TOURISM WATER USE DURING THE COVID-19 SHUTDOWN

A natural experiment in Hawai‘i

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Abstract. Many popular tourist destinations are on small islands whose resources are in limited supply, and the effects of climate change and burgeoning tourism tend to worsen the outlook. In this study, we identify the relationship between tourism and water use on the Hawaiian island of O‘ahu. Hawai‘i closed almost entirely to tourism during the COVID-19 pandemic, which provides a unique natural experiment to study the relationship between tourism and water use. We estimate a 1% decline in the number of tourists was associated with a 0.4% to 0.65% lower water use in the hotel sector. However, no such relationship was found in the Airbnb market, which we hypothesize is due to work-from-home arrangements in the residential sector during the pandemic.

Keywords: Tourism, water demand, COVID-19

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Highlights

- The tourism shutdown on Oʻahu during COVID-19 provided a unique natural experiment
- A variety of data sources and methods were used to study the effect on water use
- Water consumption in hotels dropped significantly, as expected
- No measurable change in water use was detected in residential areas with Airbnbs

Author contributions

- Nathan DeMaagd – Conceptualization, methodology, software, formal analysis, data curation, writing - original draft, visualization
- Peter Fuleky – Conceptualization, methodology, formal analysis, supervision, funding acquisition, project administration, writing - review and editing
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1 Introduction

Water security is often understood as the capacity of a population to safeguard access to water resources in sufficient quantity and quality to sustain livelihoods and socio-economic development (United Nations Educational and Organization 2012). Globally, more than 600 million people do not have access to clean drinking water and a staggering 2.4 billion lack adequate sanitation (Economist Intelligence Unit 2017). Maintaining adequate freshwater supplies in Pacific islands is of particular concern as sea-level rise, changing temperature, and shifting rainfall patterns stress fragile water resources (Mcleod et al. 2019; Izuka and Keener 2013). As acknowledged at the 2021 United Nations Climate Change Conference, water is the primary medium through which humanity will feel the effects of climate change (United Nations Climate Change Conference COP26 2021). The importance of water management is accentuated when there is near complete reliance on groundwater as in Hawai'i, where 99% of drinking and half of all water use is sourced from aquifers (Izuka, Engott, et al. 2018; Holding et al. 2016; Tribble 2008). While the situation has not yet escalated to a dire stage on the island of O'ahu, which accommodates Honolulu, the capital of and largest city in Hawai'i, there is growing evidence that available freshwater resources on the island have been diminishing over time (Bassiouni and Oki 2013; Bremer et al. 2021).

In most countries, the tourism sector comprises less than 5% of total domestic water use (Gössling 2015), but hotels and resorts tend to be intensive water users (Environmental Protection Agency 2012). In 2019, the number of tourists was about 17% and 12% of the resident population in the state of Hawai'i and the island of O'ahu, respectively, so it is important to understand the impact of the tourism industry on the precariously-balanced water supply. This is especially true given the potential climate change effects on water availability and further expansion of the tourism industry. Although tourism only increases global water consumption by less than 1% and this is not forecasted to increase significantly in the future, an increase in tourism may strain water resources in regions of the world where tourism is highly concentrated (Gössling et al. 2012). Regions like Nicaragua (LaVanchy 2017) and islands such as Bali (Cole 2012; Sudiajeng et al. 2017) and Zanzibar (Gössling 2001) whose economies rely heavily on tourism already show evidence of unsustainable groundwater use. Further, in many of these regions where the tourism sector out-competes residents for water resources, some of the negative effects may not be equally distributed, with lower-income residents (Stonich 1998) and women (Cole 2017) potentially experiencing greater adverse outcomes.

In the case of Bali, research into the relationship between tourism and water use has been instrumental in raising awareness and shaping public policy (Cole, Wardana, and Dharmiasih 2021). While tourists' perceptions of their environmental impact have been shown to have a measurable effect on their actual environmental impact (Hillery et al. 2001), additional experimental results suggest that active engagement with tourists can have a greater effect on water sustainability than passive engagement (León and Araña 2020).

This concentration of tourism and the effects it may have on water resources is emerging as a concern in Hawai'i, and on O'ahu in particular, where the number of tourists visiting the state/island grew by 50% between 2009 and 2019 (see Fuleky, Zhao, and Bonham 2014; Hirashima et al. 2017, for recent estimates of tourism demand in Hawaii). However, unlike the developing economies of the aforementioned locations, O'ahu is a tourist destination with a highly-developed economy where the strain on water resources is a concern even without consideration of tourism-specific use. As a case in point, the recent contamination of Honolulu's primary drinking water source by a fuel leak could result in a moratorium on new construction, closure of swimming pools, and limiting irrigation of city parks (Bonham et al. 2022). Residential water consumption on the island accounts for about 55% while hotels and resorts account for about 5% of total municipal water use but, in per-capita terms, tourists use approximately the same amount of water as residents. Thus, our study serves to be one of the first to examine tourism and water use on a dense, urban island. We aim to answer two main research questions with our work:

1. What is the net effect of tourism on water resources on O'ahu and did the shutdown of tourism produce noticeable changes in water consumption, and

2. What is the mechanism by which these changes in consumption operate? How much of the change can be linked to reduced hotel occupancy, reduced Airbnb occupancy, and other factors such as reduced tourism-related business patronage?

The majority of previous literature on the topic of tourism and water use has largely focused on direct water use by tourist infrastructure such as hotels, swimming pools, spas, golf courses and water parks (Charara et al. 2011; Gössling 2001; Hof and Schmitt 2011; Rico-Amoros, Olcina-Cantos, and Saurí 2009; Deyà-Tortella and Tirado 2011). We also start with a direct approach, examining how water consumption is related to tourism infrastructure utilization. We first analyze the relationship between tourism levels and the associated changes in hotel water consumption, while controlling for other variables like temperature and rainfall that are expected to affect water use decisions. We also examine the connection of water use to transient vacation rentals, specifically, we analyze water use in residential neighborhoods as a function of Airbnb reservations. Finally, we use granular data representing daily foot traffic at tourism-related businesses such as restaurants and other so-called "points of interest" in high traffic tourist areas to examine indirect water use outside of hotels and accommodation, a component of tourism-related water consumption that has received considerably less attention in the existing literature. The underlying data comes from SafeGraph[1], which tracks the locations of cellular devices to determine where and how long residents and tourists stay at various locations. Throughout the paper, we refer

[1] https://www.safegraph.com

to SafeGraph tracking data as *foot traffic* to differentiate it from tourist counts. We hope these results may be used in other studies examining tourism projections to understand the effect of future trends on water use.

Our main source of identification of the tourism/water consumption relationship is the large-scale statewide shutdown of tourism due to the COVID-19 pandemic, which has had a significant impact on the global tourism industry through its effects on travel restrictions, shutdowns, and tourist sentiment (Liu, Kim, and O'Connell 2021; He et al. 2022; Williams et al. 2022; Xiang et al. 2022). This event provides a unique natural experiment to study the relationship between tourism and water use on Oʻahu, and adds to the growing body of research investigating the effects of COVID-19 on tourism (Yang, Zhang, and Rickly 2021) and literature using experiments in hospitality and tourism (Viglia and Dolnicar 2020). Despite the opportunity, to date a very limited number of studies took advantage of the chance to employ a natural experiment methodology presented by COVID-19 (Yang, Zhang, and Rickly 2021). Although environmental indicators appear to have improved in some areas during the pandemic, due to observed improvements in water and air quality and corresponding improvements in linked ecosystems, much COVID-19 research related to environmental outcomes has been advocacy-driven and more speculative than empirical (Viglia and Dolnicar 2020). In Hawaiʻi, recreational travel was put on hold due to this exogenous shock, with hotel and resort occupancy dropping to essentially zero for about six months. As seen in Figure 1, the large and sudden change in the number of tourists on Oʻahu coincides with a similarly significant change in the consumption of water in these locations. We also examine how the pandemic affected water consumption at other locations, such as restaurants and residences. These results are in part likely influenced by the prevalence of transient vacation rentals such as Airbnb in residential locations, as well as a significant shift to work-from-home arrangements in many sectors. Using parcel-level water consumption data at the monthly frequency, we aim to quantify the pattern of water consumption across these various sectors on Oʻahu.

2 Data

Our analysis relied on several data sets with different spatial granularity and temporal aggregation. Monthly water use data were obtained from the Honolulu Board of Water Supply for all properties on Oʻahu for the period from February 2013 to October 2020. These data include information about billing start and end dates, and the quantity of water consumed by the property. It also provides the classification of the properties, such as commercial, hotel, single family home, high-density residential, industrial, or government. Individual properties in the data are identified by their tax map key. These tax map keys are used for identification of individual properties for all tax and other local government matters, and are used here for data matching purposes. For

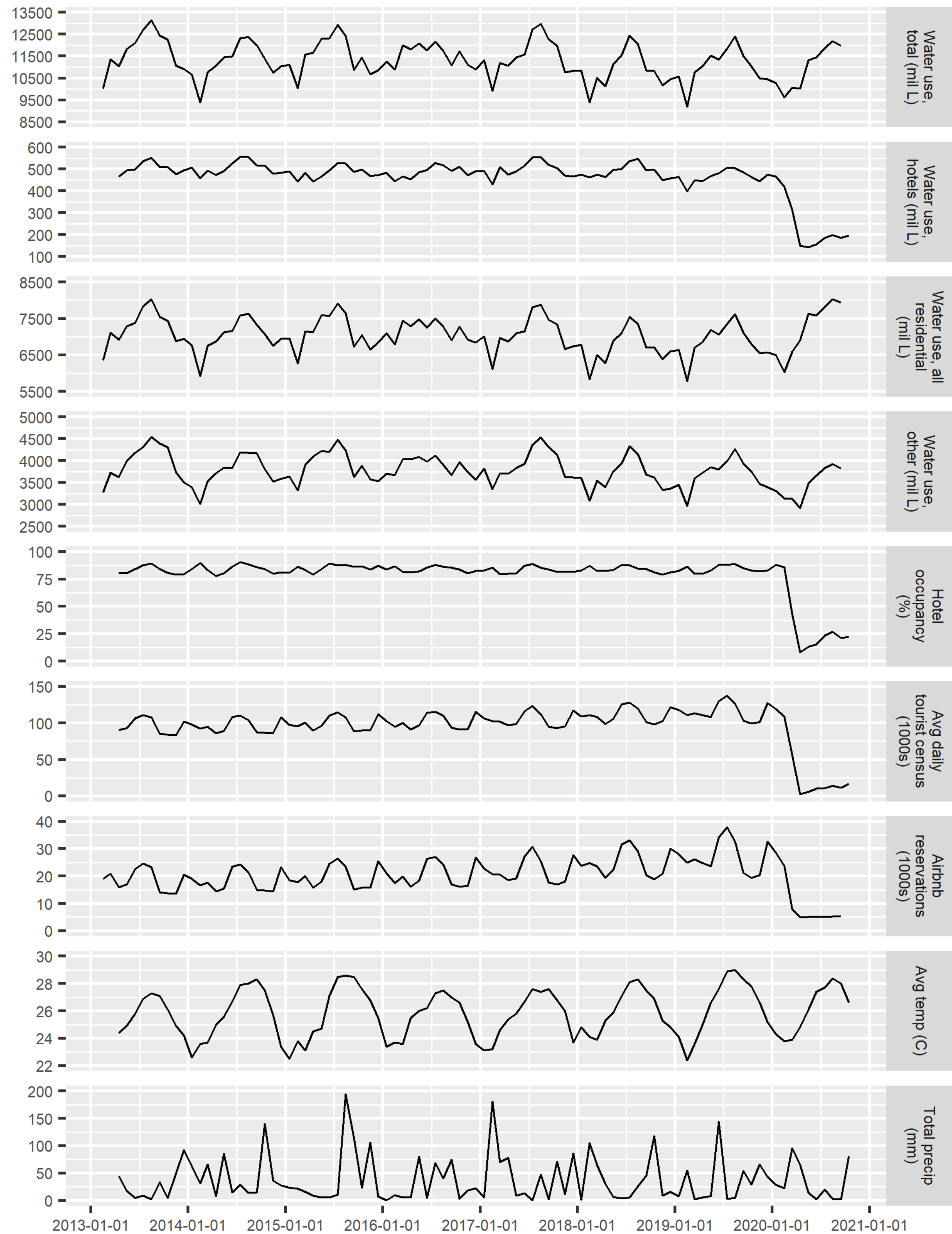

Figure 1: Aggregate (island-wide) monthly time series spanning the February 2013 to October 2020 period. Aggregate monthly water use for all other types of parcels in the fourth subplot includes offices, commercial and industrial consumers.

consistency, we refer henceforth to tax map keys and individual properties as parcels.

We obtained the monthly aggregate (island-wide) hotel occupancy data, the percent of available rooms occupied across all hotels on the island, for the sample period from February 2013 to October 2020 from the Hawai‘i Tourism Authority (2021). Although the supply of hotel rooms only fluctuated by approximately 1% over the last 5 years, some hotels effectively shut down during the COVID-19 pandemic. To make occupancy during this period comparable to the pre-pandemic period, we used the 2019 room supply to calculate occupancy rates for each month beginning April 2020 (Hawai‘i Tourism Authority 2020, p. 6).

Because seasonal weather patterns are correlated with both water use and tourist counts (see, for example, Ouyang et al. 2014; Ghimire et al. 2016), it is important to control for weather in our models. Average monthly temperature and monthly rainfall were obtained from the National Oceanic and Atmospheric Administration database for the Honolulu International Airport (National Oceanic and Atmospheric Administration 2021).

Nightly Airbnb reservation status for all units on O‘ahu from October 2018[2] to October 2020 is provided by Inside Airbnb (*Inside Airbnb* 2021). The monthly snapshots contain the reservation status for each night during the subsequent month. Since a reservation can be made or canceled between the time the data are scraped and the night of the reservation, the true occupancy status is not known with full certainty. This measurement error is assumed to be random. Because most Airbnb listings provide only an estimated location and not the exact location of the rental, data were aggregated to a grid as shown in Figure 2. Each grid cell measures one square kilometer, and we calculated each cell's aggregate monthly water use, expected Airbnb occupancy, number of residential units (with and without Airbnbs), and Airbnb density using the data above. These grid cells then become the observational units in one of the models discussed below. Figure 2 shows an aggregated time series for the data used in our hotel and Airbnb analyses. The significant drop in hotel water use in the first quarter of 2020 coincides with the decrease in tourism due to the COVID-19 pandemic but residential units see an overall increase in water use, which we hypothesize is likely due to the significant increase in work-from-home arrangements for residents of the island.

Overall, in our sample period, there are about 245,000 unique residential units on O‘ahu, of which less than 10,000, or 4%, were listed as unique transient vacation rental units at least once during the same period. As we discuss in the following sections, because the concentration of Airbnb units relative to total residential units can be quite low in many grid cells, we also perform robustness checks that limit the data to those cells with high concentrations of Airbnbs.

Finally, we use data compiled by SafeGraph to track foot traffic at various points of interest on O‘ahu. These data rely on mobile phone GPS tracking to provide information on visited loca-

[2] As we will discuss in detail in Section 3, we supplement this data with predicted Airbnb reservation status before October 2018 in order to make use of the full time series of our other datasets.

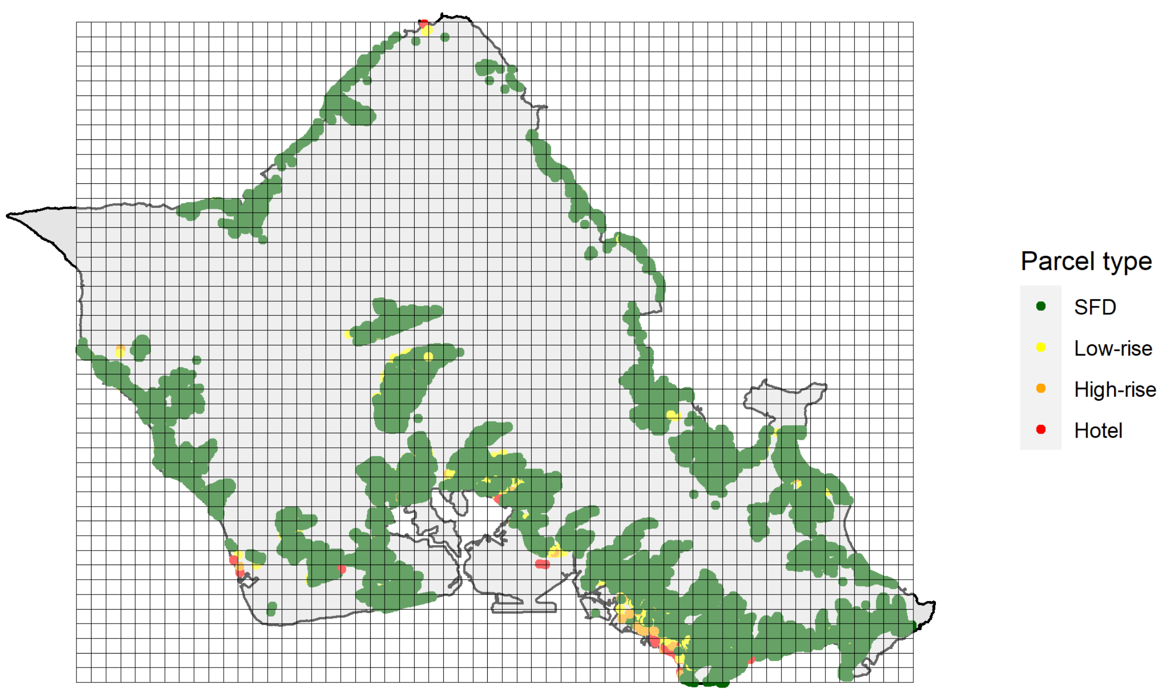

Figure 2: 1km×1km grid over all residential and hotel parcels on O'ahu. Because Airbnb locations are not exact, data were aggregated to a grid for analysis. SFDs are single family dwellings, and low- and high-rise are residential apartment and condominium units.

tions, dates of visits, and duration of stay. Points of interest include hotels, but also other public spaces like parks, restaurants, and retail outlets. Because not all patrons at a given location may have mobile phones, or location tracking services may otherwise be unavailable, foot traffic information can only be used to estimate the relative levels of patrons at the island's points of interest. We assume that the fraction of patrons who have a tracked mobile phone stays relatively constant over time, so that a percent change in the number of tracked visits to a point of interest approximates the true percent change in the number of overall visits to that location. Also note that the patrons can be either residents or tourists, so some GPS signals would still be observed even with a complete loss of tourism.

3 Empirical strategy

Next we describe several modeling and estimation approaches, tailored to the data sets in our analysis. The models range from the aggregate to the fairly granular, depending on the spatial resolution of the particular variables used. The methods, in conjunction with the data, help us analyze water consumption from several perspectives.

3.1 Hotel water use and aggregate tourism measures

Our first model uses a time series regression of monthly hotel water use on monthly island-level predictors, *estimated individually for each hotel.* In other words, each hotel's water consumption is modeled as a hotel-specific fixed amount of water consumption, plus hotel specific sensitivity to island-wide seasonal and tourism components. The seasonal components include temperature and precipitation, and the tourism component includes the hotel occupancy on O‘ahu. Specifically, we are analyzing the following random coefficient model

$$\log\left(Water_{it}\right) = \alpha_{0i} + \alpha_{1i}\log(Occup_t) + \alpha_{2i}Temp_t + \alpha_{3i}\log(Rain_t) + u_{it}, \quad \text{for each hotel } i. \quad (1)$$

The random coefficient model framework (see for example Hsiao and Pesaran 2008) allows us to consider series that do not have cross-sectional variation, such as island-wide indicators of tourism and seasonality. After running a time series regression for each hotel i, we collect the estimated coefficients to obtain their distribution across all hotels. The aggregate effect and the associated uncertainty can be obtained via the mean and variance of the individual coefficient estimates. In the equations above, $Water_{it}$ is the water use in hotel i in month t, α_{0i} is a hotel-specific fixed amount of water consumption, $Occup_t$ is the aggregate occupancy rate of hotels on O‘ahu in month t, $Temp_t$ is the average temperature in degrees Celsius on O‘ahu in month t, $Rain_t$ is the aggregate monthly rainfall in millimeters on O‘ahu in month t, and u_{it} is the error term. Note also that we use the notation $log(\cdot)$ to denote the natural log, which allows us to interpret coefficient estimates approximately as percent changes or elasticities. We maintain this notation throughout. Although the occupancy rate is recorded as a percentage, without the log-transformation of this variable the estimated a_{1i} parameter in Equation 1 would not be comparable to other models. For example, when the occupancy rate is at 50%, a one percentage point increase or decrease in the original units to 51% or 49%, respectively, is actually a two percent change ($0.01/0.50 = 0.02$). The model in Equation 1 estimates the relationship between individual hotel water use and aggregate tourism activity, while controlling for island-wide weather[3]. Next we turn to models utilizing more granular explanatory variables.

3.2 Point of interest water use and SafeGraph data

To exploit the full panel of water consumption that contains hotels but also includes other commercial locations like malls and restaurants, we use foot traffic data from SafeGraph. While water consumption is available at the parcel level, SafeGraph data can be even more granular when there are multiple individual points of interest within a parcel. For example a building may contain several restaurants, but we only have water billing data for the whole building. To maintain compatibility with water consumption, we use the number of patrons aggregated to the parcel level. We use the term "patron" instead of "tourist" since we cannot differentiate between traffic by tourists and residents at various points of interest. Just like in Section 3.1, we use the random coefficient framework to estimate the relationship between water consumption and total patrons. First, for each parcel i we run the time series regression

$$\log\left(Water_{it}\right) = \beta_{0i} + \beta_{1i}\log\left(Patron_{it}\right) + \beta_{2i}Temp_t + \beta_{3i}\log(Rain_t) + u_{it}, \quad \text{for each parcel } i \tag{2}$$

where $Water_{it}$ is the water use for parcel i in month t, β_{0i} is a parcel-specific fixed amount of water consumption, $Patron_{it}$ is the patron count (i.e., the number of devices tracked by SafeGraph), and u_{it} is the error term. Once we have the distribution of coefficient estimates from the individual time series regressions, we can calculate their mean and variance to estimate aggregate effects. The random coefficient model allows us to keep the cross-sectionally invariant temperature and rainfall in the model.

For comparison with the random coefficient model, we also run a two-way fixed effects re-

[3]As noted in the data section, we only have temperature and precipitation readings for Honolulu International Airport which is located in a central location of the island, only 5 miles (8 km) from Waikiki, the center for tourism on O'ahu. The overwhelming majority of hotels typically experience similar rainfall and temperature, hence there is no need for parcel specific weather variables in our models.

gression with the full panel data

$$\log(Water_{it}) = \beta_{0i} + \beta_1 \log(Patron_{it}) + Month_t + u_{it}. \tag{3}$$

In this model, β_{0i} is the parcel-specific fixed water consumption and $Patron_{it}$ is the number of patrons at parcel i in month t. In contrast to Equation (2), β_1 is forced to take on the same value across all parcels. The time series regressions in Equation (2) allowed us to control for temperature and rainfall — which did not vary spatially in our data — via the location specific β_{2i} and β_{3i} coefficients. Here we replace the island-level temperature and rainfall controls with a month fixed effect, $Month_t$, to avoid collinearity, since we use the full panel data set all at once.

A similar model can be used to study the relationship between water use and foot traffic differentiated by parcel type. For example, the impact of patrons on water use in hotels may differ from that in restaurants. The water billing data contains the type of the parcel, which we include in a two-way fixed effects regression with type-specific patron impacts

$$\log(Water_{it}) = \beta_{0i} + \sum_{j=1}^{J} \beta_j \log(Patron_{it}) \times Type_j + Month_t + u_{it}. \tag{4}$$

Again, β_{0i} is the parcel-specific fixed water consumption, $Month_t$, is a month fixed effect, $Patron_{it}$ denotes the number of patrons to parcel i in month t, and $Type_{j=1\ldots J}$ are indicator variables assigning the parcel to one of J type categories: city government, commercial, city park, hotel, mixed use, religion, and other miscellaneous types[4].

3.3 Airbnb occupancy empirical strategy

For the Airbnb analysis using our gridded data described above, we again use a two-way fixed effects regression. The empirical model estimating the relationship between residential water use and Airbnb reservations is thus

$$\log(GridWater_{it}) = \gamma_{0i} + \gamma_{1i} \log(BnbRes_{it}) + month_t + grid_i + u_{it}, \text{ for each grid cell } i, \tag{5}$$

where $GridWater_{it}$ is the quantity of water consumed by the residential units in grid-cell i in month t, $BnbRes_{it}$ is the last known Airbnb reservation status in grid-cell i in month t, $month_t$ and $grid_i$ are monthly and grid fixed effects, respectively, used to control for spatial and temporal effects, and u_{it} is the error term. We do not have Airbnb occupancy data before October 2018, so

[4]These include all types of residential parcels, industrial parcels, and other types we group together in the analysis that are less relevant when studying the effect of human pressure (approximated by foot traffic) on water use.

Table 1: Summary table describing which datasets are used in each analysis. "Hotel" refers to models using aggregate tourist measures, "POI" refers to the parcel-level analysis using the panel of billing data and SafeGraph point of interest foot traffic data, and "Airbnb" refers to the grid cell-level analysis of Airbnb reservations.

Model	Data				
	Water use	Aggregate tourism	Temperature and rainfall	Airbnb reservations	SafeGraph foot traffic
Hotel	X	X	X		
POI	X		X		X
Airbnb	X		X	X	

we impute the missing data with predicted values from the model

$$BnbRes_{it} = \delta_{0i} + \delta_1 Tour_t + v_{it}, \text{ for each grid cell } i. \tag{6}$$

That is, using available data for the period from October 2018 to October 2020, we estimate a regression of monthly grid-level Airbnb reservations on aggregate monthly tourist counts, with grid cell fixed effects δ_{0i} and error term v_{it}. Using the estimated coefficients in Equation (6) and actual tourist numbers before October 2018, we impute grid-level Airbnb reservations before October 2018, which we denote $\widehat{BnbRes}_{it}$, and Equation (5) becomes

$$\log\left(GridWater_{it}\right) = \gamma_{0i} + \gamma_{1i}\log\left(\widehat{BnbRes}_{it}\right) + month_t + grid_i + w_{it}, \text{ for each grid cell } i, \tag{7}$$

where w_{it} is the new error term. Many grid cells have low numbers of Airbnb units relative to the number of residential units, which can obscure the effect of Airbnb occupancy. Therefore we run this model with several Airbnb concentration cutoffs as a robustness check. Table 1 summarizes which datasets are used in which analyses.

4 Results

In the following subsections we discuss the results obtained in each of the models described above.

4.1 Hotel water use and aggregate tourism results

We first present the results of Equation (1), where we regress water use on hotel occupancy with controls for weather, in Table 2. Here, a 1% lower hotel occupancy is associated with a 0.46% lower hotel water use, on average (since the main identification channel is the COVID-19-related shutdown, we interpret the coefficients with a weakening economic environment in mind).

Table 2: Regression results corresponding to Equation (1). For each of the 74 hotels in our data, a time series of monthly water use is regressed onto a time series of aggregate tourism measures, with controls for aggregate monthly weather. The mean coefficient estimates across all regressions are reported, along with their corresponding standard errors in parentheses.

	Dependent variable:
	Log mean water use (L/day)
	(1)
Log hotel occupancy	0.46***
	(0.058)
Avg. temp. (C)	2.82e-3
	(0.019)
Log total precip. (mm)	2.35e-3
	(0.025)
Constant	9.06***
	(1.64)
Number of hotels	74
Number of time periods (months)	93
Mean R^2	0.519
Mean Adj. R^2	0.502
Mean Resid. Std. Error (df = 89)	0.317
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3: Random coefficient model results corresponding to Equation (2). For each parcel, a time series of water use was regressed on the associated aggregate number of patrons at the parcel identified by SafeGraph cellular device tracking. Time series of temperature and rainfall were included as controls. The table presents the aggregated results of the random coefficient model: the means of the individual coefficients are reported, along with their standard errors in parentheses.

	Dependent variable:
	Log mean water use (L/day)
	(1)
Log patron count	0.16^{***}
	(0.013)
Avg. temp. (C)	0.017^{***}
	(2.89e-3)
Log total precip. (mm)	-0.016^{***}
	(1.49e-3)
Constant	8.78^{***}
	(0.10)
Number of parcels	5060
Number of time periods (months)	31
Mean R^2	0.262
Mean Adj. R^2	0.157
Mean Resid. Std. Error (df = 27)	0.429
Note:	*p<0.1; **p<0.05; ***p<0.01

4.2 Point of interest water use and SafeGraph results

Table 3 presents the results corresponding to Equation (2). As noted in Section 3, the results are the average estimates in a random coefficient model, where the monthly water use of each parcel was regressed onto the monthly patron count at that parcel with controls for monthly weather. The average coefficient of 0.16 suggests that a 1% lower patron count at a parcel is associated with an expected 0.16% lower water use at that parcel. The standard error of this mean coefficient is about 0.01.

With the random coefficient model, we obtained one regression result for each parcel, which allowed the coefficient of interest, log patron count, to vary for each parcel. To check whether the aggregated mean of these coefficients presented in Table 3 is robust to the estimation method, we

Table 4: Regression of parcel water use onto SafeGraph foot traffic using the full panel data. In column 2, foot traffic is interacted with parcel type to compare the sensitivity of select location types to foot traffic. The 'Other' category includes state government, industrial, golf courses, all residential parcels, irrigation, agriculture, federal government, and fire hydrants. Parcel and month fixed effects are included. Errors are clustered by parcel and month.

	Dependent variable:	
	Log mean aggregate water use (L/day)	
	(1)	(2)
Log patron count	0.191***	
	(0.027)	
Log patron count × City gov't		0.139**
		(0.053)
Log patron count × Commercial		0.273***
		(0.036)
Log patron count × City park		0.160**
		(0.065)
Log patron count × Hotel		0.356***
		(0.035)
Log patron count × Mixed use		0.133***
		(0.042)
Log patron count × Religion		0.204***
		(0.055)
Log patron count × Other		0.084***
		(0.019)
Month FE	**Yes**	**Yes**
Parcel FE	**Yes**	**Yes**
Observations	145,182	145,182
R^2	0.940	0.940
Adjusted R^2	0.938	0.938
Residual Std. Error	0.564 (df = 140133)	0.562 (df = 140127)
Note:		*p<0.1; **p<0.05; ***p<0.01

run a panel regression with the same data using Equation (3). Because temperature and rainfall vary only by time, not spatially, we cannot use them in a standard panel regression, and we replaced them with month fixed effects. Unlike the random coefficient model where each parcel has its own coefficients, the panel model forces the coefficient to take the same value for all parcels. The results of this robustness check are given in column 1 of Table 4. The coefficient on log patron count, 0.191, is similar to the coefficient in Table 3, confirming there is little difference between aggregating coefficients from the random coefficient model and the single coefficient of the panel model.

The panel regression also enables us to examine the differences in the relationship between water use and patron count across location types. In column 1 of Table 4, the coefficient 0.19 is much smaller than the coefficient estimates we found with our aggregate model for hotels in Section 4.1. One reason for this result is that the data used for the present model includes a wide variety of locations. In addition to hotels, it includes public parks and other government buildings, retailers, restaurants, etc. Reporting only a single coefficient for all location types may hide a wide range of coefficients whose magnitudes may depend on the type of locations the parcels represent. In column 2 of Table 4, we extend the panel model to include interactions with parcel type using Equation (4). Note that this model includes all parcel types but, for table size purposes, only select parcel types are reported. The 'Other' category includes those types that were not reported separately: state government, industrial, golf courses, all residential parcels, irrigation, agriculture, federal government, and fire hydrants.

The parcel type interactions reveal the variation in the coefficient we expect; specifically, for hotels, a 1% lower patron count is associated with a 0.36% lower water use, which is a much larger difference than the 0.19% found when all location types were pooled. Note, however, that this coefficient is still smaller than the estimate we found in our regression using hotel occupancy (0.46%). One reason for this may be that some foot traffic in and around hotels is not attributable to hotel guests and therefore does not result in large amounts of water use. For example, many hotels on the beach may experience foot traffic that does not result in the use of hotel facilities. This would lead to a lower coefficient than we would expect to see if we measured only hotel guests. Commercial locations have a significant coefficient likely because they often contain businesses whose water use is highly dependent on the number of patrons, like restaurants. The accuracy of estimation is better when there is clear separation of a parcel from its surroundings and from unrelated foot traffic, which is likely the case for religious institutions. In contrast, the foot traffic signal in city parks and at mixed use parcels is likely quite noisy. For parcels containing multiple point of interest locations like malls, we cannot further disaggregate the analysis since we only have water use at the parcel level rather than the point of interest level. Finally, recall that the data only track patrons with cell phone signals, and we assume the proportion of those with and without cell phones remains relatively stable throughout the study period. If, however, this proportion changes, the true foot traffic may differ from the observed foot traffic and bias our results. Still, we believe we can glean useful information about how water use at various types of businesses may be associated with the number of patrons they receive.

4.3 Airbnb occupancy results

The results of the Airbnb reservation analysis in Equation (7) are reported in Table 5. Note that each column is a separate model, where we limit the data to grid cells with higher and higher concentrations of Airbnb units. Airbnb density within grid cell g is calculated by finding

$$Airbnbdensity_g = \frac{TotalAirbnbunits_g}{Totalresidentialunits_g}.$$

That is, within a grid cell, the density of Airbnb units is the ratio of the number of Airbnb units within the grid cell to the total number of residential units in the grid cell. Results for Airbnb density percentiles 50%, 75%, and 90%[5] indicate that the coefficient estimate on the variable of interest (log-transformed Airbnb reservations) is neither statistically nor economically significant even in those grid cells with high concentrations of Airbnb units. This suggests that reservation status, and thus Airbnb occupancy, have no significant measurable effect on water usage at an aggregate level in our data. A robustness check using a random coefficient modeling strategy confirms these results.

There are several potential reasons behind this result. First, due to uncertainty regarding the exact locations of Airbnb units, some error may have been introduced when sorting the Airbnb units into the 1 km^2 grid cells. To test for this we run the model with units aggregated to a 2 km^2 grid instead of the original 1 km^2 grid. This will reduce the error associated with sorting Airbnbs with an imprecise location into a grid, but necessarily reduces the number of observations. The results of this model are not significantly different from the original results presented in Table 5.

Second, during the COVID-19 related shutdown of tourism there was an offsetting shift in residential behavior. A precipitous drop in tourism almost certainly led to a similarly sharp reduction in water use at Airbnb hosts. Unfortunately, the data does not allow us to isolate individual Airbnb locations from residential ones. During the shutdown, residents spent much more time at home due to loss of employment, work-from-home arrangements, and/or a lack of participation in activities that would have brought them out of their homes (Fuleky 2021). In fact, SafeGraph data suggest that the fraction of island residents staying at home for the entire day doubled from about 20% prior to the pandemic to 42% in April of 2020 (Tyndall and Hu 2020). In short, we

[5] For reference, Airbnb density is 3.6% in the median grid cell, 12.7% in the 75th percentile cell, and 46.2% in the 90th percentile cell.

Table 5: Results corresponding to Equation (7). Column (1) uses all grid cells in the data, whereas columns (2) through (4) limit the data to the indicated grid-level Airbnb density percentiles. Density is calculated as the number of Airbnb units relative to total residential units in the grid cell. Fixed effects for month and grid cell are included. Errors are clustered by grid cell and month.

	Dependent variable:			
	Log mean aggregate water use (L/day)			
	(1)	(2)	(3)	(4)
Log Airbnb reservations	0.0002	0.005	−0.002	−0.011
	(0.002)	(0.007)	(0.009)	(0.019)
Airbnb density percentile	All data	50th	75th	90th
Month FE	**Yes**	**Yes**	**Yes**	**Yes**
Grid FE	**Yes**	**Yes**	**Yes**	**Yes**
Observations	33,368	16,367	8,187	3,364
R^2	0.982	0.786	0.731	0.704
Adjusted R^2	0.981	0.782	0.725	0.691
Residual Std. Error	0.212 (df = 32843)	0.245 (df = 16070)	0.315 (df = 7995)	0.451 (df = 3229)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

hypothesize that any decrease in water use at Airbnbs during the shutdown may have been offset by residents consuming more water while staying at home.

These results and their robustness checks leave us with the conjecture that the insignificant results are likely driven by a change in resident behavior during the COVID-19 pandemic, rather than by data limitations. In Section 4.1 where residents were not a confounding factor, the COVID-19 shock helped to identify the relationship between tourism and water consumption. Here the decline in water consumption due to the lack of tourists appears to be offset by an increase in water consumption due to residents staying at home. Though we are unable to formally test this hypothesis using the available data, our conjecture is supported by the unusually high residential water use observed during the pandemic, also visible in Figure 1.

5 Discussion

In summary, this study aims to measure the relationship between tourism and water use on the island of Oʻahu using several different strategies. First, we analyze aggregate tourist counts and their association with aggregate hotel water use. When tourism is measured by hotel occupancy, a 1% lower occupancy is associated with a 0.46% lower water use. The lack of a 1-to-1 relationship (i.e. a 1% change in occupancy does not equate to a 1% change in hotel water use) may be due to large fixed water uses by hotels such as landscape irrigation and pools.

We also aim to understand what the decline in mobility may reveal about patterns of water use at various points of interest in Hawai‘i. When we measure location visits with SafeGraph foot traffic data, our results suggest that a 1% lower foot traffic in hotels is associated with about a 0.36% lower water use in hotels. Here the low coefficient value may be due to the fact that not all foot traffic visiting the hotel comes from hotel guests. For example, many hotels have beaches and other attractions that may cause foot traffic to be on-location long enough to enter our data set, but ultimately use little to no water during their stay. We were also able to show that water consumption at various points of interest had different sensitivities to foot traffic depending on the location type.

Finally, considering our results and conclusions from the hotel water use above, we turned to Airbnb water use to see how much more water use could be explained by tourists who choose these accommodations. Regardless of our model, we were unable to estimate any relationship that was significantly different from zero, despite many tourists choosing to stay in these rentals and a clear decline in reservations during the pandemic. We think that the drop in Airbnb reservations during the COVID pandemic, which we hoped to use for identification, was offset by an increase in work-from-home arrangements for residents of the island. The decrease in water use from a lack of Airbnb reservations may then be offset by residents staying home and consuming more water there. Indeed, if we look again at Figure 1, we see that aggregate residential water use increased in 2020 compared to previous years. Limitations with the data that prevented us from accurately matching households and Airbnb units may have also been a contributing factor.

Looking ahead, the importance of understanding the relationship between water use and transient vacation rentals such as Airbnbs relative to hotels and resorts may become less important on O‘ahu, as the number of vacation rentals has recently been significantly limited by local policymakers. However, this will not be the case in all locations across the country. A similar analysis may prove beneficial to understand this relationship in other tourist destinations that have a high number of vacation rentals, so long as it does not suffer from the same difficulties as our COVID-period study. Gaining a better understanding of the relationship between water use and vacation rentals relative to hotels and resorts would help to inform policy decisions that could potentially incentivize tourists to shift from one accommodation type to the other, e.g., more stringent permitting requirements for vacation rentals or increased hotel taxes.

An additional point worth discussing is the analysis using foot traffic data and the makeup of tourists before, during, and after the COVID shutdowns. As mentioned in the data section above, foot traffic is measured only by tracked cell phones, whose visited locations and duration of stay can be determined. We thus likely only have a small sample of the overall number of tourists to a location, which we assumed remained a constant fraction of total tourists over time. There is a possibility that this may not be the case, since during the shutdown the makeup of tourists (and even local families visiting various locations) may have changed to some degree.

The pandemic and its effects on the economy of Oʻahu allowed for an interesting study of the shifts in water consumption behavior before and during the large-scale shutdowns of tourism and other related commercial activities, along with the potential effects of a shift to work-from-home arrangements for many residents. However, care should be taken when interpreting the results beyond the scope of this analysis. The significant disruptions caused by the pandemic followed in the wake of extremely high capacity utilization in the tourism industry. The negative shock created (temporary) “slack” in the system, and we likely only observed a partial adjustment in water consumption. Since most hotels did not completely shut down, there remained a “fixed” amount of water consumption, for example for pools and other amenities. Consequently, we expected our coefficient estimates to be less than one, while a complete shutdown of hotel operations may have resulted in estimates closer to one. Further work will be required to determine whether our results carry over for more marginal changes, like a gradual change in tourism over time. Also, had the tourism industry experienced a positive shock, it would have been pushing against existing capacity constraints, a different situation from ours. Applying the relationships found here to an increase in tourism may not be appropriate since increases and decreases in tourism may affect water consumption asymmetrically.

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