University of Hawai`i at Mānoa
Department of Economics
Working Paper Series

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www.economics.hawaii.edu

Working Paper No. 20-20

How Will Climate Change Affect Water Demand? Evidence from Hawaii Microclimates

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July 2020

How Will Climate Change Affect Water Demand? Evidence from Hawaiʻi Microclimates

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The effect that climate change will have on water resource sustainability is gaining international interest, particularly in regions where stocks are strained due to changing climate and increasing populations. Past studies focus mainly on how water availability will be affected by climate change, with little attention paid to how consumer behavior is likely to react. How a changing climate affects water demand could be equally or more important to management solutions as its influence on water supply. In this paper, we analyze the relationship between residential water use and climate on the Hawaiian island of Oʻahu, and apply downscaled climate projections to estimate end-of-century water use. The island is serviced by only one water utility yet has a wide range of consumers and microclimates, which make it an ideal location for studying these relationships. We find that climate is strongly associated with residential water use in a manner that is likely causal. If the association is causal, it implies that demand will increase by 20–37% island-wide by the end of the century, holding all else the same, depending on the climate model projection. Strategies for offsetting the projected increase in demand are also considered, along with the study's place in literature examining watershed management and consumer welfare.

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. O'ahu 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. O'ahu 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 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

[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.

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 (3) details our historical climate and billing data. Section (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 (5), and section (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 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

$$w_i = \alpha_0 + \alpha_1 NLWD_i + X_i\mathbf{A} + u_i, \tag{1}$$

[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)

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 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.

3 Data

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

[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).

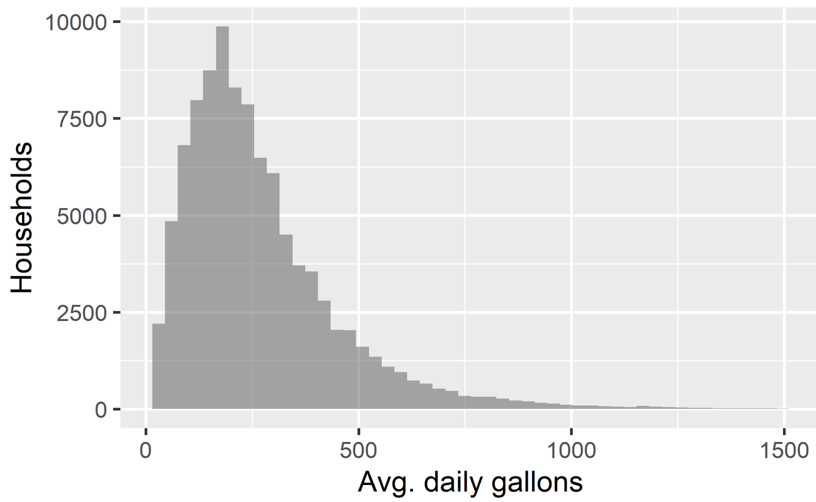


Figure 1: Histogram of water use by single family homes on O'ahu

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 (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 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 O'ahu 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

[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.

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.

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 Hawai'i (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 O'ahu. Wind direction data were also obtained from windfinder.com. Vapor pressure 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 (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, ahupua'a, watershed, census tract, and census block. Districts are major land divisions of O'ahu that correspond to the Honolulu Board of Water Supply's Watershed Management Plan, and which are further divided into ahupua'a. Ahupua'a 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 (pua'a), or because a pig or other tribute was laid on the

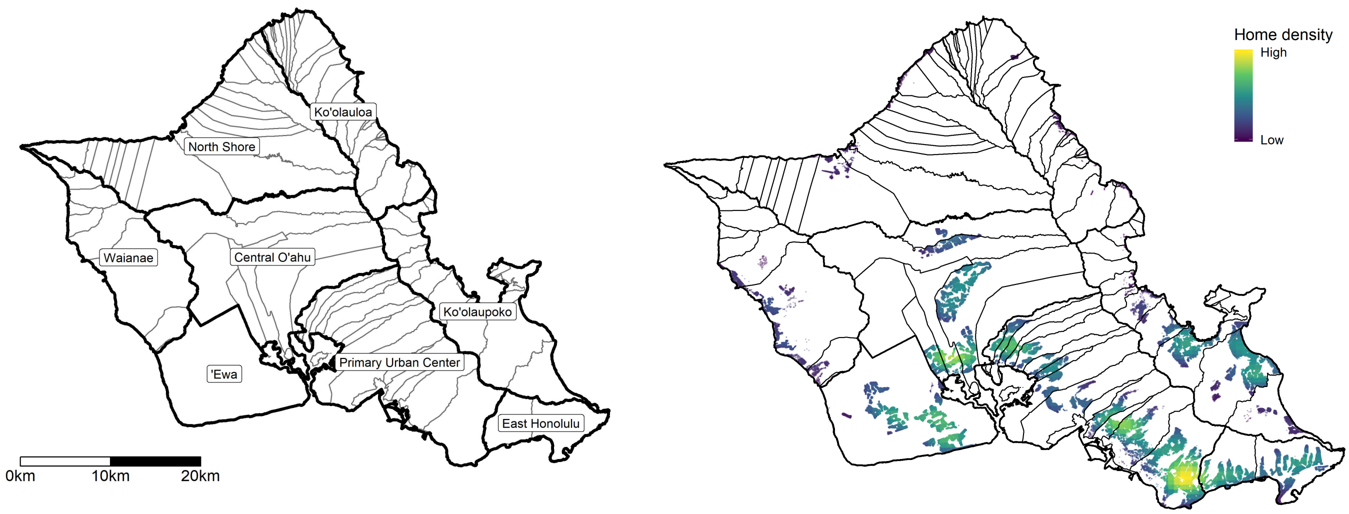
Table 1: Summary of home characteristics and climate data. NLWD is net landscape water demand. Mean climate variables are historical averages for the period from 1978 to 2005.

	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

alter as tax to the chief'.[5] A map of Oʻahu's districts and their ahupuaʻa is shown in figure (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 (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 prevailing winds is shown in figure (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 (4).

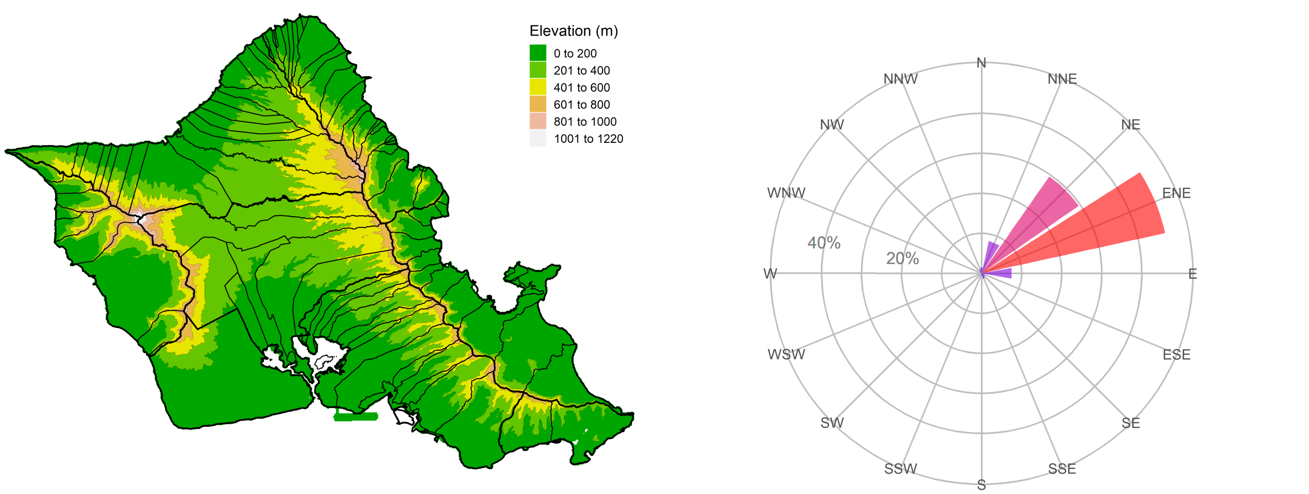
[5] Pukui/Elbert Hawaiian Dictionary, `http://www2.hawaii.edu/~dhonda/ahupua'a.htm`



(a) Districts and ahupuaʻa

(b) Home location and density

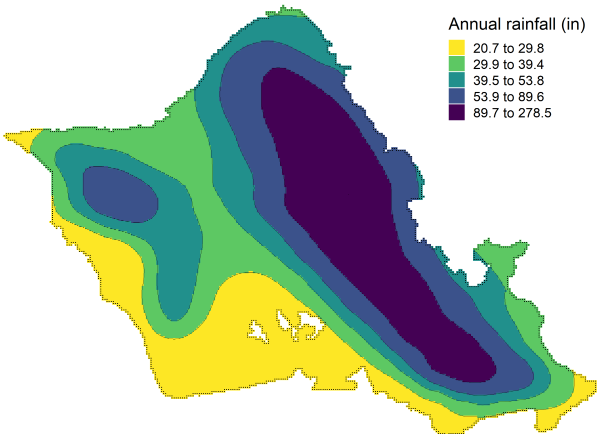
Figure 2: Districts, ahupuaʻa, and home locations on Oʻahu



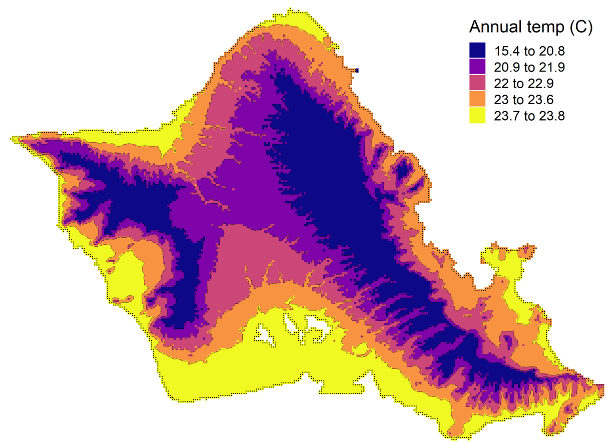
(a) Elevation contour map

(b) Annual average wind direction distribution

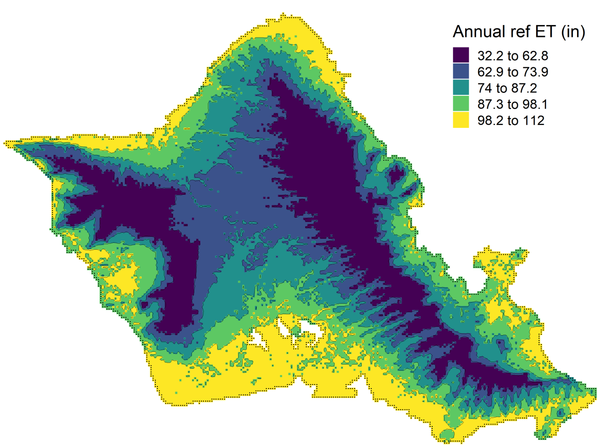
Figure 3: Oʻahu elevation and prevailing winds



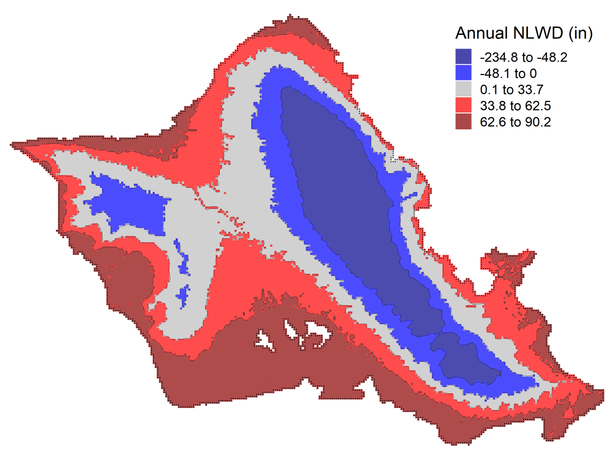
(a) Rainfall



(b) Temperature



(c) Grass reference evapotranspiration



(d) Net landscape water demand

Figure 4: Oʻahu historical average annual climate, 1978 to 2005.

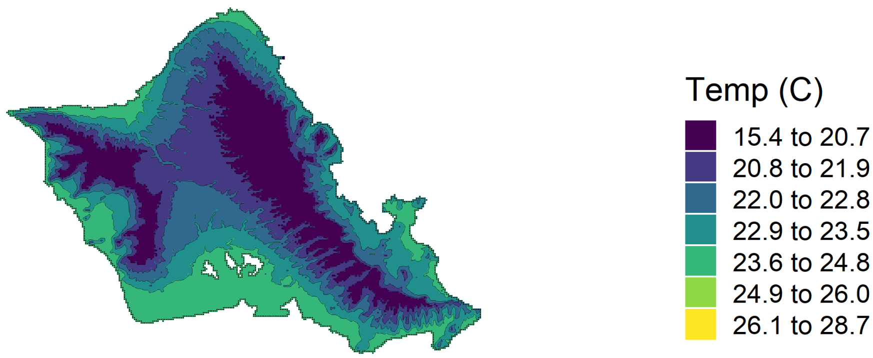
4 Future climate projections

4.1 Climate scenarios

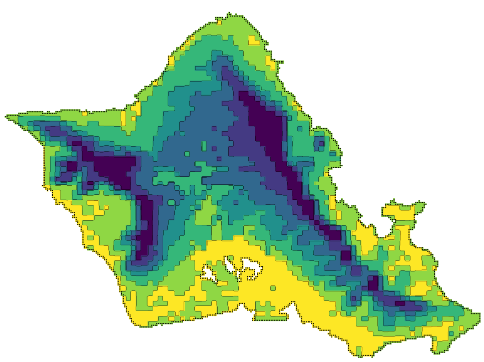
We use data from two models for our climate change projections. Both models give downscaled projected changes to temperature and rainfall for CMIP5 RCP 4.5 and RCP 8.5. Although we focus on using the deltas associated with the period from 2071 to 2099, we also present results using deltas for the mid-century 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. 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.

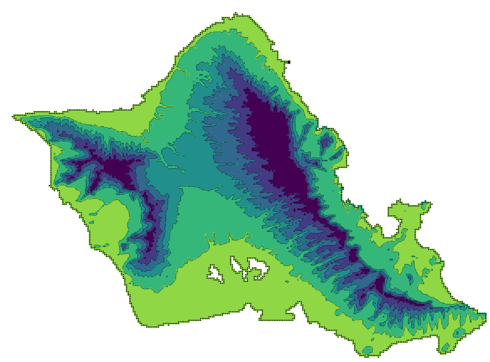
Figure (5) shows the current and projected end-of-century average annual temperatures for both RCP scenarios under the dynamical and statistical models. The dynamical model predicts a more extreme increase in temperature than the statistical model, particularly under RCP 4.5, but the models are otherwise 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.



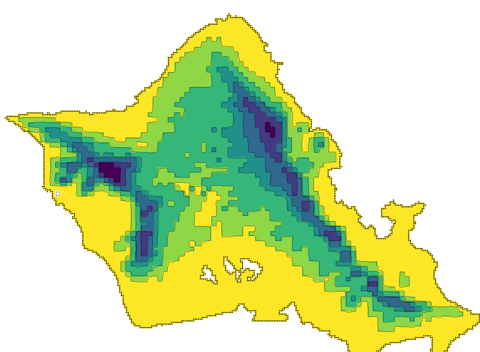
(a) Current



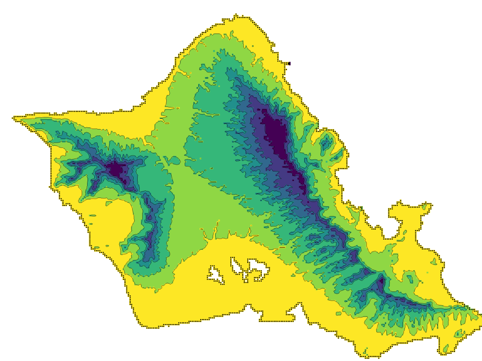
(b) Dynamical RCP 4.5



(c) Statistical RCP 4.5



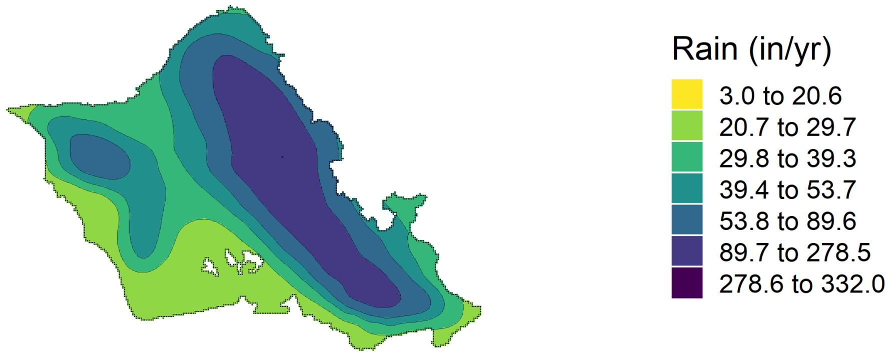
(d) Dynamical RCP 8.5



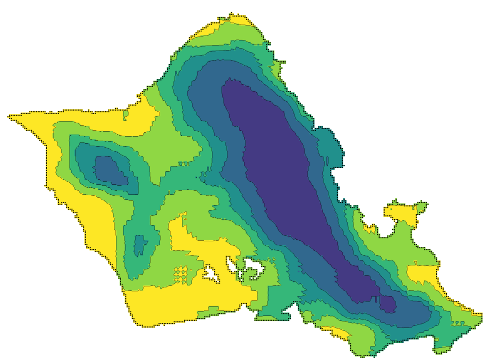
(e) Statistical RCP 8.5

Figure 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.

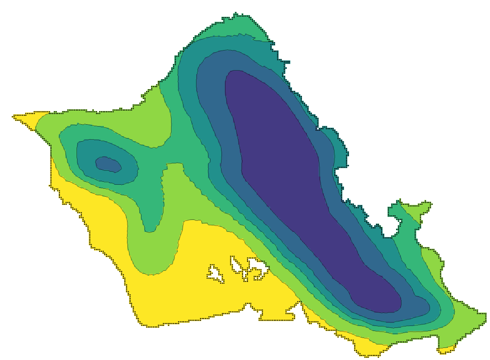
Historical average and projected end-of-century average annual rainfall values for all models are depicted in figure (6). Here, the dynamical and statistical models differ slightly in their projections. As in the temperature projection figure, the lightest contour is used to indicate areas of Oʻahu that 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.



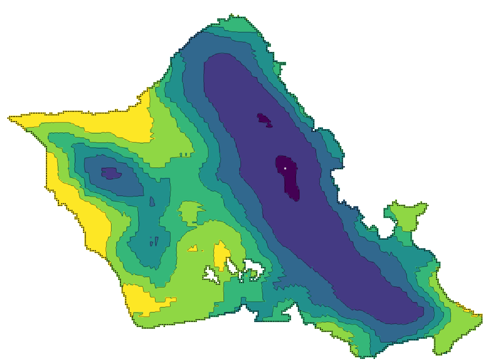
(a) Current



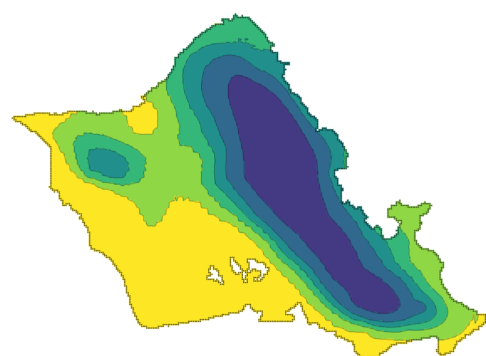
(b) Dynamical RCP 4.5



(c) Statistical RCP 4.5



(d) Dynamical RCP 8.5



(e) Statistical RCP 8.5

Figure 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: 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

4.2 NLWD proxy for future climate

The model in equation (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) 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), 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 (1) we generate a proxy for NLWD,

$$NLWD_j = \beta_0 + \beta_1 T_j + \beta_2 R_j + A_j + v_j, \tag{2}$$

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,

Table 3: Calibration of NLWD proxy using equation (2).

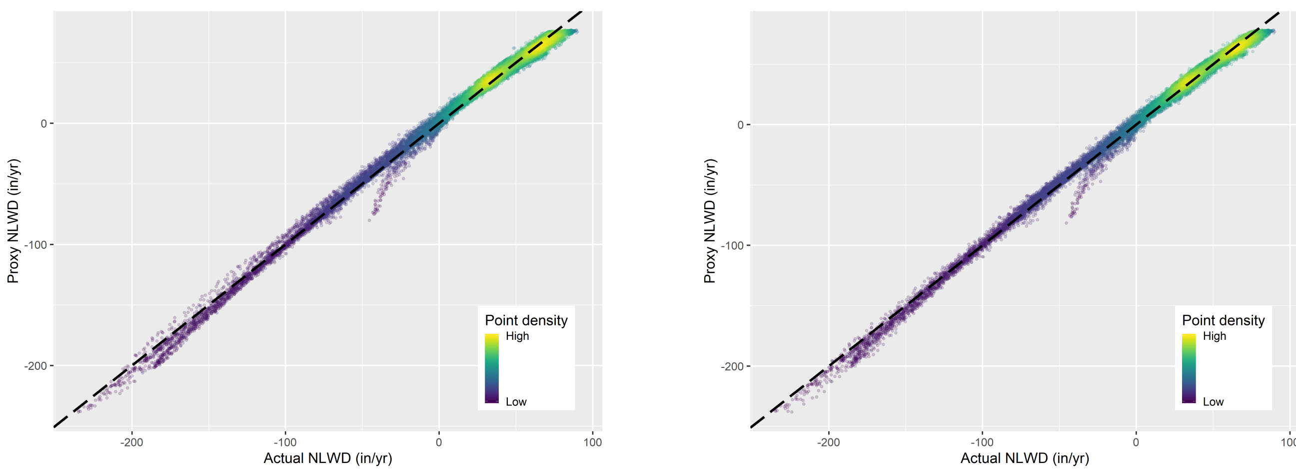
	Dependent variable:			
	NLWD (in/yr)			
	(1)	(2)	(3)	(4)
Mean temperature (°C)	33.113***		12.210***	12.371***
	(1.977)		(0.362)	(0.415)
Mean rainfall (in/yr)		−1.259***	−0.935***	−0.922***
		(0.037)	(0.021)	(0.023)
Ahupuaʻa FE	No	No	No	**Yes**
Observations	26,289	26,289	26,289	26,289
R^2	0.781	0.951	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.

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 (3) shows the results for equation (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 (7) show the NLWD proxy (calibrated with and without ahupuaʻa 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 (3a), this is the high peak on the northern tip of the western Waiʻanae mountain range. No homes are located in this area.

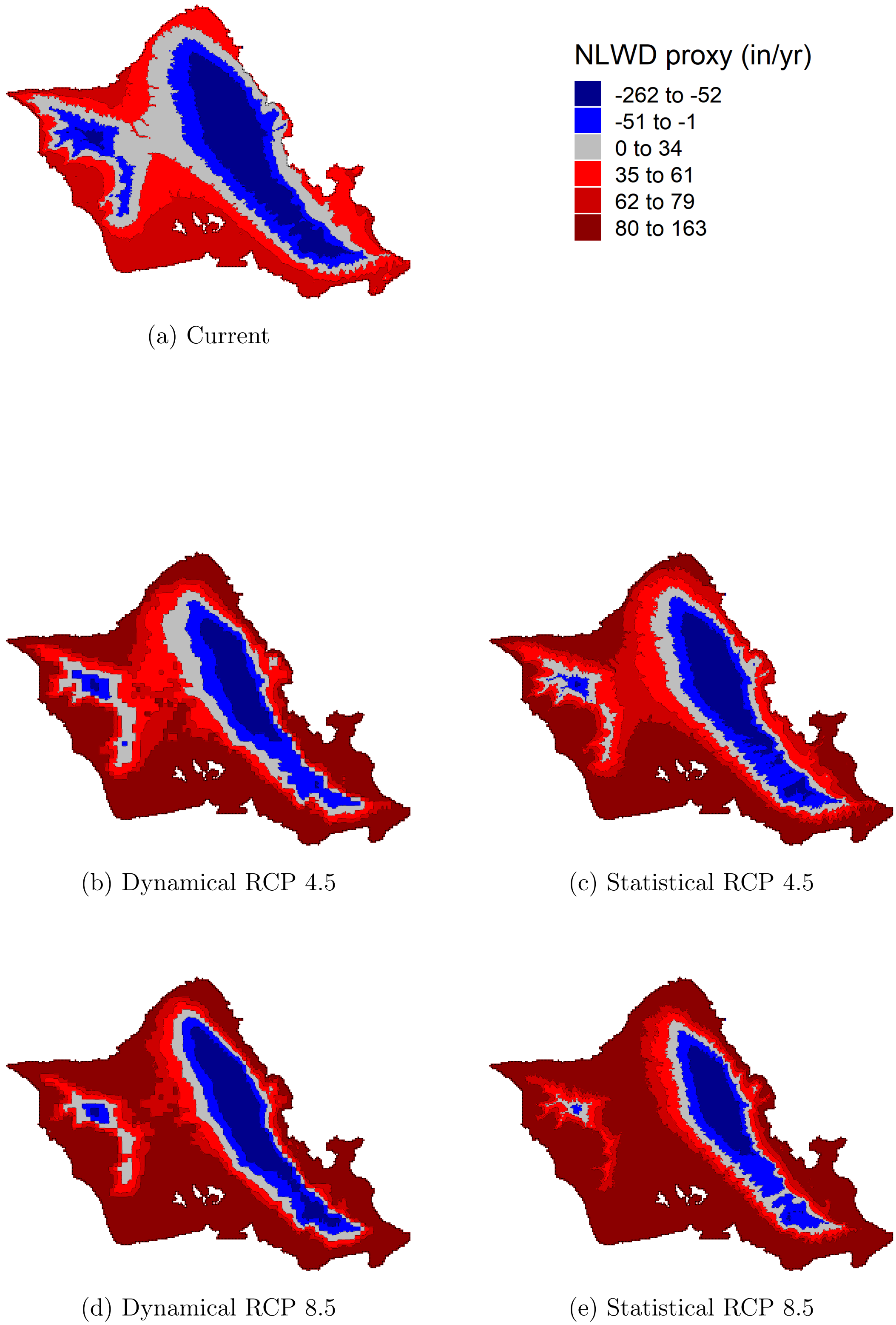
Using the results of model (4) in table (3) and the downscaled climate projection data, we calculate projected end-of-century NLWD values under RCP 4.5 and RCP 8.5. Maps of these changes are shown in figure (8). The darkest red contour indicates areas of Oʻahu that may experience NLWD that is larger than any current NLWD. Projections are similar between statistical and dynamical models, with statistical RCP 8.5 projecting the largest changes in NLWD.



(a) NLWD proxy calibrated with temperature and rainfall.

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

Figure 7: Scatterplot of calibrated NLWD proxy and actual NLWD. The left and right panels correspond to columns (3) and (4) in table (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.



(a) Current

(b) Dynamical RCP 4.5

(c) Statistical RCP 4.5

(d) Dynamical RCP 8.5

(e) Statistical RCP 8.5

Figure 8: Projected net landscape water demand proxy for the period 2071 to 2099 under the statistical and dynamical models.

Table 4: Results for the model in equation (3). NLWD cal. with ahupuaʻa FE indicates the proxy was calibrated with ahupuaʻa 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/ 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	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

5 Results

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 (1) becomes

$$w_i = \gamma_0 + \gamma_1 \widehat{NLWD}_i + X_i \Gamma + u_i. \tag{3}$$

Table (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 ahupuaʻa 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 ahupuaʻa 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.

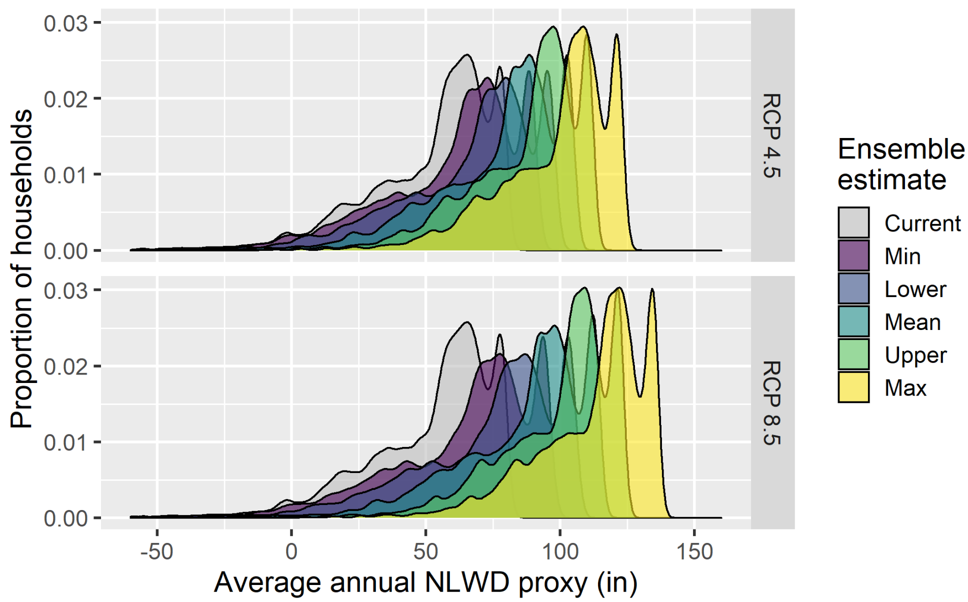
5.2 Water use and future climate

Table (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 (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 (A6) 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 (9) and (10), respectively.

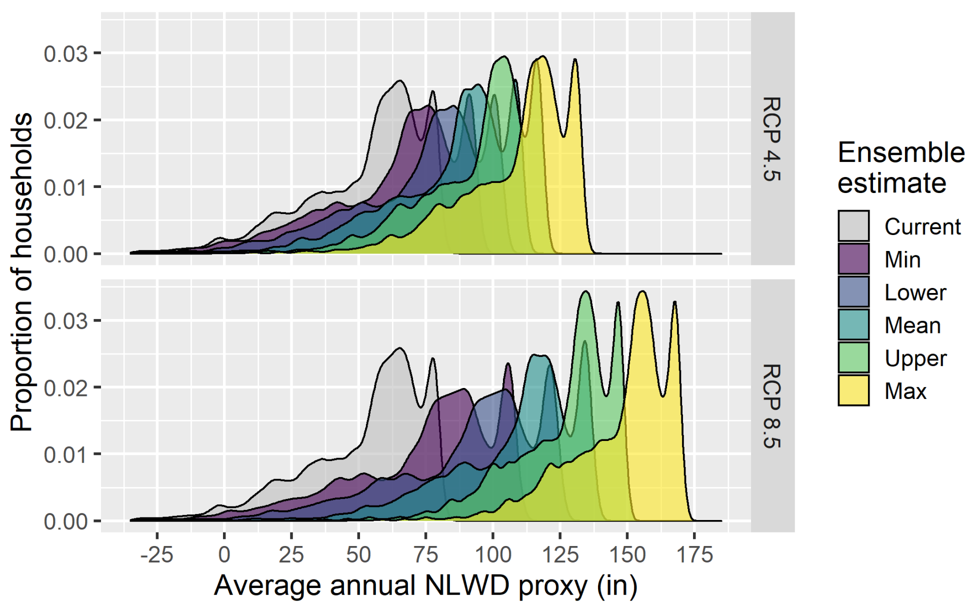
Mean estimates for future water use indicate about a 20% increase under RCP 4.5 for both the statistical and dynamical models. RCP 8.5 under the dynamical model estimates an increase of about 30%, but the statistical model implies an increase of about 37%. However, these means hide a wide range of potential 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.

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

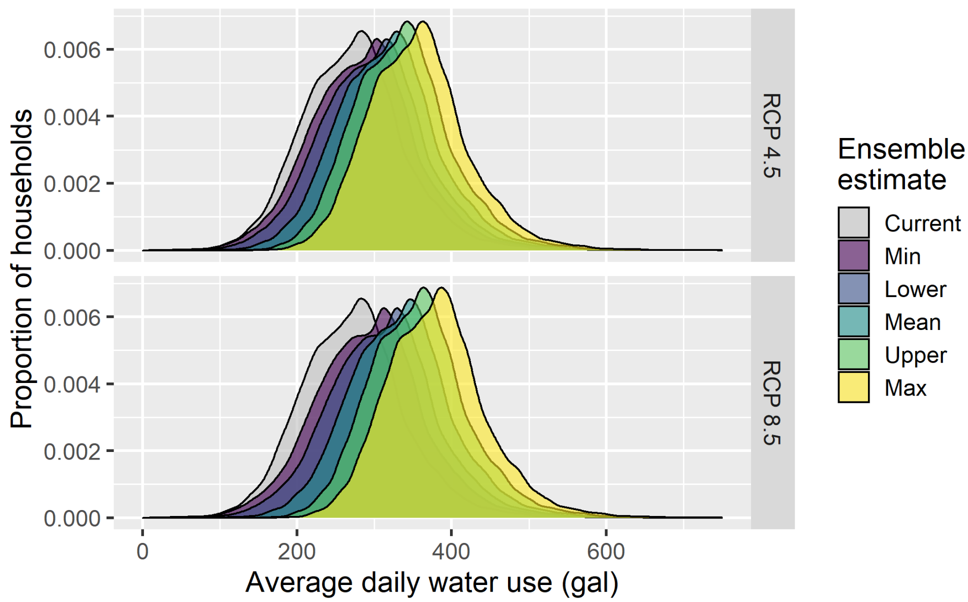


(a) NLWD proxy, average 2040 – 2070

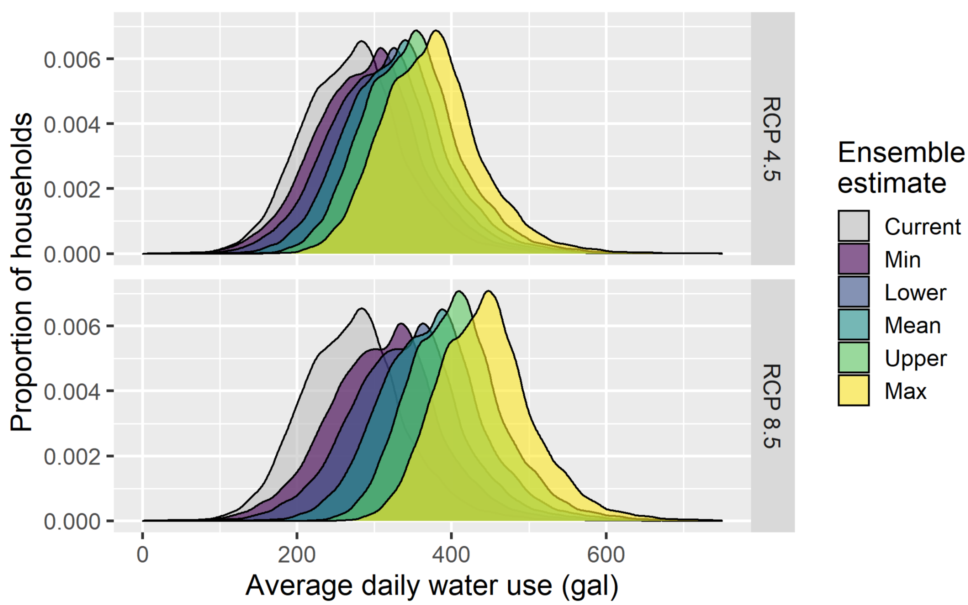


(b) NLWD proxy, average 2071 – 2099

Figure 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 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.

Table 5: Percent change in island-wide water use, corresponding to the uncertainty summarized in table (A6). 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		

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 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 (Olmstead, Hanemann, and Stavins 2007; Olmstead and Stavins 2009; Mansur and 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 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 (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.

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Table A1: 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

A Appendix

A.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 (A1), 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.

A.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,

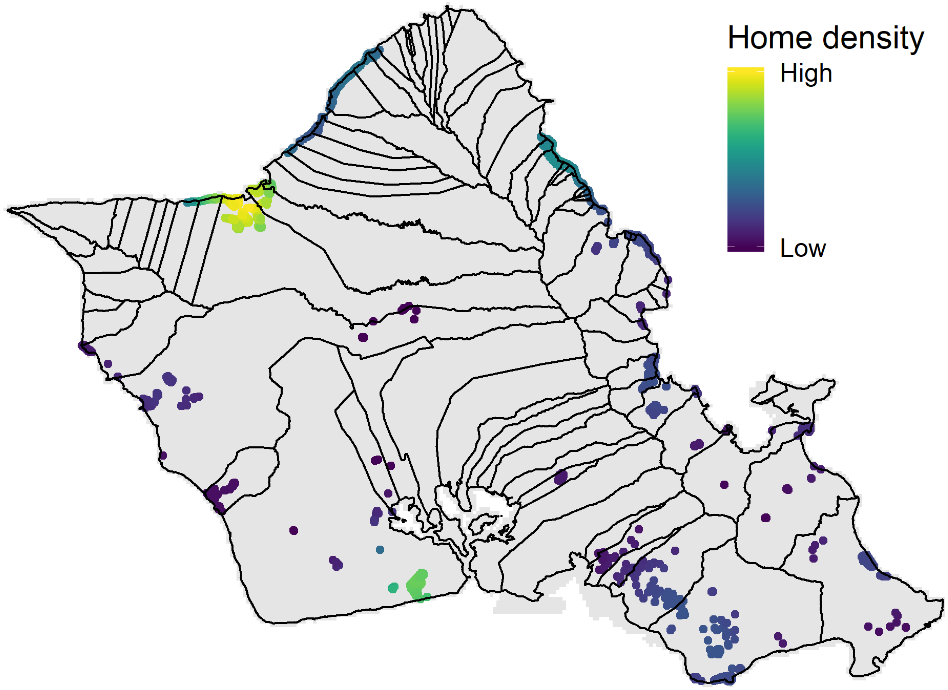

Figure A1: Location of homes with OSDS. Point color indicates the density of the homes.

on average. Figure (A1) 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 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 (A2) is a recreation of the results presented in table (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.

Table A2: Reproduction of table (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

A.3 NWLD and NLWD proxy comparison

Whether or not the models resulting from equations (1) and (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 (A3) compares the coefficients of table (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[6] 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%.

A.4 Ahupuaʻa-level regressions

In our main specification, equation (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 (A2). 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

[6] 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 A3: Comparison of coefficients of NLWD and NLWD proxy when regressed with water use. Columns correspond to models in table (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

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 (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 (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.

A.5 Dependent variable placebo tests

Table (A4) 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,

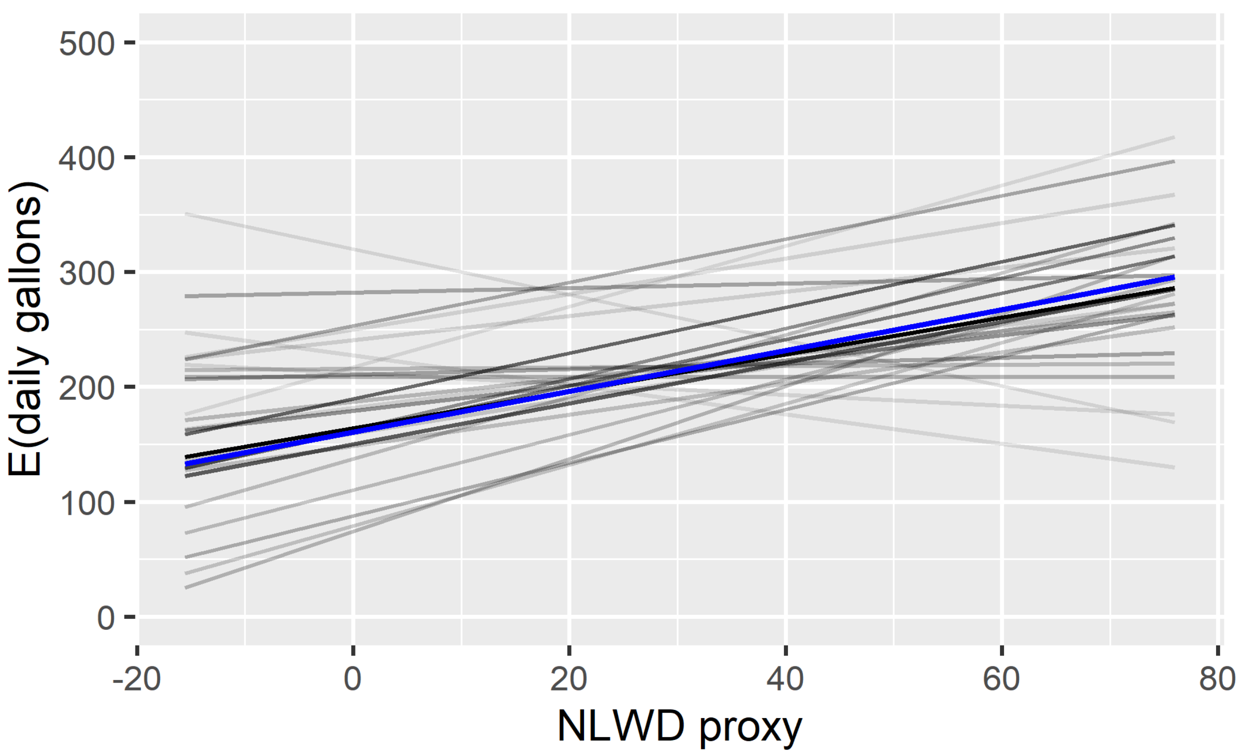

Figure A2: Regressions by ahupua'a. The model from equation (3) was run on individual ahupua'a and plotted here. Each regression line represents one ahupua'a. Line shading represents the standard error of the corresponding coefficient, with darker lines indicating a smaller standard error. The blue line is the weighted average of all regression lines, and has a slope of 1.78. Compare this to the corresponding coefficient in table (4) specification (6), which has a value of 1.80.

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 (A5) summarizes 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 A4: 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 A5: Mean and median values of dependent variables by watershed region. These are the household characteristics used for the placebo tests in table (A4)

Dependent variable	Regional mean (median) value							
	Central O‘ahu	East Honolulu	‘Ewa	Ko‘olauloa	Ko‘olaupoko	North Shore	Primary Urban Center	Wai‘anae
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)

A.6 Climate model uncertainty

Table (A6) 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 A6: 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