical	RCP 4.5	Mean	28.9	31.2	14.8	7.6	129.1	25.0	24.8	0.62	22.4	25.6	89.1	82.9	20.7	−25.4	114.9
	RCP 8.5	Mean	36.3	39.2	18.4	10.9	152.0	26.6	26.3	0.63	23.9	27.4	101.9	97.4	23.8	−27.1	138.6

Appendix C

Chapter Three Appendix

C.1 Additional tables and figures

This section contains additional figures referenced throughout the text. Figure (C.1) shows the average Airbnb occupancy across the data, aggregated by month. For example, the map for January provides the average occupancy for all months of January in the 7-year sample period. We see Airbnb occupancy is dominated by units located in and around Waikiki on the south shore of the island, which is the center for hotels and tourism. Other notable hotspots are Airbnbs located in and around the several resorts on the southwest shoreline, the Kailua area on the eastern shoreline, and the Turtle Bay area on the northernmost point of the island. These areas remain relatively stable in their occupancy over the year. This is shown more clearly in figure (C.2), which shows Airbnb occupancy demeaned by grid cell. The popular tourist areas listed previously remain relatively stable around a demeaned value of 1, indicating occupancy does not depart much from the mean from month to month. However, during the summer months and in December, popular tourist seasons in the state, we see the "overflow" tourists who are not staying in the desirable areas begin occupying units across the island.

Table (C.1) shows the results of the model given by equation (3.2). The results from column (2) are used to create fitted values of Airbnb occupancy at the grid level where no data were available. This specification suggests that the arrival of an additional 1000 tourists in a given month is associated with grid-level Airbnb occupancy increasing by about 6.7 nights per month.

C.2 Robustness check: 2 km $\times$ 2 km grid

Table (C.2) reproduces table (3.3), but increases the size of the grid cells from 1 km by 1 km to 2 km by 2 km. As with the previous results, there is no apparent economically-significant effect of Airbnb occupancy on residential water use. Here, we estimate an increase in Airbnb occupancy nights by 1% in a grid cell is associated with a 0.03 – 0.07% *reduction* in per-residence water use in the grid cell.

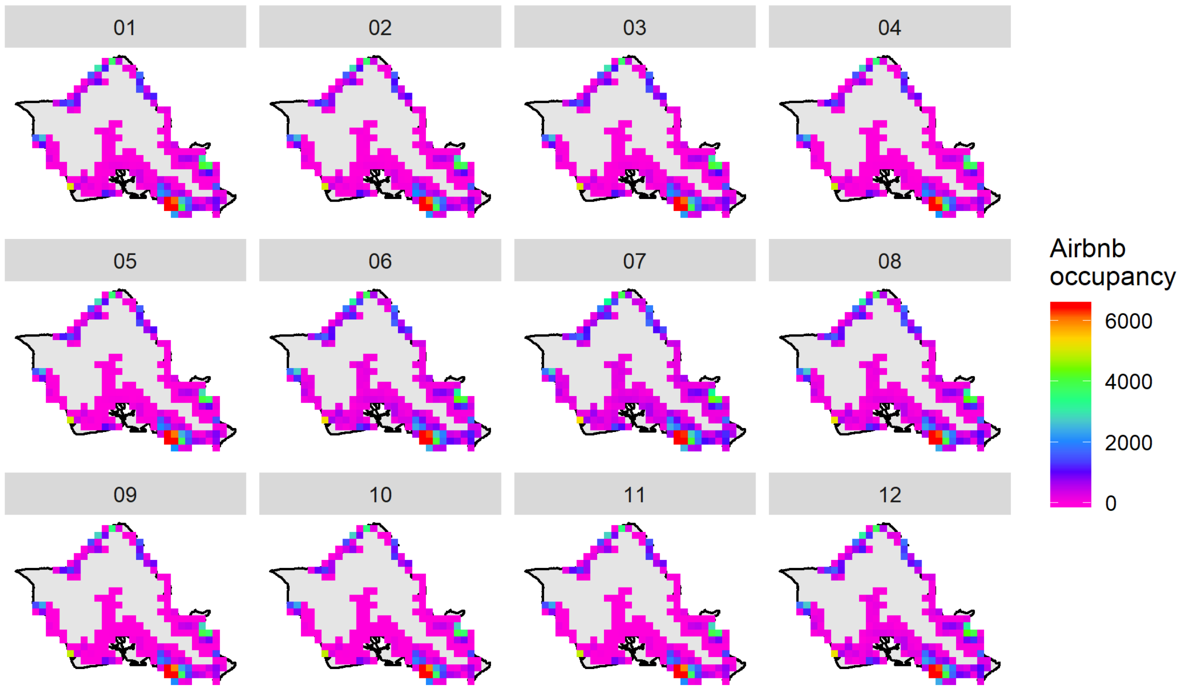

Figure C.1: Airbnb average occupancy by month. Occupancy is defined as 1 Airbnb unit being occupied for 1 night in a given month. Values provide average occupancy in a grid cell across the given month for the entire sample period (e.g. the map for January provides the average occupancy for all months of January in the 7-year sample period).

Table C.1: Regression of grid-level monthly Airbnb occupancy nights on tourist count. Errors clustered by grid cell.

	Dependent variable:	
	Grid-level Airbnb occupancy nights	
	(1)	(2)
Tourism count (1000s)	5.738*	6.751***
	(3.020)	(0.570)
Constant	−165.748	
	(353.812)	
Grid FE	No	**Yes**
Observations	4,499	4,499
R^2	0.001	0.970
Adjusted R^2	0.001	0.966
Residual Std. Error	2,331.193	436.773
F Statistic	3.611*	305.422***
Deg. freedom	4497	4073
Note:	*p<0.1; **p<0.05; ***p<0.01	

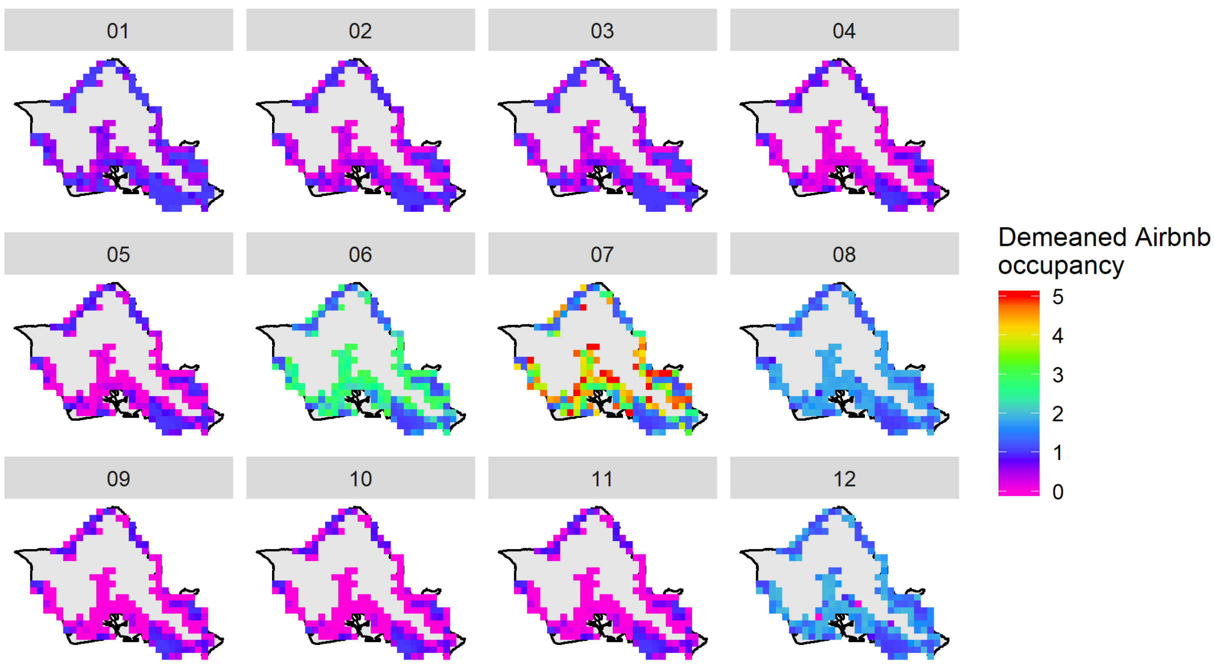

Figure C.2: Airbnb average occupancy as in figure (C.1), but demeaned by grid cell. Popular regions, like Waikiki on the southern shoreline and the North Shore, remain relatively stable year-round. All other regions tend to fluctuate seasonally, with peaks in the summer and winter months.

Table C.2: Reproduction of table (3.3), but with a grid with resolution of 2 km by 2 km. The lack of an economically-significant result between Airbnb water use and Airbnb occupancy suggests incorrect Airbnb grid cell assignment is not a significant source of bias or error. Errors clustered by grid cell.

	Dependent variable:					
	Log daily gallons per unit					
	(1)	(2)	(3)	(4)	(5)	(6)
Log actual	-0.027^{***}	-0.022^{**}	-0.065^{*}			
Airbnb occupancy days	(0.011)	(0.010)	(0.034)			
Log predicted				-0.046^{***}	-0.046^{***}	-0.033^{***}
Airbnb occupancy days				(0.004)	(0.004)	(0.005)
Log avg temp (C)		-1.211^{***}	-1.158^{***}		0.461^{***}	0.507^{***}
		(0.206)	(0.156)		(0.085)	(0.054)
Log total rainfall (in)		0.046^{***}	0.042^{***}		-0.006	-0.008^{***}
		(0.012)	(0.009)		(0.005)	(0.003)
Constant	5.725^{***}	9.661^{***}		5.942^{***}	4.444^{***}	
	(0.061)	(0.668)		(0.023)	(0.275)	
Grid FE	No	No	**Yes**	No	No	**Yes**
Observations	1,970	1,970	1,970	8,819	8,819	8,819
R^2	0.003	0.028	0.992	0.017	0.021	0.996
Adjusted R^2	0.003	0.027	0.991	0.017	0.020	0.996
Residual Std. Error	0.736	0.727	0.539	0.574	0.573	0.351
F Statistic	6.800^{***}	19.164^{***}	$1,140.879^{***}$	150.970^{***}	61.878^{***}	$12,404.400^{***}$
Deg. freedom	1968	1966	1784	8817	8815	8633
Note:						*p<0.1; **p<0.05; ***p<0.01

Table C.3: Reproduction of table (3.3), but with levels instead of log-transformed data. Like with the original table, the coefficients suggest Airbnb occupancy does not have an economically-significant effect on water use at the grid cell level. Errors are clustered by grid cell.

	Dependent variable:					
	Avg. daily gallons per unit					
	(1)	(2)	(3)	(4)	(5)	(6)
Actual Airbnb occupancy days (100s)	-0.429^{***}	-0.425^{***}	-0.077			
	(0.129)	(0.129)	(0.280)			
Predicted Airbnb occupancy days (100s)				-0.389^{***}	-0.384^{***}	-1.298^{**}
				(0.038)	(0.038)	(0.647)
Avg temp (C)		-2.059	-2.004		10.675^{***}	9.246^{***}
		(3.291)	(1.272)		(1.293)	(0.576)
Total rainfall (in)		7.670^{**}	7.400^{***}		-2.445^{*}	-1.515^{**}
		(3.582)	(1.379)		(1.432)	(0.608)
Constant	336.835^{***}	379.782^{***}		342.957^{***}	70.783^{**}	
	(6.866)	(84.651)		(2.509)	(33.600)	
Grid FE	No	No	**Yes**	No	No	**Yes**
Observations	1,970	1,970	1,970	8,819	8,819	8,819
R^2	0.006	0.008	0.941	0.012	0.020	0.946
Adjusted R^2	0.005	0.006	0.935	0.012	0.019	0.945
Residual Std. Error	297.196	296.995	113.905	227.703	226.803	95.350
F Statistic	11.054^{***}	5.245^{***}	152.704^{***}	105.467^{***}	59.455^{***}	817.058^{***}
Deg. freedom	1968	1966	1784	8817	8815	8633
Note:						*p<0.1; **p<0.05; ***p<0.01

C.3 Levels regressions

In table (C.3) we present the results from equation (3.3) using levels rather than logs. Columns (1) to (3) regress per-unit water use onto actual Airbnb occupancy, while columns (4) to (6) regress per-unit water use onto Airbnb occupancy with the missing values predicted by the model in equation (3.2). While most coefficients on Airbnb occupancy have statistical significance, the economic significance is minimal. Whether we look at actual or fitted Airbnb occupancy, the coefficients suggest an increase of 100 Airbnb occupancy nights per month yields at most a 1.3 gallon decrease per residential unit in the grid cell.

C.4 High Airbnb density limited sample

Many grid cells have a limited number of Airbnb units relative to the total number of residential units. In these grid cells, the variation in water use for reasons other than Airbnb occupation is likely to be much larger than water used by the visitors in the Airbnb. Thus, the true signal may be lost resulting in economically insignificant results. To test this hypothesis, we limit the sample to grid cells with a minimum Airbnb density of 25%. That is, grid cells with at least 25 Airbnb listings per 100 residential units. With this sample, we once again run the model in equation (3.3). The results are provided in table (C.4). The coefficients on both actual and predicted Airbnb occupancy suggest, even within grid cells with a relatively high number of Airbnbs, Airbnb occupancy has little effect on grid-level water use.

Table C.4: Daily average water use per unit regressed on Airbnb occupancy, with data limited to grid cells with a density of Airbnb units of at least 25%. Errors clustered by grid cell.

	Dependent variable:					
	Log daily gallons per unit					
	(1)	(2)	(3)	(4)	(5)	(6)
Log actual Airbnb occupancy days	-0.120^{***}	-0.129^{***}	0.012			
	(0.020)	(0.021)	(0.016)			
Log predicted Airbnb occupancy days				-0.127^{***}	-0.128^{***}	0.031^{***}
				(0.008)	(0.008)	(0.008)
Log avg temp (C)		0.496	0.455^{**}		1.115^{***}	1.200^{***}
		(0.452)	(0.222)		(0.136)	(0.086)
Log total rainfall (in)		0.033	-0.001		-0.021^{***}	-0.036^{***}
		(0.023)	(0.013)		(0.007)	(0.005)
Constant	6.096^{***}	4.530^{***}		6.473^{***}	2.867^{***}	
	(0.087)	(1.468)		(0.044)	(0.442)	
Grid FE	No	No	**Yes**	No	No	**Yes**
Observations	287	287	287	4,034	4,034	4,034
R^2	0.110	0.122	0.998	0.053	0.071	0.996
Adjusted R^2	0.107	0.112	0.998	0.053	0.070	0.996
Residual Std. Error	0.557	0.556	0.255	0.591	0.586	0.371
F Statistic	35.220^{***}	13.061^{***}	$2,170.901^{***}$	227.685^{***}	102.619^{***}	$15,168.000^{***}$
Deg. freedom	285	283	222	4032	4030	3968
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$